PRECISION LIVESTOCK FARMING APPLICATIONS

edited by:
Ilan Halachmi

Precision livestock farming applications

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Making sense of sensors to support farm management

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Editorial

In 2014, the EU-PLF[1] dissemination committee and the EAAP[2] program committee made a creative and farsighted decision to associate EU-PLF with the EAAP annual meeting in Copenhagen in August 2014. As far as I am aware, this was the first international symposium on Precision Livestock Farming (PLF) that was held by an animal science federation. This symposium was a joint-venture of the EU-PLF project and the three EAAP scientific commissions 'cattle production', 'pig production', and 'health and welfare'. The special joint-session held on 25 August 2014 finally resulted in the publication of this book.

The aim of the joint-session was to facilitate 'cross-disciplinary' discussions focusing on real-time interpretations of animal response and its associated management actions. Several livestock sectors and multidisciplinary science participated in the discussions: (1) animal sensing technology (start-up companies and sensor developers, either active in research institutions and universities or in the R&D departments in the private-sector); (2) matured industries, such as retailers, animal feed suppliers, farm equipment providers, farm designers and vets (all active in the livestock sector, animal farms and other industries along the animal and human food chains); and (3) animal geneticists, nutritionists and health experts (i.e. all aspects of animal-focused scientists, zoology, biology and environment scientists and farmer organizations that usually participate in an EAAP annual meeting). Unique of this 'cross-disciplinary' approach is that 'animal-focused' scientists, engineers, companies, as well as farmers' organizations interacted and combined their strengths and views. 'Precision Livestock Farming Applications – making sense of sensors to support farm management' therefore provides an update on the state of the art of PLF in interaction with the other scientific and applicative expertise.

The structure and strategy of the joint-session encouraged a 'cross-disciplinary atmosphere' – an occasion for fruitful discussions between people with a wide range of specialisations. At the end of each topic, such as lameness, added value, genetics, or rumen sensing and animal health, all presenters of that topic were invited on the stage and answered questions from the audience in what was called a 'panel discussion'. I take the opportunity to gratefully thank Anne Verbrugge, Andrés Schlageter Tello, Alberto Peña Fernández, Tom van Hertem, Vered Sibony, Sarah Weyl-Feinstein, and Rebecca Neilson who punctually, quickly and efficiently wrote the questions in real-time during the discussions. It is known that the most vivid part in a typical scientific lecture is the discussions, without their help this book could not include the discussions nor could they have been documented. The note takers did their best to describe all the discussions, however, in some cases where the debates were in exceptional high speed, not all details were taken.

This book follows the same format as the joint-session; the separate parts of the book concern the specific topics of LPF. The discussions at the end of each part relate to the specific topics and are based on the 'meeting-minutes' taken during the panel discussions. The selection of the papers for this book (based on presentations given in the joint-session) was performed by the presidents of the EAAP study commissions (Marija Klopčič, Charlotte Lauridsen and Hans Spoolder) and the EU-PLF dissemination committee members (Marcella Guarino, Michel Bonneau, Rebecca Neilson, Kees Lokhorst, Thomas Banhazi, Heiner Lehr, Anne Verbrugge, Per Peetz Nielsen and

[1] EU-PLF: European precision livestock farming. Smart Farming for Europe: value creation through precision livestock farming; the authors acknowledge the European Community for financial participation in Collaborative Project EU-PLF KBBE.2012.1.1-02-311825.

[2] European Federation of Animal Science (EAAP).

Ilan Halachmi). Each member reviewed several papers and I would like to thank them all. Their names are listed in the acknowledgements.

Part 1 of the book provides an introduction to precision livestock farming from an European and an American perspective. The following parts of the book concern the specific topics of PLF; the chairpersons for each topic, Daniel Berckmans (Part 3), Bernadette Earley (Part 4), Marcella Guarino (Part 5), Kees Lokhorst (Part 6), Hans Spoolder (Part 7) and Marija Klopcic (Part 8) are hereby gratefully acknowledged.

Part 2 of the book contains papers on early detection technologies for animal lameness. Lameness in cows, sheep and pigs can be detected by either camera-based sensors, weight response surface matrix, or by leg and neck activity sensors. The discussion focuses on what can be learned from the different species and the different lameness sensing technologies presented. For example, are there any common health, genetics, and nutrition issues that can be generalised by comparing the different species management practices and comparing the different technologies?

Part 3 of the book 'How does PLF deliver *added value* to farmers', brings together various case studies about PLF's added value in pigs and cattle farms from the Netherlands, Spain and Australia. The 'added value' discussion follows the chapters of the book. In addition to technology comparison used with different species and estimating their added value to the farmer, wider questions, such as what is the PLF added value to the food consumer (human), to the animal-care activists, to the retailers, to the global environment and to the local nearby rural community were frequently asked in the discussions (see Discussion Chapters 2.5, 3.5, 4.6, 5.7, 6.4, 7.4 and 8.5).

Part 4 of the book presents studies on PLF in the area of genetics and health of beef, calves and heifers. Presentations in this session looked at monitoring stress responses and rumination among beef, calves and heifers applying various sensing technology. Part 5 focuses on 'Rumen sensing in relation to feed intake'. Part 6 of the book concerns 'PLF for automatic detection of animal health in poultry and pigs' while Part 7 covers the same subject but for cows. Finally, Part 8 'Sensors for milk quality and milk contents and their applications' contains questions and answers on the topic, as well as a finalizing discussion.

Overall, it is clear that the joint EAAP/EU-PLF approach has a distinctive and valuable role, facilitating cross-disciplinary discussion among the technology-oriented scientists, animal scientists, farmers, industries and other players. The content of this book provides evidence of the initial integration of PLF into the animal-scientists community, while a widening and deepening of research, development and evaluation of underlying concepts of PLF (defined as real-time measurement and management of the smallest manageable production unit temporal variability) to a vast and diverse world of livestock production. The prospects for further developments are manifold.

Ilan Halachmi
Editor

Part 1. Precision livestock farming

1.1. Precision dairy monitoring: what have we learned?

J.M. Bewley, R.A. Russell, K.A. Dolecheck and M.R. Borchers*
University of Kentucky, 407 W.P. Garrigus Building, Lexington, KY 40546-0215, USA; jbewley@uky.edu

Abstract

Technologies are changing the shape of the dairy industry across the globe. In fact, many of the technologies applied to the dairy industry are variations of base technologies used in larger industries, such as the automobile or personal electronic industries. Undoubtedly, these technologies will continue to change the way that dairy animals are managed. This technological shift provides reasons for optimism for improvements in both cow and farmer well-being moving forward. Many industry changes are setting the stage for the rapid introduction of new technologies in the dairy industry. Dairy operations today are characterized by narrower profit margins than in the past, largely because of reduced governmental involvement in regulating agricultural commodity prices. The resulting competition growth has intensified the drive for efficiency, resulting in increased emphasis on business and financial management. Furthermore, the decision-making landscape for a dairy manager has changed dramatically, with increased emphasis on consumer protection, continuous quality assurance, natural foods, pathogen-free food, zoonotic disease transmission, reduction of the use of medical treatments, and increased concern for the care of animals. Lastly, powers of human observation limit dairy producers' ability to identify sick or lame cows or cows in heat. Precision dairy management may help remedy some of these problems. Precision dairy management is the use of automated, mechanized technologies toward refinement of dairy management processes, procedures, or information collection. Precision dairy management technologies provide tremendous opportunities for improvements in individual animal management on dairy farms. Although the technological 'gadgets' may drive innovation, social and economic factors dictate technology adoption success.

Keywords: precision dairy farming, benefits, costs, adoption rate, unfamiliarity

Introduction

Technologies are changing the shape of the dairy industry across the globe. This rapid introduction of new technologies should come as no surprise given the technological culture shift in every facet of our society. In fact, many of the technologies applied to the dairy industry are variations of base technologies used in larger industries such as the automobile or personal electronic industries. Undoubtedly, these technologies will continue to change the way that dairy animals are managed. This technological shift provides reasons for optimism for improvements in both cow and farmer well-being moving forward. Many industry changes are setting the stage for the rapid introduction of new technologies in the dairy industry. Across the globe, the trend towards fewer, larger dairy operations continues. Dairy operations today are characterized by narrower profit margins than in the past, largely because of reduced governmental involvement in regulating agricultural commodity prices. Consequently, small changes in production or efficiency can have a major impact on profitability. The resulting competition growth has intensified the drive for efficiency, resulting in increased emphasis on business and financial management. Furthermore, the decision-making landscape for a dairy manager has changed dramatically, with increased

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emphasis on consumer protection, continuous quality assurance, natural foods, pathogen-free food, zoonotic disease transmission, reduction of the use of medical treatments, and increased concern for the care of animals. Lastly, powers of human observation limit dairy producers' ability to identify sick or lame cows or cows in heat.

Precision dairy farming

Precision dairy farming (PDF) is often used to describe many technologies aimed at improving dairy management systems. Bewley (2010) described PDF as the use of technologies to measure physiological, behavioural, and production indicators on individual animals to improve management strategies and farm performance. Eastwood *et al.* (2004) defined PDF as 'the use of information technologies for assessment of fine-scale animal and physical resource variability aimed at improved management strategies for optimizing economic, social, and environmental farm performance.' Spilke and Fahr (2003) stated that PDF, with specific emphasis on technologies for individual animal monitoring, 'aims for an ecologically and economically sustainable production of milk with secured quality, as well as a high degree of consumer and animal protection.' With PDF, the trend towards group management may be reversed, with focus returning to individual cows through the use of technologies (Schulze *et al.*, 2007). Technologies included within PDF range in complexity from daily milk yield recording to measurement of specific attributes (e.g. fat content or progesterone) within milk at each milking. The main objectives of PDF are maximizing individual animal potential, early detection of disease, and minimizing the use of medication through preventive health measures. PDF is inherently an interdisciplinary field incorporating concepts of informatics, biostatistics, ethology, economics, animal breeding, animal husbandry, animal nutrition, and engineering (Spilke and Fahr, 2003). The ideal PDF technology explains an underlying biological process that can be translated into meaningful action with information readily available to the farmer and a reasonable return on investment. Additionally, the best technologies are flexible, robust and reliable and demonstrated to be effective through research and commercial demonstrations.

The list of PDF technologies used for animal status monitoring and management continues to grow. Because of rapid development of new technologies and supporting applications, PDF technologies are becoming more feasible. Many PDF technologies, including daily milk yield recording, milk component monitoring (e.g. fat, protein and SCC), pedometers, automatic temperature recording devices, milk conductivity indicators, accelerometers for monitoring lying behaviour, rumination monitors, automatic oestrus detection monitors, and daily body weight measurements are already being utilized by dairy producers. Despite its seemingly simplistic nature, the power of accurate milk weights should not be discounted in monitoring cows, as it is typically the first factor that changes when a problem develops (Philpot, 2003). Other new PDF technologies have been introduced to measure jaw movements, ruminal pH, reticular contractions, heart rate, animal positioning and activity, vaginal mucus electrical resistance, feeding behaviour, biological components (enzymes, antibodies or microorganisms), odour, glucose, acoustics, progesterone, individual milk components, colour (as an indicator of cleanliness), infrared udder surface temperatures, gain analysis and respiration rates. Unfortunately, the development of technologies tends to be driven by availability of a technology, transferred from other industries in market expansion efforts, rather than by need. Compared with some industries, the dairy industry is relatively small, limiting corporate willingness to invest extensively in development of technologies exclusive to dairy farms. Many PDF technologies measure variables that could be measured manually, while others measure variables that could not have been obtained previously.

Realistically, the term 'Precision Dairy' should not be limited to monitoring technologies. Perhaps a more encompassing definition of Precision Dairy Management is the use of automated, mechanized technologies for refinement of dairy management processes, procedures or information collection. This definition incorporates monitoring technologies, automated milking systems, automated calf feeding systems and precision feeding systems. Automated milking systems have already been widely adopted in Europe. Adoption rates in North America have increased in recent years. The introduction of robotic milking components to rotary parlours will increase mechanization of milking in larger farms in the near future. Automated calf feeding systems have created a paradigm shift in how to raise dairy calves. Despite initial concerns about increased disease transmission, the benefits to automated calf feeding seem to outweigh the drawbacks when managed properly. New options for monitoring total mixed ration delivery and consumption will also improve how lactating dairy animals are fed. This is a particularly important economic and social concern given increased feed prices and concern for dairy efficiency and greenhouse gas emissions.

Benefits

Perceived benefits of PDF technologies include increased efficiency, reduced costs, improved product quality, minimized adverse environmental impacts, and improved animal health and well-being. These technologies are likely to have the greatest impact in the areas of health, reproduction and quality control (De Mol, 2000). Realized benefits from data summarization and exception reporting are anticipated to be higher for larger herds, where individual animal observation is more challenging and less likely to occur (Lazarus *et al.*, 1990). As dairy operations continue to increase in size, PDF technologies become more feasible because of increased reliance on less skilled labour and the ability to take advantage of economies of size related to technology adoption.

A PDF technology allows dairy producers to make more timely and informed decisions, resulting in better productivity and profitability (Van Asseldonk *et al.*, 1999). Real time data can be used for monitoring animals and creating exception reports to identify meaningful deviations. In many cases, dairy management and control activities can be automated (Delorenzo and Thomas, 1996). Alternatively, output from the system may provide a recommendation for the manager to interpret (Pietersma *et al.*, 1998). Information obtained from PDF technologies is only useful if it is interpreted and utilized effectively in decision making. Integrated, computerized information systems are essential for interpreting the mass quantities of data obtained from PDF technologies. This information may be incorporated into decision support systems designed to facilitate decision making for issues that require compilation of multiple sources of data.

Historically, dairy producers have used experience and judgment to identify outlying animals. While this skill is invaluable and can never be fully replaced with automated technologies, it is inherently flawed by limitations of human perception of a cow's condition. Often, by the time an animal exhibits clinical signs of stress or illness, it is too late to intervene. These easily observable clinical symptoms are typically preceded by physiological responses which are evasive to the human eye (e.g. changes in temperature or heart rate). Thus, by identifying changes in physiological parameters, a dairy manager may be able to intervene sooner. Technologies for physiological monitoring of dairy cows have great potential to supplement the observational activities of skilled herdspersons, which is especially critical as more cows are managed by fewer skilled workers (Hamrita *et al.*, 1997). Dairy producers with good 'cow sense' are the ones who will benefit the most from technology adoption. Those who view technologies as a way to do something they don't like to do are likely to struggle.

Adoption

The list of PDF technologies used for animal status monitoring and management continues to grow. Despite widespread availability, adoption of these technologies in the dairy industry has been relatively sparse thus far (Huirne *et al.* 1997; Gelb *et al.*, 2001). Perceived economic returns from investing in a new technology are always a factor influencing technology adoption. Additional factors impacting technology adoption include degree of impact on resources used in the production process, level of management needed to implement the technology, risk associated with the technology, institutional constraints, producer goals and motivations, and having an interest in a specific technology (Dijkhuizen *et al.* 1997; Van Asseldonk, 1999). Characteristics of the primary decision maker that influence technology adoption include age, level of formal education, learning style, goals, farm size, business complexity, increased tenancy, perceptions of risk, type of production, ownership of a non-farm business, innovativeness in production, average expenditure on information, and use of the technology by peers and other family members. Research regarding adoption of PDF technologies is limited, particularly within North America.

To remedy this, a five-page survey was distributed to all licensed milk producers in Kentucky (n=1,074) on July 1, 2008. Two weeks after the first mailing, a follow-up postcard was mailed to remind producers to return the survey. On August 1, 2008, the survey was re-sent to producers who had not returned the survey. A total of 236 surveys were returned; 7 were omitted due to incompleteness, leaving 229 for subsequent analysis (21%). The survey consisted of questions covering general farm descriptive demographics, extension programming and decision-making behaviour. With regard to PDF the following question was presented to survey participants: *'Adoption of automated monitoring technologies (examples: pedometers, electrical conductivity for mastitis detection) in the dairy industry has been slow thus far. Which of the following factors do you feel have impacted these modest adoption rates? (check ALL that apply).'* Data were entered into an online survey tool (KeySurvey, Braintree, MA, USA). Statistical analyses were conducted using SAS® (Cary, NC, USA). Surveys were categorized by herd size, production system, operator age and production level. Least squares means among categories were calculated for quantitative variables using the GLM procedure of SAS®. Statistical differences were considered significant using a 0.05 significance level using Tukey's test for multiple comparisons. For qualitative variables, χ^2 analyses were conducted using the FREQ procedure of SAS®. Statistical differences were considered significant at a 0.05 significance level.

Among the 229 respondents, mean herd size was 83.0±101.8 cows and mean producer age was 50.9±12.9. Reasons for modest adoption rates of PDF technologies and dairy systems software are presented in Table 1. The reasons selected by the highest percentage of respondents were (1) not being familiar with technologies that are available (55%), (2) undesirable cost to benefit ratios (42%) and (3) too much information provided without knowing what to do with it (36%). The high percentage of producers who indicated that they were unfamiliar with available technologies indicates that marketing efforts may improve technology adoption. Actual or perceived economic benefits appear to influence adoption rates, demonstrating the need for economic models to assess technology benefits and re-examination of retail product prices. As herd size increased, the percentage of producers selecting 'poor technical support/training' and 'compatibility issues' increased (P<0.05), which may be reflective of past negative experiences. In developing technologies, manufacturers should work with end-users during development and after product adoption to alleviate these customer frustrations. Few significant differences were observed among age groups, though the youngest producers were more likely to select 'better alternatives/easier to accomplish manually.' Prior to technology development, market research should be conducted to ensure that new technologies address a real need. Utilizing this insight should help PDF technology manufacturers and industry

Table 1. Factors influencing slow adoption rates of precision dairy farming technologies.

Factor	N	Percentage
Not familiar with technologies that are available	101	55%
Undesirable cost to benefit ratio	77	42%
Too much information provided without knowing what to do with it	66	36%
Not enough time to spend on technology	56	31%
Lack of perceived economic value	55	30%
Too difficult or complex to use	53	29%
Poor technical support/training	52	28%
Better alternatives/easier to accomplish manually	43	23%
Failure in fitting with farmer patterns of work	40	22%
Fear of technology/computer illiteracy	39	21%
Not reliable or flexible enough	33	18%
Not useful/does not address a real need	27	15%
Immature technology/waiting for improvements	18	10%
Lack of standardization	17	9%
Poor integration with other farm systems/software	12	7%
Compatibility issues	12	7%

advisors develop strategies for improving technology adoption. Moreover, this information may help focus product development strategies for both existing and future technologies.

Borchers *et al.* (unpublished data) submitted another survey to assess dairy producer technology needs. A survey to identify producer perception of PDF technologies was distributed in March 2013 through written publications and email. Responses were collected in May 2013 (n=109) and statistical analysis was performed using SAS (SAS Institute, Inc., Cary, NC). Herd size, producer age and role on the farm were collected and analysed but significant differences were not found (P>0.05). Producers were asked to indicate parameters currently monitored on their farm from a predetermined list and producers most often selected daily milk yield (52.3%), cow activity (41.3%), and not applicable (producers not currently implementing technologies: 1.2%). Producers were asked to rank the same list on usefulness using a 5-point Likert Scale (1: not useful and 5: useful). Least-squares means were calculated using the GLM procedure of SAS and producers indicated (mean ± SE) mastitis (4.77±0.47), standing heat (4.75±0.55), and daily milk yield (4.72±0.62) to be most useful. Pre-purchase technology selection criteria were ranked using a Likert Scale (1: not important and 5: important) by producers and benefit to cost ratio (4.57±0.66), total investment cost (4.28±0.83), and simplicity and ease of use (4.26±0.75) were found most important. Producers were categorized into United States or an 'other countries' category based upon their farm location. Significant differences (P<0.05) were identified between country and the adoption of technologies monitoring animal position and location, body weight, cow activity, daily milk yield, lying and standing time, mastitis, milk components, rumen activity and rumination, with other countries being higher in all cases. Producers were categorized based upon technology use (using technology vs not using technology) and least-squares means were calculated across technology usefulness, with daily milk yield (using technologies: 4.83±0.07, vs not using technologies: 4.50±0.10) and standing heat (using technologies: 4.68±0.06, vs not using technologies: 4.91±0.09) differing significantly (P<0.05). Least-squares means were calculated for technology use categories, with producer pre-purchase considerations and availability of local support (using technologies: 4.25±0.11, vs not using technologies: 3.82±0.16) differing significantly (P<0.05).

Pre-adoption considerations

PDF technology investments should be considered on an individual operation basis. These technologies do not follow a 'one size fits all' model well. Each dairy is different and what works on one may not work on another. To assess whether a technology will work for your operation, start by asking these questions:

- Does your dairy's management currently involve a computer? Being comfortable around a computer is important in PDF. Almost all PDF technologies work through a computer program and will require daily interaction to produce useful reports and information for decision-making. Dairy operations which are most likely to benefit from these technologies are those that already use dairy management software (i.e. PCDART, DairyComp 305). However, regardless of an individual's familiarity with computers, working with any new computer program will require some training and adjustment.
- Is the farm currently using good management practices? PDF cannot completely correct poor management nor does it replace current management systems. In fact, when applied to unorganized systems, PDF technologies may make managing the operation harder through information overload. Technologies and computers do not replace good management but can enhance it. Dairy farmers who already understand, evaluate and respond to cow signs and needs and the animal management associated with them are those who will benefit most from these technologies.
- Does the operation know its own strengths and weaknesses? Being aware of which areas need improvement on a dairy farm will allow easier decisions to be made about investment in PDF, including which technologies will work best for you. Focusing on areas that are already strong will result in very few observed benefits. For example, a farm that is already doing a good job with heat detection may not see as much benefit from investing in a heat detection technology.
- What is the dairy's willingness to take risks? Many PDF technologies are rather new and not yet widely adopted. Sometimes investing in an early technology may involve some risk (i.e. the company going out of business or development of a newer, improved model). However, the first adopters of new technologies are generally the ones who benefit from them most because they see returns first.
- Do you understand the economic benefits? An investment analysis considers how a potential investment will affect a business. No matter how great a technology is, the benefits of investing in the technology must outweigh the costs. Before investing in any technology, farm management should set a threshold for minimum acceptable returns. A net present value analysis will help determine the true investment and profitability. Some technologies may not prove to be profitable, but investment may still be worthwhile because of improvements in quality of life.

The answers to these questions will help determine whether PDF technologies are a good fit for an operation. However, it is still important to consider other farm-specific and economic factors when making this decision. If PDF technologies are not a realistic option now, they may be in the future. Continually reassess the dairy operation to determine when PDF technologies may become a good choice for improving dairy management.

Choosing a technology

The list of available PDF technologies is growing rapidly. Once you have decided you are ready for PDF, the next step is to choose a technology (or multiple ones) to use. An ideal technology will be low-cost, reliable, robust, flexible, easy to maintain and update, and will provide information about something going on within an animal that a producer can immediately turn into an on-farm action. Consider some of these other questions when looking at potential technologies for your operation:

Technology purpose: determine whether the technology will bring value to the operation.
- Does the technology fulfil a need for the operation or is it addressing something that does not require changing?
- What will improve on the operation by getting/using this technology?

Company interaction: installing PDF technologies will involve long-term interaction with the company that manufactures it. Be sure to talk to farmers or extension agents who have worked with the company previously to answer these questions.
- Has the technology been used on commercial farms, not just the manufacturing company's research farms?
- What kind of customer service, training and technical support does the manufacturer provide and for what length of time?
- Does the company value farmers' opinions when updating or making changes to the device?

How the technology works: know whether the technology will work in a way that is convenient for your operation before committing your time and money to it. Again, talking to other farmers and extension agents about these concerns may be beneficial.

What is required for collection of data from the technology?
- How reliable is the technology? How often does it fail to perform as desired?
- Is data measured continuously or does the animal have to make a trip to the parlour to collect the data?
- How frequently are tags misread?
- How do notifications about animals appear on the computer? Are reports easy to understand?
- Does the computer specify what to do with detected animals or do you have to interpret it?
- If the technology is designed for event detection (i.e. heat, mastitis or disease):
  - Can the manufacturer provide data indicating what percentage of cases (sensitivity) are detected (Goal>80%)? A technology should capture most of the desired events to be worthwhile.
- Can the manufacturer provide data indicating how many false alerts (specificity) occur (Goal <1%)? This is where some technologies fall short. Although this is a strict criterion to use, false alerts can waste time and resources for a dairy producer. A 1% false alert means you will receive 10 false alerts for every 1000 milkings. By comparison, 10 or 25% false alert rates would lead to 100 or 250 false alerts per day.
- How long is the data stored on the computer?
- How does the system handle transferring units (tags, etc.) from one animal to another?

Outlook

Though PDF is in its infancy, new PDF technologies are introduced to the market each year. As new technologies are developed in other industries, engineers and animal scientists find applications within the dairy industry. More importantly, as these technologies are widely adopted in larger industries, such as the automobile or personal computing industries, the costs of the base technologies decrease, making them more economically feasible for dairy farms. Because the bulk of research focused on PDF technologies is conducted in research environments, care must be taken when trying to transfer these results directly to commercial settings. Field experiments or simulations may need to be conducted to alleviate this issue. Because there is a gap between the impact of PDF technologies in research versus commercial settings, additional effort needs to be directed towards implementation of the management practices needed in order to fully utilize information provided by these technologies. To gain a better understanding of technology adoption shortcomings, additional research needs to be undertaken to examine the adoption process, not only for successful adoption of technology but also for technology adoption failures. Before investing in a new technology, a formal investment analysis should be conducted to make sure that the technology is right for your farm's needs. Examining decisions with a simulation model accounts for more of the risk and uncertainty characteristics of the dairy system. Given this risk and uncertainty, a stochastic simulation of investment analysis will show that there is uncertainty in the profitability of some projects. Ultimately, the dairy manager's level of risk aversion will determine whether or not he or she invests in a technology using the results from this type of analysis. PDF technologies provide tremendous opportunities for improvements in individual animal management on dairy farms. In the future, PDF technologies will change the way dairy herds are managed.

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1.2. Smart farming for Europe: value creation through precision livestock farming

D. Berckmans
Department of Biosystems, Division M3-BIORES: Measure, Model & Manage Bioresponses, KU Leuven, Kasteelpark Arenberg 30, 3001 Heverlee, Belgium; daniel.berckmans@biw.kuleuven.be

Abstract

The world population keeps growing and in several big countries the diets are changing since more people can afford to eat animal products. The result is that the worldwide demand for meat and animal products might increase by 40% in the next 15 years. A question is how to achieve high-quality, sustainable and safe meat production that can meet this demand. At the same time, livestock production is currently facing serious problems, such as animal health in relation to food safety and human health. Europe wants improved animal welfare and has made a significant investment in it. At the same time, the negative environmental impact of the livestock sector is far from being solved. Finally, we must ask how the farmer, who is the central stakeholder in this process, will make a living from more sustainable livestock production. One tool that might provide real opportunities for practical implementation is Precision Livestock Farming (PLF). PLF systems aim to offer to the farmer a real time monitoring and managing system based on continuous monitoring of the animals by using modern technology. This is fundamentally different from all approaches that aim to offer a monitoring tool without improving the life of the individual animal under consideration on that moment in the process. The idea of PLF is to provide a real-time warning when something goes wrong so that immediate action can be taken by the farmer. Continuous, fully automated monitoring and improvement of animal health, welfare, yields and the environmental impact becomes a reality. The first objective of this paper is to show several examples of PLF systems that are operational today in about 60 compartments/barns for pigs, broilers and cows all over Europe. We give details of which variables these systems measure in real time in a fully automated way. Moreover, we show how in the running EU-PLF project (EU-PLF) the real time data analyses can generate added value for the farmer. PLF systems can replace the ears and the eyes of the farmer and work 24 h a day and 7 days a week. The second objective is to give ideas on how the farmer gets an advantage from these PLF systems as we start to see that within the EU-PLF project. Collaboration between so called 'animal people' (physiologists, veterinarians, ethologists, animal scientists, etc.) and 'technical people' (bio-engineers, software and hardware engineers, ICT people) is needed to make these systems to become successful support systems for farmers.

Keywords: collaboration, monitoring, animal welfare, animal health, sustainable livestock production

What is precision livestock farming?

Precision Livestock Farming (PLF) means that we use modern ICT technology to improve livestock monitoring and efficiency of processes to grow meat and animal products, like milk and eggs. PLF creates management systems based on continuous automated real-time monitoring and control of animal health and welfare, production/reproduction and environmental impact of livestock production.

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Precision Livestock Farming is based on the assumption that fully automated continuous direct monitoring of animals will enable farmers to detect and control in real time the health and welfare status of their animals. The farmer is already used to have modern technologies in order to measure a number of parameters on the farm. For example, for climate control, financial programmes, equipment that automatically measure the feeder provided to the animals, programmes that quantify production outcome (e.g. milk production), etc. Most of these tools, however, do not focus on the central part of the production process: the animal.

Technological development and progress have advanced to such an extent that accurate, powerful and affordable tools are now possible. These include the intelligent use of cameras, microphones, sensors (such as 3D accelerometers (including gyroscopes), temperature sensors, skin conductivity sensors and glucose sensors), wireless communication tools, internet connections, cloud storage and many others. Modern technology makes it possible to use cameras, microphones and sensors sufficiently close to the animal so that they can replace the farmers' eyes and ears in monitoring individual animals and this during 7 days a week, 24 hours a day, 3,600 seconds per hour.

The aim of PLF is to combine all the available hardware with intelligent software in order to extract information from a wide range of animal data and use this in real time in the management of the process. PLF can indeed offer real time management tools that enable a farmer to monitor animals automatically and to create added value by helping to secure improved health, welfare, yields and environmental impact. This real time aspect and being part of the management system is quite different from other solutions like the use of so called Iceberg indicators (FAWC, 1979). Similar to an iceberg, in which the visible part is only a small part of what is hidden under the water, a bitten tail in the slaughterhouse is an indication of a bigger problem of tail biting during the fattening period. Another approach is the yearly visit by human experts to score the animal welfare in farms as proposed by the Welfare Quality approach (Welfare Quality, 2014). These are very fruitful concepts that help to create awareness of the problem of animal welfare. PLF, however, aims to help and adapt the process management on the spot in real time for the animal that is followed continuously during the production process and warn the farmer immediately.

Examples of PLF technology: what is possible today?

There are several techniques that can be used to collect data on animals in a fully automated and continuous way. This can be done by using sensors on the animals (e.g. position measurement, accelerometer, temperature sensor, heart rate signal), by camera and image analysis or by analysing the sound produced by the animals (Figure 1).

Lameness monitor for cows

One of the biggest problems in animal welfare for cows is the occurrence of lameness and leg problems. In a modern farm up to 25% of the animals might get lameness and leg problems. When detected fast enough the animal might be helped, but in severe cases the animals will be replaced. In literature over 200 possible causes have been described. In the past when a farmer had a much lower number of cows and he could spend more time for observations of the individual animals he could notice upcoming problems in an early stage. Today, however, the farmer needs to have more cows to make his living and he has not enough time for each individual animal. With pleasure farmers would like to do this, but consumers are not prepared to pay for this more expensive way of working.

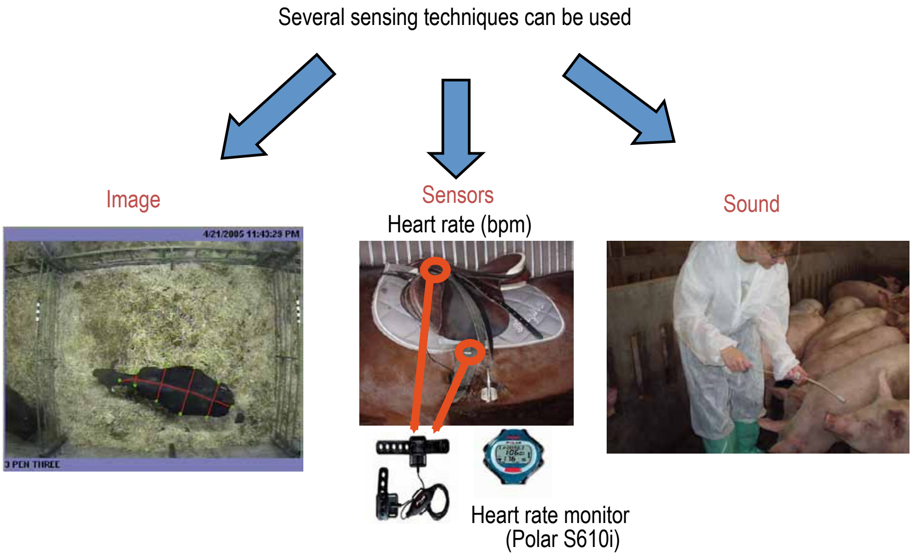


Figure 1. Continuous animal data can be collected by several sensing techniques.

In collaboration with several partners, a lameness monitor has been developed based upon the use of modern camera technology (EU-BioBusiness project, IWT-Landbouw project). This lameness monitor is based upon the use of a camera that is filming each individual animal every time when she is walking to or coming back from the milking robot. The cow is identified and filmed over a small distance to calculate gait parameters and these are compared to the previous results for this individual cow. Twelve different models have been tested going from complex analysis of the dynamic walking behaviour to more simple parameters (Figure 2). The result is a rather simple parameter that was found as the best indicator, namely the back arch of the cow (Poursaberi *et al.*, 2010) (Figure 3).

The implementation of this technology is further developed with the low cost 3D Kinect camera that is positioned above the animals which allows an easier implementation at farm level because of a fixed background image. It has been shown that this individual approach compared to

Figure 2. Real time calculation of gait parameters can be done with complex dynamic models on life stream video of the full dynamic walking pattern.

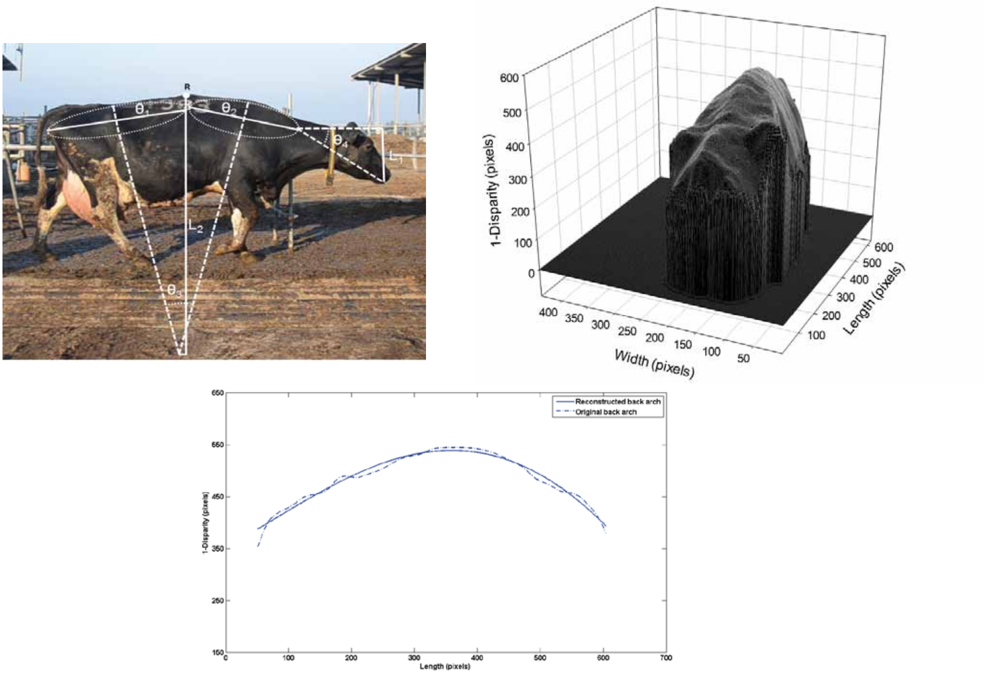


Figure 3. Back posture came out as the best indicator for detection of lameness.

population models allows to improve the sensitivity of the system with more than 10% as shown in Figure 4 (Viazzi *et al*., 2014). Human scoring has been done weekly over a 6 months period in a commercial farm (24 scoring sessions including 200 cows) to be used as a gold standard during the development of this technology.

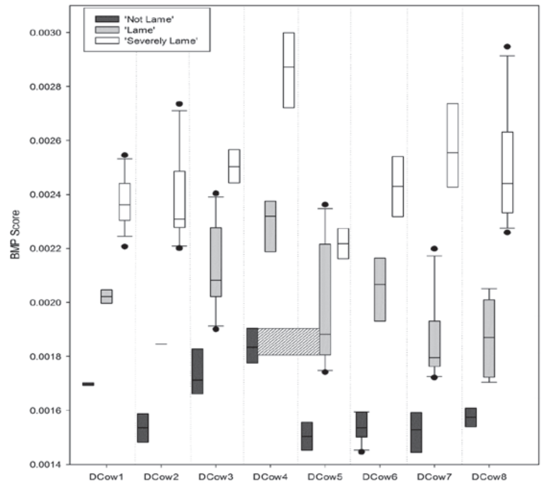
Such a lameness monitor can create value for the farmer and the veterinarian by identifying a cow with an upcoming lameness problem. The monitor will recognise the transition from a sound gait status to the first signs of lameness. The value is the following:

- faster and improved care for the animal;
- money can be saved by preventing the animal conditions from deteriorating;
- time can be saved by not requiring the farmer to continuously observe each individual cow;
- time can be saved since automated reports will inform the farmer on which individuals have to be checked;
- the assurance that all animals are followed continuously in time might give more rest for the farmer;
- the farmer who wants to show his way of working with animals can gain social recognition;
- there is no need to enter the farm with hidden cameras since the PLF system is filming each cow at every milking moment.

On-line pig sound analysis for disease detection

For long the extensive use of antibiotics in food animals has been criticised with good reasons since for animal and human health this is not the way to go. For the farmer, who is working with fattening pigs, the daily threat of respiratory diseases remains a serious threat since profit or

Individual threshold can increase the sensitivity with more than 10%



Cow	True Positive Rate	False Positive Rate	Accuracy
1	0.93	0.01	0.93
2	0.89	0.22	0.89
3	0.86	0.11	0.86
4	0.91	0.05	0.91
5	1.00	0	1.0
6	1.00	0	1.0
7	0.86	0.08	0.86
8	0.88	0.05	0.88
Total	0.91	0.06	0.91

Dataset	True Positive Rate	False Positive Rate	Accuracy
Group	0.80	0.12	0.80
Individual	0.91	0.06	0.91

Figure 4. Individual thresholds improve the sensitivity of the detection system.

loss can depend on these few days during the growth period that his pigs get sick. Farmers and veterinarians use the coughing of pigs to detect infections when entering the compartment. About 15 years ago a project was started to develop a pig cough monitor for fattening pigs (Van Hirtum and Berckmans, 2003; Van Hirtum *et al.*, 2003). The system was further developed in collaboration between academia and industry between 3 partners and resulted in a product: the Pig Cough Monitor (SoundTalks NV, Belgium) for fattening pigs. Each compartment has a microphone and unit that is counting the number of coughs by continuous (20,000 samples per second day and night) real time analysis of the sounds produced by the animals. By counting the coughs per compartment an early warning is given to the farmer when this number varies too much in time (Figure 5). The aim is that the farmer gets information when the first sick animals are detected, which allows treating only the animals in one pen immediately, instead of waiting until all animals are sick. The system send can send a SMS to the farmer when actions need to be taken, which allows the farmer to participate in other (social) activities, knowing his animals are monitored for diseases.

Monitoring pig's drinking behaviour

Another way to detect sick animals can be the monitoring of their behaviour and more specifically the drinking behaviour. By using a single camera above a pen with 10 fattening pigs, the idea was to check whether the amount of used water could be estimated from the life stream video. A project was done where animal scientists and PLF engineers collaborated to test the concept (Welzijnsmonitor).

In the experimental set-up a camera with a PLF algorithm was used that estimated the drinking time of a single pig by analysing the behaviour of the pig close to the drinking nipple. As a reference, a water flow meter was installed on the water line to check the accuracy of the image algorithm (Figure 6). Results show that the accuracy of this PLF system with a single top view camera positioned above the centre of the pen, reaches an agreement of 92% with the amount registered by the water meter (Kashiha *et al.*, 2013a).

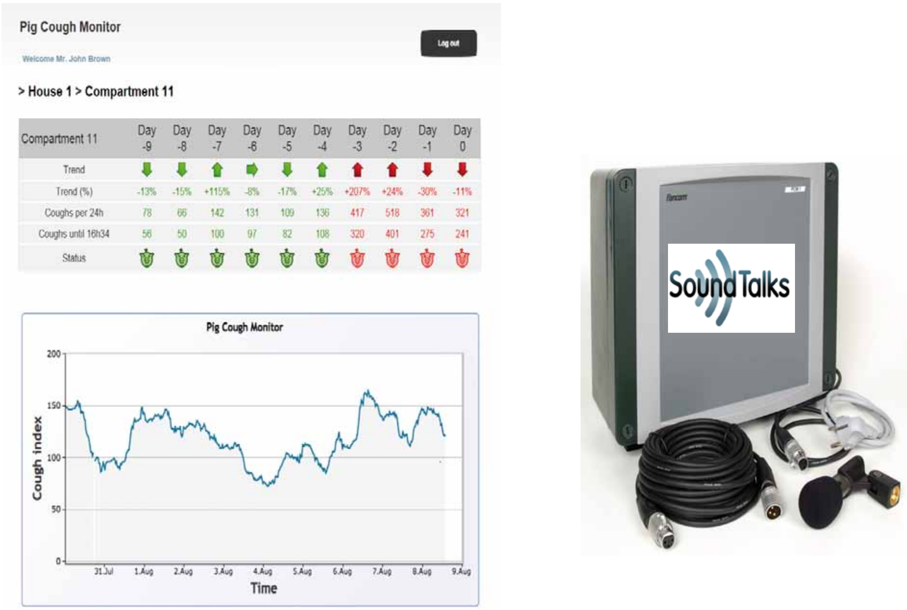


Figure 5. Pig Cough Monitor doing continuous sound analysis.

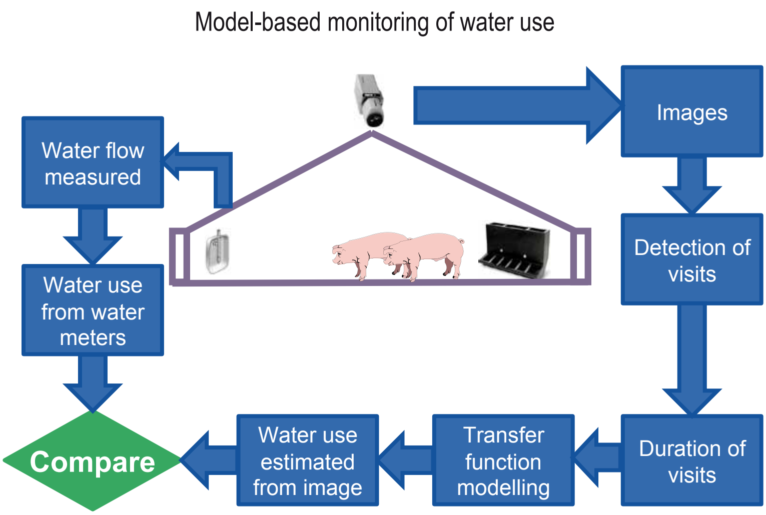


Figure 6. Test installation with reference flow meter and camera about pig pen.

The real-time monitoring of animal health as demonstrated by the Pig Cough Monitor and the pig's drinking behaviour show that the farmer can get value in saving money for disease treatment, giving guarantee and trust to the consumer in continuous automated health monitoring, saving labour and time in monitoring and treating animals, saving visit costs from the veterinarian, getting automated reports that prove the absence of respiratory diseases and less production losses due to diseases.

Early warning system for broiler houses

Farmers with broiler houses are squeezed into a situation that they always need to grow more animals to make their living from this business. A broiler house with 20,000 animals in one house is not exceptional at all, but it becomes very hard to observe such a high number of birds. Many problems can occur like animal diseases, climate control problems, blocked feeder lines, electricity problems, dysfunctional drinking lines, failing lighting systems and others.

We have tested whether the PLF eYeNamic system (Fancom BV, the Netherlands) is able to detect the daily problems in broiler houses. The eYeNamic system consists of 3 or 4 cameras mounted at the ceiling that give pictures of the distribution of the birds (Figure 7 and 8).

The setup of the experiment in a commercial farm was the output of the eYeNamic system that calculates in real time the activity number of the birds and the distribution of the birds: is the number of birds per m^2 equally spread all over the ground surface. The farmer was asked to fill in a logbook, where he noted down all problems that occurred during the whole fattening period (Figure 9). The PLF system used an algorithm that compared the actually measured distribution of animals with a predicted value at that time of the day. When the real measured value was more than 25% different from the predicted value an alarm was given to the farmer. As can be seen in Figures 10 and 11 the behaviour of the broilers is quantified continuously and by measuring the distribution of the birds, indications of blocked feeder lines and other problems are given.

The PLF system shows that 95% of all problems are detected from the behaviour of the birds (Kashiha *et al.*, 2013b). It used a single parameter: the variation in time of the birds' distribution of the available space. This confirms again that the continuous measurement of animal responses is the way to go and there is no need to measure many variables to get systems that give added value. In this case, the fact that most problems are detected means that the farmer can win working

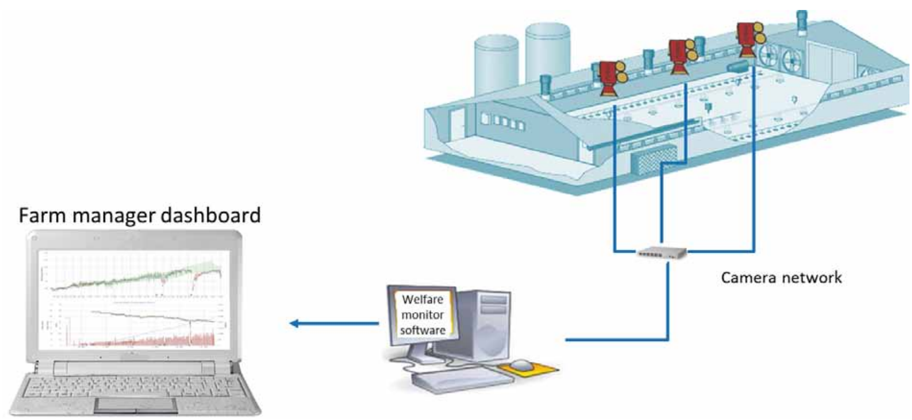


Figure 7. Three top view cameras and real time image analysis of broilers behaviour.

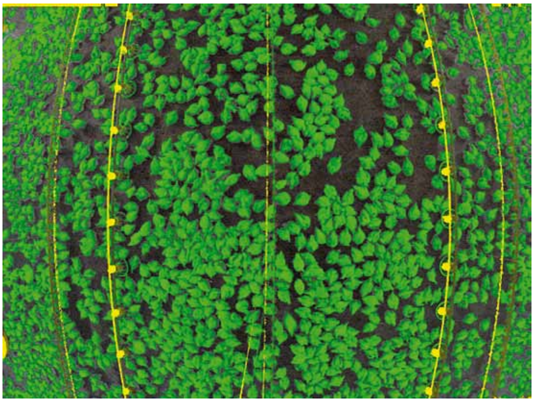


Figure 8. Image from the broilers as analysed in real time by the eYeNamic system.

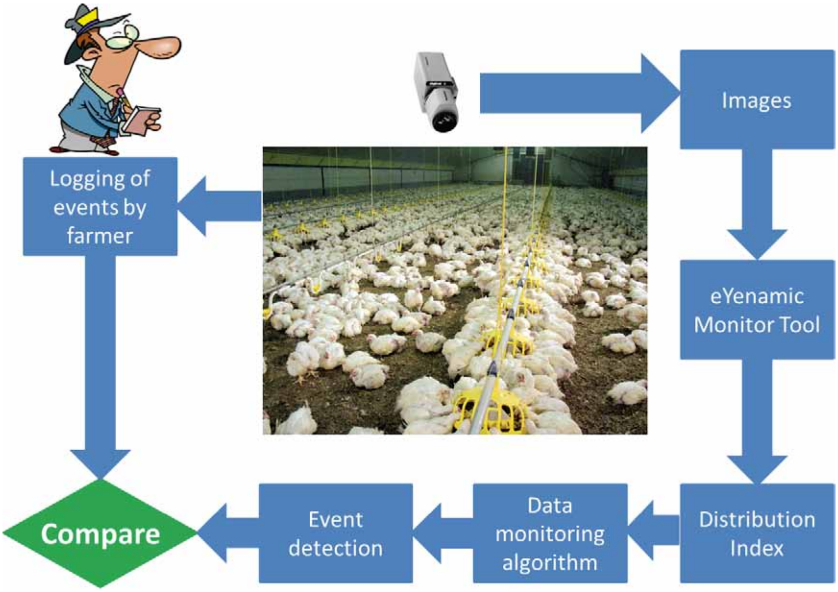


Figure 9. Farmer's logbook as a reference to check the precision livestock farming system's warnings.

hours that he normally spends for controls. He can enter the building and disturb the birds to solve problems, but there is no need to disturb them if no problems occur.

Conclusions

PLF systems are becoming available as products and are getting operational in commercial farms. From there, we have to discover how they can create value for the animals and the farmers in the first place. So far, it looks that there are several ways that these system can create value. The fundamental advantage is that PLF systems are monitoring continuously and this can be 25 images

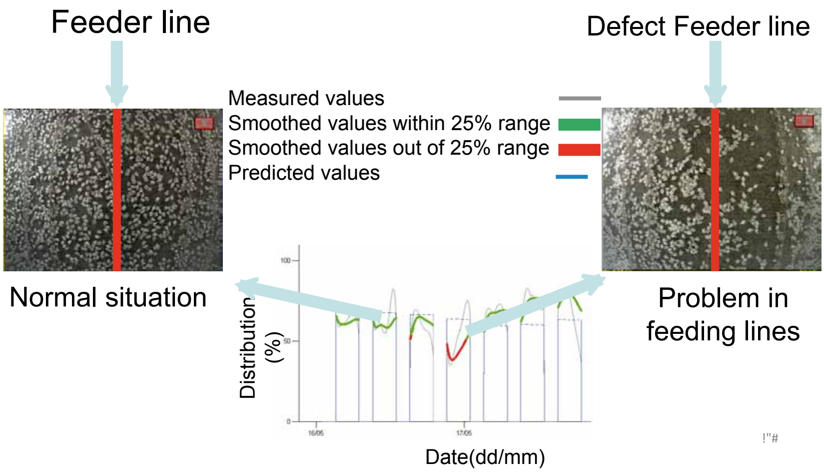


Figure 10. Event detection algorithm based upon variation of the measured broiler's distribution.

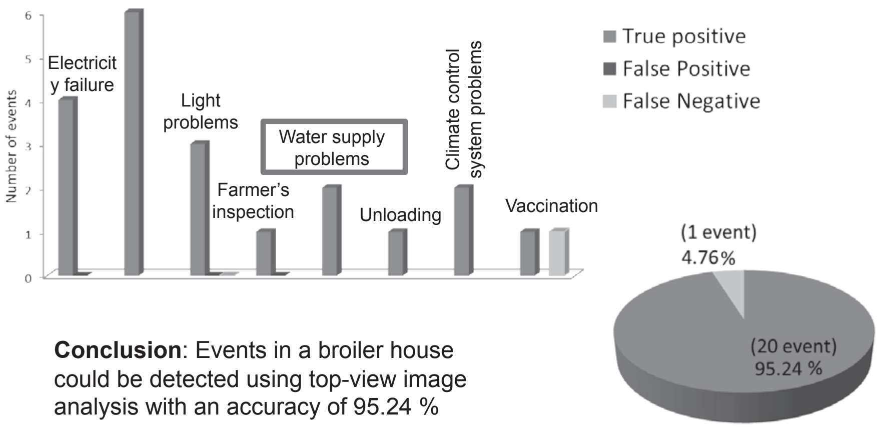


Figure 11. The precision livestock farming system gives a warning for 95% of the problems that have occurred.

per second, 20,000 sound samples per second or 250 sensor samples per second and this 7 days a week and 24 hours a day. This is much more than what any farmer or human observer can do.

From examples today we see that value creation can be done in several ways: saving labour time, saving time in detecting problems, giving less stress to the farmer, solving problems on the spot immediately instead of later for other animals, giving social recognition to the farmer, giving quantitative numbers about what happens to the animals and others.

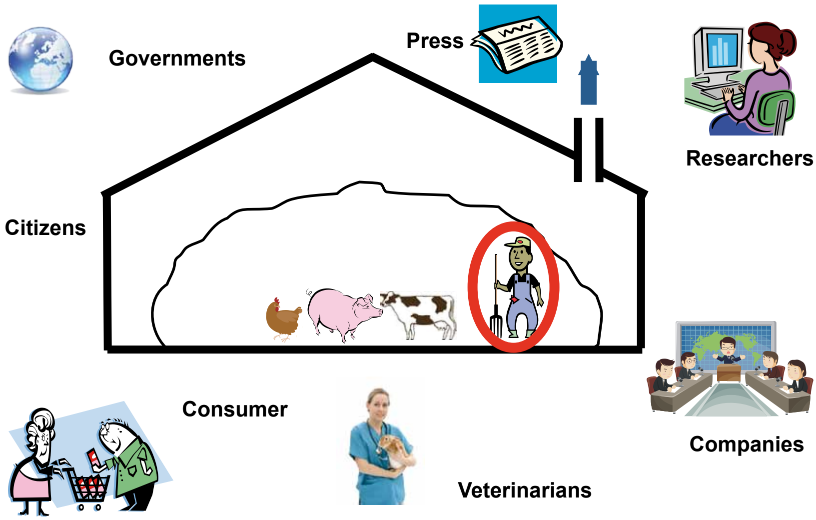


Figure 12. Precision livestock farming systems can create values in different ways and for different stakeholders.

It also becomes clear that other stakeholders as well can get value from these systems, like veterinarians, companies, consumers, citizens, governments, press and researchers. In such case we need to check how value can be created for all stakeholders.

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Part 2. Precision livestock farming applications for automatic lameness detection

2.1. Detecting lameness in sows using acceleration data from ear tags

C. Scheel, I. Traulsen and J. Krieter*
Institute of Animal Breeding and Husbandry, Christian-Albrechts-University, Olshausenstr. 40, 24098 Kiel, Germany; cscheel@tierzucht.uni-kiel.de

Abstract

The aim of this work is to detect lameness at an early stage in group housed sows by recognizing and extracting an expected behaviour in an individual sow from time series of acceleration data sampled from ear tags. Deviations from this time series were measured and utilized to provide a reliable indication of the start of lameness. Data was obtained from a system from MKW-Electronics which was deployed at the Futterkamp agricultural research farm. From May 2012 onwards, about 200 sows were continuously fitted with ear tags to measure acceleration. A number of features from the total acceleration time series were computed for a sample of 14 sows, 7 of which were diagnosed as lame on the last day of the sample period of 14 days each. These included measures of general activity such as daily variance, average variation and average squared variation. Wavelet analysis was used to obtain representations of the signals on the various scales. Further features derived from these measures were computed from each scale of the wavelet coefficient representations. It was assumed that feature values were drawn from the normal distributions provided by the data D for individual sows. A feature was said to be 'on' (or abnormal) for a day d if its value v given the data D previous to d lay outside ±1.8σ so the probability of observing it was less than about 0.08, i.e. $p(v|D)<0.08$. In order to collect statistics for the count 'features per sow in state on', it was assumed that $(\text{mean, med, min, max})_d$ denoted the tuple for a day d containing these statistics. For lame sows, substantially more features deviated significantly: they yielded $(14.6, 11, 1, 41)_{13}$ and $(18.4, 15, 6, 50)_{14}$, while $(5.4, 3, 0, 12)_{13}$ and $(8.3, 8, 1, 20)_{14}$ were found for healthy sows. Furthermore, the 13th day suggested predictive value for lame sows. Among the wavelet based features, simple means of the wavelet coefficients showed the least discriminative value. Currently, an autocorrelation model on finer timescales and more sophisticated features are being developed.

Keywords: lameness, sows, acceleration sensors, time series, wavelet

Introduction

EU Directive 2001/88/EC states that group housing of sows is mandatory. Group housed sows tend to have a higher rate of lameness then sows kept in a gestation crate. As group housing during gestation is becoming increasingly common, it can be challenging for farm staff to constantly monitor for lameness. It is therefore desirable to have an automatic lameness monitoring system. Acceleration sensors are cheap and potentially offer the ability to detect changes in patterns of movement exhibited by animals (Cornou and Lundbye-Christensen, 2008; Cornou *et al.*, 2011; Pastel *et al.*, 2009).

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Monitoring system and data

An experimental monitoring system from MKW Electronics (Vienna, Austria) was deployed at the Futterkamp agricultural research farm from May 2012 to autumn 2013 (Figure 1). The gestation unit was equipped with 10 receivers to record the signal transmitted by the ear tags fitted to the sows. Well over 200 ear tags were in use during data collection.

These ear tags feature an inward and an outward temperature sensor, a positioning system and an accelerometer. The accelerometer data consists of (x,y,z)-triples of acceleration values measured along its three internal axes. The sample rate of the accelerometer is programmable. Thus, a trade-off has to be made between battery life and data resolution. Since battery life was a major concern, particularly for the early versions of the ear tags, the sample rate was set to 1 Hz. A real-valued total acceleration signal was then calculated from the 3D output using Pythagoras' formula.

Lameness in the sows was diagnosed by a veterinarian, and the date of diagnosis and the severity and duration of lameness were recorded.

The following figures illustrate typical data and behaviour of sows as measured by an accelerometer. Figure 2 shows the total acceleration signal for 5 different (healthy) sows on the same day. The

Figure 1. Ear tag from MKW Electronics, Vienna, Austria.

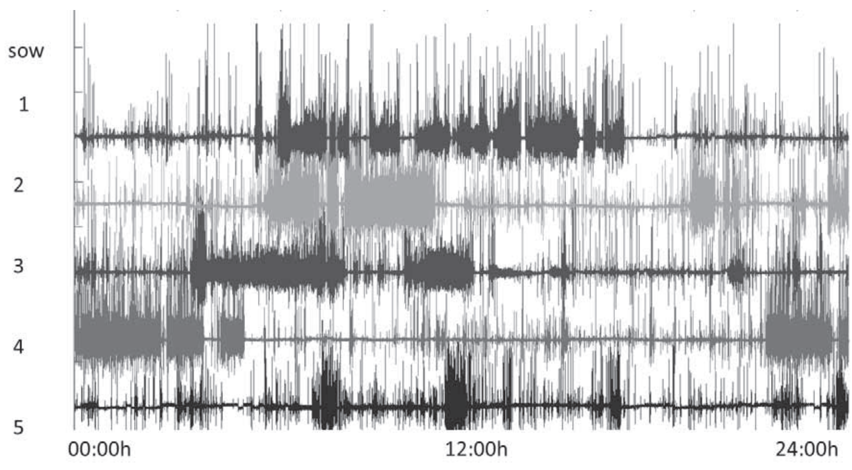

Figure 2. Stacked acceleration data for five different sows recorded on the same day. The distribution of acceleration varies among sows.

distributions of acceleration for these sows are distinctly different. Figure 3 shows the acceleration signal for one single sow on five consecutive days. This shows that behavioural patterns vary significantly from day to day. Finally, an eleven-day history of acceleration data for a lame sow is shown in Figure 4. This is to illustrate some observed development of behavioural patterns up until lameness diagnosis.

Signal representation

To further facilitate feature extraction from the signal, a discrete wavelet representation of the original signal was considered instead of using only the original signal. In a discrete wavelet representation, a signal is first split into a detail part d_1 and an approximation a_1 and thus represented as:

$$s = a_1 + d_1 \tag{1}$$

Here, d_1 is the projection of s onto the space spanned by the translates of the chosen wavelet, i.e. a linear combination with certain coefficients, which yields the high 'frequency' part of the signal as measured by the wavelet. The remaining part a_1 is called the first approximation and is guaranteed to be capable of representation as linear combinations of the accompanying scaling function of the wavelet. To move on to the next scale, a_1 is considered to be the new signal and splitting is repeated, until finally a decomposition:

$$s = d_1 + \ldots + d_i + \ldots + d_I + a_I \tag{2}$$

up to a desired level I is achieved.

Feature functions can then be applied not only to the signal itself, but to the 'new signals' which are also given by the scales (the coefficients) of its wavelet representation. The rationale behind

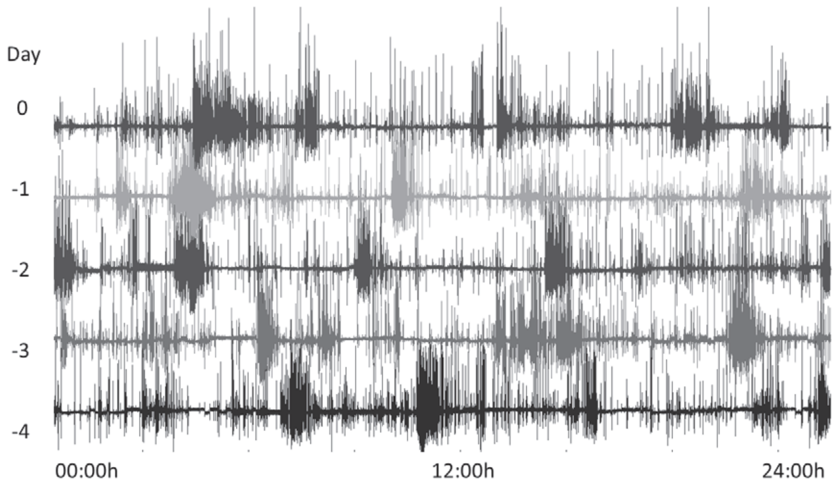

Figure 3. Stacked acceleration data for five consecutive days recorded for a single healthy sow. The distribution of acceleration varies from day to day.

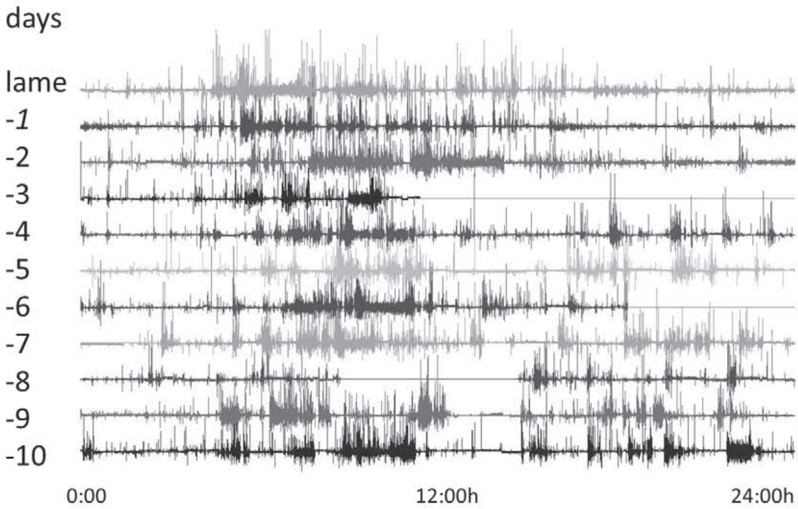

Figure 4. The day shown at the top is the day of lameness diagnosis. Flat lines are damaged data. Note that the days before diagnosis show a different acceleration pattern or distribution: bursts of movement are missing in the last third of these days. Note also that computing a single number such as variance for each day will yield practically undistinguishable values even for the day of lameness diagnosis and days -9, -10.

this is that different behavioural patterns of sows, as identified by the accelerometer, might not be clearly distinguishable from the original signal but rather by distributing it over the various scales. An illustration of a wavelet decomposition is shown in Figure 5.

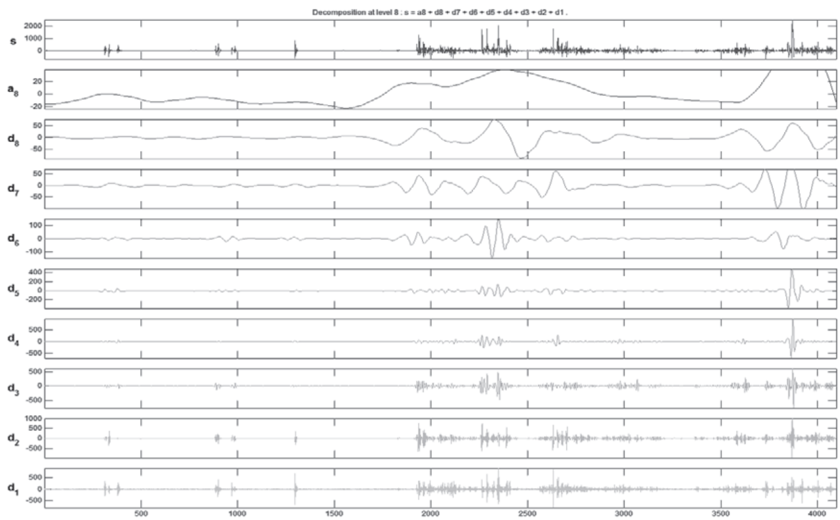

Figure 5. Example of a wavelet decomposition for a piece of signal using the Matlab Wavelet Toolbox. The signal s as well as the approximation a_l and details d_i serve to supply features of the signal.

Method

A continuously recorded acceleration signal s was split into a past record of acceleration data s_p and a current record s_c. To predict the start of lameness from s_c, it is necessary to compare s_c with s_p.

One way of making such a comparison feasible is to construct or define a collection f_i of feature functions. These may be any functions which are applicable to a time series and thus to a signal: $f_i(s)$. Then a series of values of feature functions, calculated from past data s_p, is used to determine an expected range of values. It is also necessary to devise a measure or statistic to decide whether feature values calculated from s_c exhibit an unusual deviation from the past record. A feature is then said to be abnormal, or on, if its value is extreme for that statistic.

Following the general principles described above, the following were chosen as basic feature functions:

- the variance;
- length adjusted p-variation for p = 1, 2;
- mean and standard deviation.

Applying these to a signal and its wavelet (coefficient) representation yields a feature representation, a collection of values that can be used as proxies for some features of the signal.

The following numerical experiment was subsequently devised to determine the basic feasibility of feature representation. Features for 7 lame sows with a relatively complete record of 14 days of acceleration data up to the day of diagnosis (the 14^{th} day) were calculated per day. In order to contrast and compare their feature values, data for 7 healthy sows, matched for day and age, were chosen and the features were then calculated. The concrete model for unusual deviation was as follows: the uncertainty of each feature was assumed to follow a normal distribution. Sufficient statistics (i.e. mean and standard deviation) of the distributions to fit were extracted from feature values for previous days. Then a $\pm w^*\sigma$- interval was used to determine whether a newly calculated feature value for an unseen day was extreme in the sense that it lay outside the interval for a parameter *w* to be determined.

Results

For the 13^{th} and 14^{th} day, the number of features 'on' for each sow was calculated for different values of the parameter *w*. The tuples $(\text{mean, med, min, max})_d$ of statistics, where d indicates the day, were calculated from it.

The parameter *w* could be adjusted or learned as to have and the basic statistics in this tuple were at least twice as high in the lame group. The values obtained were:

- For the lame sows, $(14.6, 11, 1, 41)_{13}$ and $(18.4, 15, 6, 50)_{14}$;
- and for the healthy sows $(5.4, 3, 0, 12)_{13}$ and $(8.3, 8, 1, 20)_{14}$.

This showed that for this simple model a parameter exists which enables the sample groups, at least, to be identified on the day of diagnosis and the day before, which is essential for a prediction of lameness. Of course, strictly speaking, this parameter was only shown to be valid for the sample used and no conclusions can be drawn in relation to its suitability for generalised use.

Summary and outlook

A very basic feature representation and model to measure unusual deviations has been developed. The results suggest that the method is feasible, although it has several drawbacks.

Day-wise feature calculation is obviously very broad in terms of time, and important information on the distribution of acceleration over a day will be lost. But this cannot be remedied simply by computing features for smaller fixed time intervals as the distribution of acceleration tends to be different between days for the same sow.

A day is a natural cyclic unit of time, while hours are an arbitrary division. Data quality is also an issue in developing a better localization scheme, which wavelets in principle allow. While the system consistently produced relatively reliable data towards the end of its deployment in Futterkamp, data from its early days tend to be damaged (i.e. patchy). A system for localization in time will overcome the difficulty that it cannot be assumed with any certainty that it will be possible to find a good piece of data for any specific point in time.

It is still necessary to seek higher-resolution feature representation and to augment it with proper autocorrelation measures. One method of dealing with damaged data might be to inflict systematic damage, modelled on the worst elements of genuinely damaged data, on a whole data series and to calculate the features afterwards, making it possible to compare feature values under the same conditions.

As the number of samples of lameness is limited, future plans include training a machine (neural network) to compress feature representations of healthy sows only. The reconstruction error on data from lame sows might then be higher than on unseen test data from healthy sows. Similarly, a machine might be developed with arbitrary but specific responses to feature representations of age-grouped healthy sows. As noted above, a bigger error in data from lame sows than in test data from unseen healthy sows would then be indicative of lameness.

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2.2. Risk factors for system performance of an automatic 3D vision locomotion monitor for cows

T. van Hertem[1,\2], S. Viazzi[1], A. Schlageter-Tello[3], C. Bahr[1], M. Steensels[1], C.E.B. Romanini[1], C. Lokhorst[3], E. Maltz[2], I. Halachmi[2] and D. Berckmans[1]*
[1]M3-BIORES: Measure, Model & Manage Bioresponses, KU Leuven, Kasteelpark Arenberg 30, bus 2456, 3001 Leuven, Belgium; [2]Institute of Agricultural Engineering, Agricultural Research Organization (ARO) – the Volcani Center, P.O. Box 6, 50250 Bet Dagan, Israel; [3]Livestock Research, Wageningen UR, P.O. Box 65, 8200 AB Lelystad, the Netherlands; daniel.berckmans@biw.kuleuven.be

Abstract

The aim of this study was to identify the factors that affect the system performance of a three-dimensional based vision system for automatic monitoring of dairy cow locomotion implemented on a commercial dairy farm. Data were gathered from a Belgian commercial dairy farm with a 40-stand rotary milking parlour. This resulted in forced cow traffic twice a day when all Holstein cows passed through an alley on their return to the pen. The video recording system with a 3D depth camera, positioned in top-down perspective, was installed in this alley. The entire monitoring process, including video recording, filtering and analysis and cow identification, was automated. System performance was defined as the number of analysed videos per session. To investigate how many video recordings could be used for monitoring dairy cow locomotion, videos were captured during 566 consecutive milking sessions. For each session, 224±10 cows were identified on average by the RFID-antenna, and 197±17 videos were recorded (88.0±6.2%) by the camera. After linking the cow identification to the recorded videos, 178±14 cow videos (79.5±5.7%) were available for analysis. After all video processing, an average of 110±24 recorded cow videos (49.3±11.0%) per session was used for analysis. The number of analysed videos per cow per week was individually variable. Cow traffic in the alley where the recordings were made had a big influence on the performance of the system. Heavy cow traffic reduced the number of recordings and the number of identified cows in each video, and more videos were filtered out due to incorrect cow segmentation in the videos.

Keywords: computer vision, back posture, ID-merging, cow traffic, individual variation

Introduction

Lameness is a health and welfare issue in modern intensive dairy farming (Kossaibati and Esslemont, 1997, Bruijnis *et al.*, 2012). The prevalence of lameness is often underestimated (Espejo *et al.*, 2006, Bruijnis *et al.*, 2012), and is affected by many different risk factors (Barker *et al.*, 2010, Becker *et al.*, 2014). The most common method of obtaining a lameness prevalence rate for a herd is visual locomotion scoring (Flower and Weary, 2009, Schlageter-Tello *et al.*, 2014). However, this procedure is subjective, time-consuming and costly. Monitoring cow behaviour and performance is a key factor in health and welfare management. Due to increased farm size and limited time per animal, visual observation of cow health and welfare is evolving towards more automated monitoring systems. Computer vision is a promising technique for animal monitoring because it is relatively low cost and simple to install. Studies using computer vision for gait analysis focus on back arch curvature (Poursaberi *et al.*, 2010, Van Hertem *et al.*, 2014, Viazzi *et al.*, 2014b), step overlap (Pluk *et al.*,

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2010), and hoof release angles (Pluk *et al.*, 2012b). Back curvature can be extracted from images by different feature variables, such as an inverse radius (Poursaberi *et al.*, 2010, Viazzi *et al.*, 2014b), curvature angles (Viazzi *et al.*, 2014b) and back posture measurement (BPM) (Van Hertem *et al.*, 2014). All extracted feature variables show a strong correlation with locomotion scores. However, implementing computer vision systems in commercial farm conditions tends to be challenging (Theurer *et al.*, 2013). The most important requirement for a practical computer vision system is that recordings are made frequently, the number of recordings is sufficient and the recorded images are suitable for the intended analysis. For lameness detection, the best place to position such a system is on the way out of the milking system, because cow gait is affected by udder size and udder fill (Flower *et al.*, 2006). To our knowledge, no attempt has been made to implement a fully automatic computer vision system for locomotion assessment in commercial farm conditions. The aim of this study was to identify the factors that affect system performance (number of videos to be analysed by the system per session) of a computer vision system at herd and cow level in commercial farm conditions when cow traffic is dictated by single cow release from a rotary milking parlour.

Materials and methods

Farm and management

Data were gathered from 566 milking sessions on a commercial dairy farm with a 250 head herd in Belgium between 1 September 2013 and 15 July 2014. The number of cows in the milking herd ranged between 208 and 242. All cows were Holstein-Friesians and were housed indoors all year round in a cubicle barn with slatted floors. The concrete stalls were covered with mattresses and bedded with wood shavings. The milking herd was divided into two production groups according to the production level. The proportional group distribution was on average (high) 3:2 (low). The cows were milked twice a day (06:00-08:30 h and 18:00-20.15 h) in a 40-stand rotary milking parlour. Prior to milking, both production groups were brought to the waiting area. An automatic mechanical fence moved the cows closer to the rotary. After milking, the cows stepped away from the rotary milking platform, had to turn, and then entered a 20 m long alley that led them back to the cow shed. At the end of the alley, a spray box disinfected the udder and teats after milking, and a smart selection gate automatically divided the milking herd into the two production groups and separated cows for treatment from the herd (Figure 1).

Video data acquisition

Each cow that entered the corridor passed a radio-frequency-based identification (RFID) antenna. Cow identification triggered recording of the video. The trigger signal was transferred to the computer by a low-cost USB digital input/output device (NI USB-6501, National Instruments, Austin, TX, USA). Video recordings of cow gait were made with a three-dimensional (3D) image camera (Kinect™, Microsoft corp., Redmond, WA, USA). The camera was installed in top-down perspective at a height of 345 cm above ground level. Depth recordings were made at 30 fps. The recording automatically stopped when a new cow was identified or if the photocell laser-beam of the RFID-unit was cut. The RFID antenna identified 98.9±2.1% of the cows that passed the setup, and the timestamp of the identification was used to identify the individual cow in the recorded video (= merging). All recorded videos contained a depth recording and were saved to a 2 TB hard disk (Western Digital, Irvine, CA, USA) as .oni-files. The OpenNI 1.0 Software Development Kit framework was used to make the recordings with the Kinect camera.

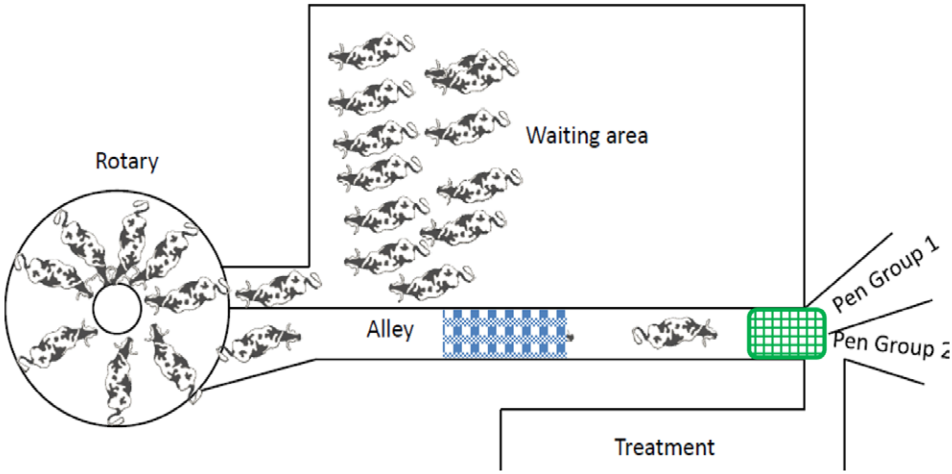

Figure 1. Schematic top view perspective of the farm layout. The cows are milked in a 40-stand rotary milking parlour. The gridded rectangle at the end of the alley represents the spray box and three-way sorting gate. The plaid rectangle in the middle of the alley indicates the video recording area.

Video processing: extracting image features

Video pre-processing filtered out the videos that contained (1) poor quality images due to sunlight sensitivity of the sensor; (2) multiple cows in the video when cow traffic was heavy; (3) less than three frames for analysis; and (4) a cow gait with an out-of-range walking speed (irregular cow gait: stopping or running) (Romanini *et al.*, 2013). In order to extract animal-based measurements that are relevant for lameness detection, the full cow body (head to tail) needed to be segmented in the video. After video recording, cow identification merging with a video and filtering, the remaining videos were further analysed. The entire recording process ((1) trigger the video recording, (2) cow ID merging with video, (3) video pre-processing (filter) and (4) video analysis) was carried out automatically.

Management software data extraction

After each milking session, a backup of the management software was copied to the operating computer over the local farm network. Three different queries automatically extracted the variables related to the identification and milking process from the database. For cow ID merging with a video, the last timestamp of each cow when passing the RFID antenna in the alley was extracted to an ASCII-format file. The number of cows milked (herd size) and milking session duration were automatically extracted from the same database using a different query. Cow individual variables such as lactation stage, cow parity and milk dump (yes/no) were automatically extracted from the same database using yet another query. Lactation stage was afterwards grouped into 30-day blocks (0-30, 31-60, … 305-end of lactation). Cows of parity ≥6 were clustered in one group.

Statistical analysis

In order to test the effect of different cow-specific factors (such as lactation stage and cow parity) and session-related factors (such as herd size and milking session duration) on the analysis rate for each recording session, a pairwise correlation between each factor and the analysis rate was performed. Correlation is a measure of the linear dependence between two variables, giving a value between +1 (total positive correlation) and -1 (total negative correlation) (Pearson, 1895). The value 0 indicates no correlation between the two variables. Pearson's correlation coefficient is defined as the covariance between the two variables divided by the product of their standard deviations. Significant correlations were found by computing the *P*-value for each correlation. The *P*-value is computed by transforming the correlation to create a Student t-statistic having (n – 2) degrees of freedom, where n is the number of recording sessions (n=566). The significance level was set to α=0.05.

Results and discussion

In the period between 20 September 2013 and 15 July 2014, 566 recording sessions were carried out and the results are shown in Table 1. On average, 224±10 cows were identified by the RFID antenna in the alley per milking (recording) session. On average 88.0±6.2% of the passing cows triggered the signal to start video recording. The cow did not trigger the signal when she was walking too close behind another cow or when she was selected to be separated from the herd by the selection gate. The first step after recording the videos was to link the cow ID to a recorded video (ID-merging). The average merging rate was 79.5±5.7%. Cow merging failed when the time between consecutive cows was too short (heavy traffic). The second step in video processing was to analyse the videos and calculate the lameness-related feature variables from the images. In the time frame presented, an average analysis rate of 49.3±11.0% was obtained. Calculation of the back curvature variables in the video analysis process only took place when the full cow body was in the image, the cow was showing a normal gait (not running or stopping), and when the cow was not hindered by other cows.

System performance in terms of the merging and analysis rate is graphically presented over time in Figure 2. System performance of the experimental setup. The white squares represent the merging rate per session (= the number of videos that are merged with a cow ID). The straight dashed line through the white squares represents the average merging rate per session (79.5±5.7%) throughout all recording sessions. The full line through the white squares represents the one-week (=14 sessions) moving average value of the merging rate. The black triangles represent the analysis

Table 1. Overview of the setup performance per recording session in 566 recording sessions. The table presents performance at the four steps in the process: entering the setup (RFID), trigger video recording, merged in the videos, and scored by the algorithm. All numbers are calculated relative to the number of cows that enter the setup.

Step in process	Absolute number	Units	Relative number (%)
Number of cows RFID	224±10	cows	100
Number of recorded videos	197±16	videos	88.0±6.2
Number of merged videos	178±14	cows	79.5±5.7
Number of analysed videos	110±24	cows	49.3±11.0

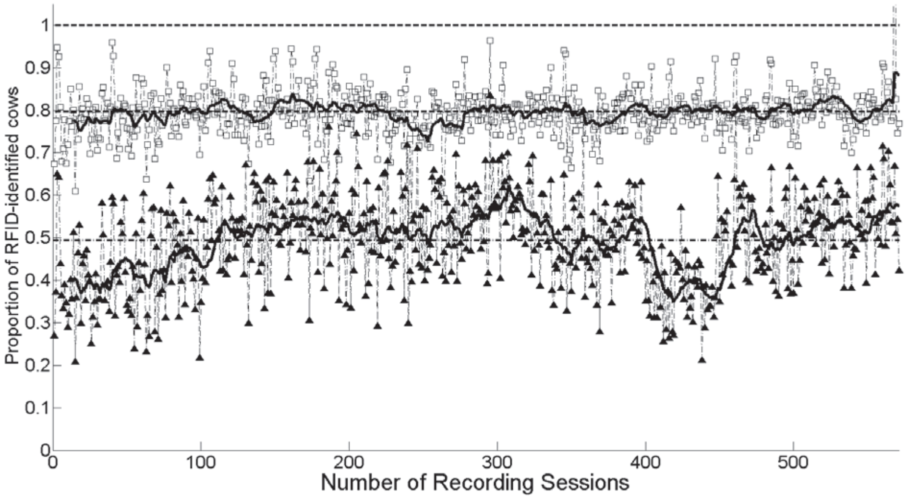

Figure 2. System performance of the experimental setup. The white squares represent the merging rate per session (= the number of videos that are merged with a cow ID). The straight dashed line through the white squares represents the average merging rate per session (79.5±5.7%) throughout all recording sessions. The full line through the white squares represents the one-week (=14 sessions) moving average value of the merging rate. The black triangles represent the analysis rate per session (number of videos that result in automatic lameness scores). The straight dashed line through the black triangles represents the average analysis rate per session (49.3±11.0%) throughout all recording sessions. The full line through the black triangles represents the one-week (=14 sessions) moving average value of the analysis rate.

rate per session (number of videos that result in automatic lameness scores). The straight dashed line through the black triangles represents the average analysis rate per session (49.3±11.0%) throughout all recording sessions. The full line through the black triangles represents the one-week (=14 sessions) moving average value of the analysis rate. The merging rate (standard deviation (std.)=5.7%) was less variable than the analysis rate (std.=11.0%). It can be clearly seen that the number of analysed videos was lower at the start of the experiments than after 150 sessions (39.0% vs 53.0%). We believe that the cows needed some time to adapt to the new setup (installation of RFID antenna in the corridor). The experiments started at the end of September, which was the peak season for harvesting crops such as maize and potatoes. Average cow throughput in the first 100 sessions was 2.60±0.24 cows/min, whereas in the following 100 sessions average milking time was 2.29±0.39 cows/min. This difference was significant (*P*<0.001), indicating that the farmer spent less time on milking, whereas the number of cows milked was not significantly different. Hence, cow traffic was higher, resulting in more filtered out videos. After 120 recording sessions, the analysis rate stabilised at around 53%. The merging rate showed a drop around session 250 due to a dirty photocell (piece of hair) in the RFID antenna. Thereafter, the farmer was asked to clean the photocell once per week on a regular basis. This shows that each sensor needs maintenance in order to provide accurate results.

The analysis rate dropped between session 400 and 450. Here, too, the cow throughput (2.58±0.41 cows/min) was higher (*P*<0.001) than in the weeks before or after. These sessions were recorded in the spring, when the farm staff were mainly focused on planting new crops, and less time was invested in cow management. When the field work was complete, the performance recovered to its fixed level.

The results of the statistical test concerning the effect of several factors on the analysis rate are presented in Table 2. Young cows (first and second lactation) had a negative impact on the analysis rate, whereas older cows had a positive effect (third and fourth parity cows) or negligible effect (fifth and higher parity). Cows in early and around peak lactation had a positive effect on the analysis rate, whereas cows in late lactation had a negative effect. This is probably due to the milking time of these cows. Longer milking times will result in a slower release rate from the rotary and hence less dense cow traffic in the alley. Herd size was negatively correlated with analysis rate (r=-0.31), indicating that the more cows there were in the herd, the fewer videos were analysed. On the other hand, milking session duration was positively correlated with analysis rate (r=0.43), indicating that the longer the milking session lasted, the more videos were analysed.

The previous graphs did not provide any information about system performance at cow level. Table 3 shows the number of automatically generated scores based on the recorded videos for each cow in a one-week time period (7 days per week × 2 sessions per day = 14 sessions). Other research has also chosen to work with seven-day periods (Bicalho *et al.*, 2007). Table 3 shows that the median value is seven automatic video-based scores per cow per week, the 25th percentile is four automatic video-based scores per cow per week, the 75th percentile is nine automatic video-based scores per cow per week.

The objective was to obtain at least five automatic scores per cow per week. As a maximum, 14 recordings (one after each milking session) were possible per week in the current setup. Table 3 clearly shows that after 566 sessions in this setup, on average 78.89% of the cows were automatically scored at least five times per week. Future research should reveal whether the number of recorded

Table 2. Correlation between cow-specific and session-related factors and the number of analysed videos. Positive correlations imply that a higher factor will result in a higher analysis rate. A negative correlation implies that a higher factor will result in a lower analysis rate. Only significant (α=0.05) factors are presented in the table.

	Factor[1]	Correlation coefficient
Positive correlation	Relative number of merged videos	0.56
	Recording session duration	0.43
	Lactation stage DIM 151-180	0.28
	Lactation stage DIM 0-30	0.25
	Lactation stage DIM 91-120	0.23
	Proportion of third lactation cows	0.18
	Number of dump milk cases	0.16
	Proportion of fourth lactation cows	0.16
Negative correlation	Proportion of first lactation cows	-0.50
	Lactation stage DIM 241-270	-0.44
	Lactation stage DIM 271-305	-0.43
	Number of cows in the herd	-0.31
	Proportion of second lactation cows	-0.16

[1] DIM = days in milk.

Table 3. Overview of the weekly number of video-based scores per cow. The maximum number of weekly video-based scores is 14 in this setup with two milk sessions per day. The cumulative sum shows the proportion of cows in the herd that have a number of scores that is less than or equal to the value in the first column.

Number of video-based scores per cow per week	Avg. proportion (%)	Std. proportion (%)	Cumulative sum (%)
0	0.71	1.23	0.71
1	1.85	2.05	2.56
2	3.95	2.79	6.51
3	6.02	2.96	12.52
4	8.58	3.02	21.11
5	10.74	2.66	31.85
6	12.22	2.59	44.06
7	12.89	2.73	56.95
8	12.80	3.03	69.75
9	11.10	3.32	80.85
10	8.79	3.10	89.64
11	5.95	2.64	95.59
12	3.11	2.02	98.70
13	1.08	0.97	99.78
14	0.22	0.33	100

and analysed videos is sufficient for automated lameness detection as performed by Viazzi *et al.* (2013b) and Van Hertem *et al.* (2014). The results of this study were obtained at one farm, and should be validated in other farm setups. Rotary milking parlours as well as tandem and robot milking parlours have the advantage that cows are released one-by-one, and smoother cow traffic can be expected when cows walk back to the housing pen. By contrast, in herringbone or parallel milking parlour systems, the cows are released in groups of up to 40 (rapid exit). This will lead to higher peaks in cow traffic. The type of milking parlour will therefore also affect the location of the recording system. In rapid-exit systems, the recording system should be located at a greater distance from the milking parlour than in a single cow release system, in order to prevent cow traffic jams in the recording system.

Conclusions

The results of this study show that cow traffic has a large influence on a computer vision system implemented at a commercial farm. Whereas 79.5±5.7% of the cow IDs were merged with a recorded video for each session, only 49.3±11.0% of the cows were automatically scored. Cow parity, lactation stage, herd size and milking session duration were the main indirect factors affecting the video analysis rate in a recording session, and hence cow traffic. At cow level, the median number of automatic video-based scores obtained per cow per week was seven, the 25th percentile was four scores per cow per week and the 75th percentile was nine scores per cow per week. This range shows that there is a large individual variation in the number of analysed videos obtained per cow per week. On average, 78.89% of the cows were automatically scored by the video-based system at least five times per week.

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2.3. Development of a multi-Kinect-system for gait analysis and measuring body characteristics in dairy cows

J. Salau[*], J.H. Haas, W. Junge, M. Leisen and G. Thaller
Institute of Animal Breeding and Husbandry, Kiel University, Olshausenstraße 40, 24098 Kiel, Germany; jsalau@tierzucht.uni-kiel.de

Abstract

In recent years, camera-based systems in dairy cattle have been an intensively studied field. Mainly single camera systems with greatly restricted applications have been presented. This study deals with the feasibility of a multi 3D-camera system to analyse cows' gait and to measure various kinds of functional traits. As necessary ground work, a preliminary prototype was built, and alpha versions of software for recording, synchronisation, sorting and segmentation of the images, and transforming the 3D-data in a joint coordinate system have been implemented.

Keywords: computer vision, 3D-camera, claw finding, Tait-Bryan-angles, synchronisation

Introduction

In dairy farming the importance of objectively analysing dairy cows' movement and body characteristics is increasing. Lameness and loss of body condition are problems which affect productivity, fertility, and animal welfare. In recent years, several camera-based studies have achieved high rates of correct classification in lameness detection. In Song *et al.* (2008), Pluk *et al.* (2012), and Viazzi *et al.* (2013) walking cows were recorded using digital 2D-cameras in the side view position. Step overlap, fetlock joint angles and back posture have been analysed. The camera distance ranged from three to six metres. Moreover, various camera-based studies of body condition score (BCS) determination have been presented. For this purpose, cow shapes were reconstructed using linear and polynomial kernel principal component analysis in Azzaro *et al.* (2011). BCS prediction models based on five anatomical points were presented in Bercovich *et al.* (2012). Both studies used 2D-cameras in the top view position. With 2D-images, changes in light and scenery complicate the definition of image background (Hertem *et al.*, 2013). For this reason, thermal images recorded from top view were considered in Halachmi *et al.* (2013). BCS was assessed by fitting a parabola to the cow shape and full automation was achieved. 3D-cameras are another approach to overcome segmentation problems. As the pixels' relative distances from the camera are known, the separation between fore- and background is easier. Krukowski (2009) analysed images from a Time-Of-Flight (TOF) 3D-camera. The rear view of dairy cows was captured when stationary using a hand-held camera in order to determine BCS. In addition, Salau *et al.* (2014) and Weber *et al.* (2014) provided an automated system based on a TOF 3D-camera mounted in top view position. The backfat thickness of dairy cows, measured by ultrasound, could be estimated, achieving 0.96 correlation between the estimator and backfat thickness. However, as TOF cameras measure depth by calculating the phase shift between emitted and reflected infrared light, motion artifacts and large differences in depth measurement according to the fur colour (J. Salau, unpublished data) were the problem. In Viazzi *et al.* (2014)

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the Microsoft Kinect[3] 3D-camera (Figure 1) was used. The Kinect camera in top view position is compared to a 2D-camera in side view position with regard to their usage in lameness detection. The abovementioned studies focus on either body condition or lameness. Livestock farmers need to monitor both of these regularly and in a cheap and reliable way. Furthermore, installations with a distance of several metres between cow and camera are not applicable on most commercial dairy farms. There is therefore a need for a system that provides holistic monitoring possibilities and easily fits in existing barn passages. This study considers the feasibility and design of a 3D cow scanner based on multiple Microsoft Kinect cameras. The approach enables gait analyses and the measurement of many kinds of body characteristics as it combines the camera's fields of view.

Materials and methods

The system presented in this study is based on the 3D-camera Microsoft Kinect. To enable movement analyses, several steps taken by a freely walking cow need to be observed, but the field of view of a single Kinect camera is too small to capture more than one or two steps. Moreover, for a holistic approach, it is necessary to take measurements on all body parts. Therefore, a multi-Kinect-system was conceived.

Microsoft Kinect and hardware

The Microsoft Kinect combines an RGB camera and a depth sensor (Figure 1). The depth sensor consists of an infrared projector and an infrared sensor and uses the 'Structured Light' measurement principle to gather depth information. A pattern of infrared laser points is projected onto the scene. Its deformation is detected by the infrared sensor and used to calculate depth values. The Kinect has a 57° horizontal and 43° vertical field of view, a resolution of 640×480 pixels and can record up to 30 depth and RGB images per second. In the present setting six Kinect cameras were recording simultaneously. Problems arising with the simultaneous usage of two or more Kinect cameras were that the cameras needed to be synchronized and the recorded data needed to be assembled. Furthermore, each Kinect had to be connected to its own USB controller to enable the computer to distinguish between the cameras. Free software to simultaneously run six Kinect cameras could not be found. Additionally, each Kinect saw not only its own projected infrared pattern but also the patterns from other Kinect cameras. This led to interference and erroneous depth measurements where the patterns overlap. In the setting of the present study, all cameras were connected to the same computer to enable later synchronization. For this purpose, a system with an AMD Phenom II X6 1100T with 3.3 GHz and 16 GB RAM was equipped with additional USB PCI cards.

Figure 1. The depth camera Microsoft Kinect. The infrared projector is placed behind the circular window on the left. The two cameras correspond to the two windows in the middle, while the RGB camera is located on the left and the infrared sensor on the right side.

[3] http://www.microsoft.com/en-us/news/press/2010/mar10/03-31primesensepr.aspx.

Preliminary prototype

A wooden framework was built as a preliminary prototype (Figure 2A). Its pass line height was 2.08 m (total height 2.18 m), and its passage width was 2.05 m (total width 2.25 m). Each side of the framework was equipped with three Kinect cameras: One is mounted approximately 0.3 m above the ground facing straight inwards, and two were mounted in the diagonal sections of the framework at a height of about 1.99 m and were facing towards the ground at an angle of 45° (Figure 3).

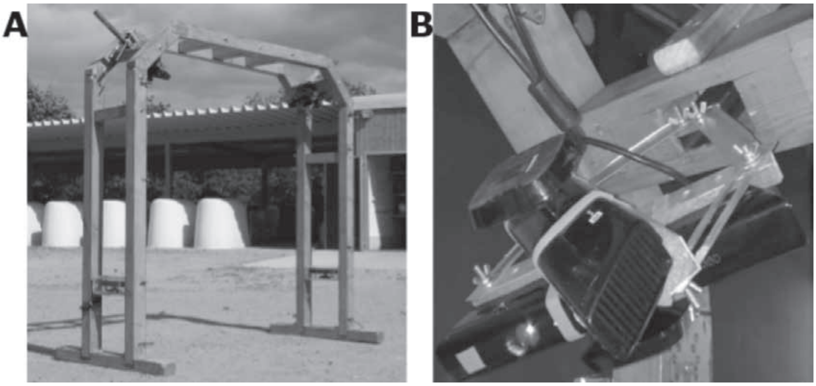

Figure 2. Preliminary prototype. A wooden framework, 2.25 m wide and 2.18 m high, was built (A) and equipped with six Kinect cameras, three on each side: one horizontally mounted and two facing the passing animals in diagonal top view fixed so that they crossed one another (B).

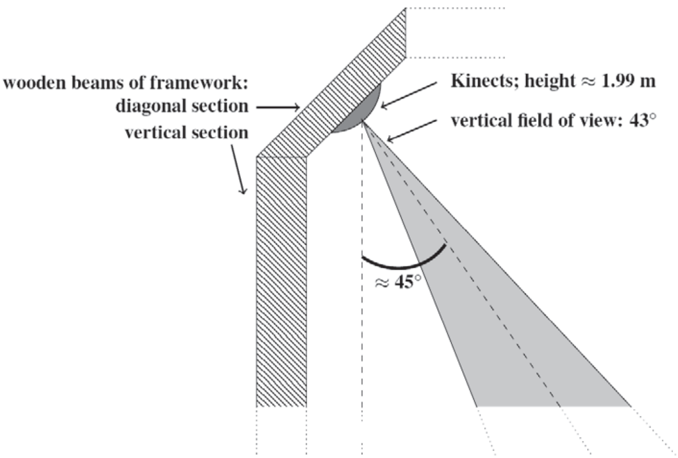

Figure 3. Side view schematic representation of the setting for recording. Kinect cameras were mounted within the diagonal section of the framework. They were facing the ground at approximately 45° with 43° vertical field of view.

Side view Kinect cameras

The front of a Microsoft Kinect was 0.28 m long. As the future construction will be used in cow barns, the lower cameras were fitted with transparent protective cases to shield them from dirt and humidity. Acrylic glass was used to prevent loss of depth measurement accuracy. Therefore, the distance between the framework's two arches was calculated to be 0.32 m to provide room for the cable duct and protective cases. The two side view Kinect cameras were directly facing each other, but when a cow passed, the depth measurement from either side of its body was not influenced by the pattern of the opposite Kinect camera.

Diagonal top view Kinect cameras

The upper Kinect cameras were mounted in diagonal top view, because the claws would be hidden in a vertical top view installation. In the setting described, the whole area between the cow's back and the claws was in the field of view. Metal mounting brackets were constructed to attach the crossed Kinect cameras topside to topside to each other with the angle between their fronts fixed at ~56° (Figure 2B). Since the pattern of the two Kinect cameras overlapped by only 1°, interferences were negligible. In combination, this gave a 112° horizontal field of view. They intersected in a rhombus with a centre line of ~2.4 m (Figure 4). This allowed us to record several steps taken by walking cows, as one Kinect camera captured the approaching animal and the other recorded the leaving animal. Again the passing cows prevented the cameras from interfering with each other.

Data collection

Development data sets for this feasibility study were gathered on 9 and 23 January 2014 at a cattle auction and at the 'Neumünster am Abend' cattle show, respectively. Both events took place

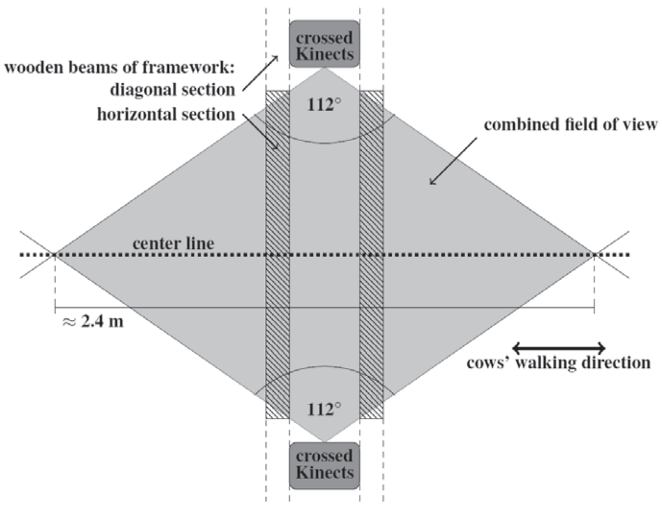

Figure 4. Top view schematic representation of the setting for recording. Crossed Kinect cameras were mounted within the diagonal sections of the framework. The combined horizontal fields of view (112°) from both sides overlapped in a rhombus with ~2.4 m diagonal. The multi-Kinect system observed several steps taken by cows walking on the centre line (dotted).

in Neumünster, Germany and were organised by Rinderzucht Schleswig Holstein eG. Holstein Friesian cows led through the framework by ropes were recorded. The cows' list numbers were written down, in order to identify the animals using the event catalogues.

Alpha versions of software and algorithms

Recording

Software to operate the Kinect cameras was implemented in C++ (based on OpenNI (2013)). The software listed all Kinect cameras connected to the system and allowed the device required to be selected. Display options RGB, depth map or both in overlay could be chosen. The data formats *.kdm (Kinect depth map) and *.kcm (Kinect colour map) were developed to store streams of depth images and colour images as binary data, respectively. Saving options included storing both streams or just one type of stream. Every Kinect camera produced its own *.kdm and *.kcm streams. Both types of stream were automatically named with the current date and time when recording started to avoid overwriting. Each recorded image was equipped with a timestamp, which was independently defined within the Kinect camera. Using these timestamps, the images acquired from the six Kinect cameras could be synchronised simultaneously.

Simultaneous synchronisation

The image timestamps provided by the cameras counted microseconds from the moment the Kinect camera was connected to electrical power. To enable synchronisation, all six Kinect cameras were plugged into an outlet strip with a switch so that they could be switched on simultaneously. The camera which started recording last was set to be the reference camera. Its first image marked the start of synchronisation. For every camera the number of images recorded up to the time when the reference camera started recording was computed (offsets, Figure 5). Every timestamp of the reference camera was compared to the timestamps of the images obtained from the other cameras after adding the corresponding offset. A time window was specified via a threshold value centred around each timestamp for the reference camera. Images were declared synchronous if and only if their timestamps were in the corresponding window. It could be observed that the Kinect cameras recorded with different frame rates and that the frame rates were not stable. If the time window did not contain all six timestamps, the synchronisation software adapted the offsets or defined a new reference camera, if necessary. The synchronisation software was written in MATLAB[4].

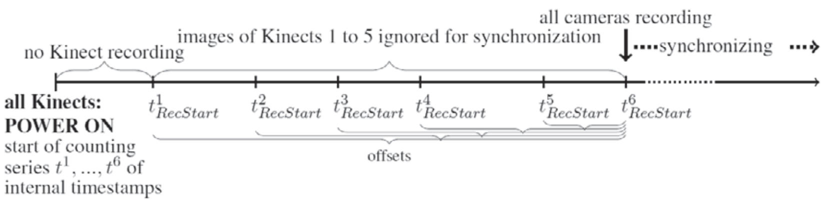

Figure 5. Illustration of synchronisation process.

[4] www.mathworks.de/de/help/matlab/release-notes-older.html.

Sorting and segmentation

For a specified lead time, the system recorded empty scenery and averaged these background images. On the one hand, this averaged background image was used to differentiate between depth maps with and without passing cows. Tolerances relating to the mean for the depth maps were applied, and the depth maps were divided into three categories: 'cow', 'parts of cow' (containing images presenting too little of the cow's body for further analysis), and 'empty'. On the other hand, the averaged background image was used for segmentation. The areas in a 'cow' image that showed large pixel differences from the averaged background could be specified as moving foreground (cow). Sorting and segmentation were implemented and automated in MATLAB.

Claw finding and spine approximation

In RGB images it was often difficult to determine the cows' claws because they were covered in manure. For the 3D-data an algorithm was developed to mark body parts as candidates for claws if they showed both small differences from the background and depth values with great distance from the Kinect. Afterwards, the neighbouring body parts of those candidates were examined to determine whether they were 'leg shaped', i.e. their diameter was approximately constant. In that case the candidates were confirmed to be claws, otherwise they were discarded. Claw determination was implemented and automated in MATLAB. As a next step, the trajectories of the claws could be calculated and used to describe the cow's gait. The recordings of the approaching cow taken by the diagonal top view cameras could be used to approximate the spine by means of a sphere (Figure 7). This yielded a measure for back posture in terms of the spine's curvature, which was an important characteristic in lameness classification. Approaches using a specialized edge detector to find the spine were implemented in MATLAB. Automation has not been achieved yet.

Transforming data into a joint coordinate system

Every Kinect recorded 3D-data within its individual coordinate system. It consisted of the axes measuring depth values, columns (both horizontal axes), and rows (vertical axis), and was left-handed. To address the problem of assembling all depth information from six cameras, a left-handed joint coordinate system needed to be defined. In the present scenario its origin was set at the intersection of the diagonals between the framework's vertical wooden beams at ground level (Figure 8A). To specify axis orientation, one side of the framework had to be defined as the front side. The joint coordinate system's positive X-axis then pointed to the right, the positive Y-axis was

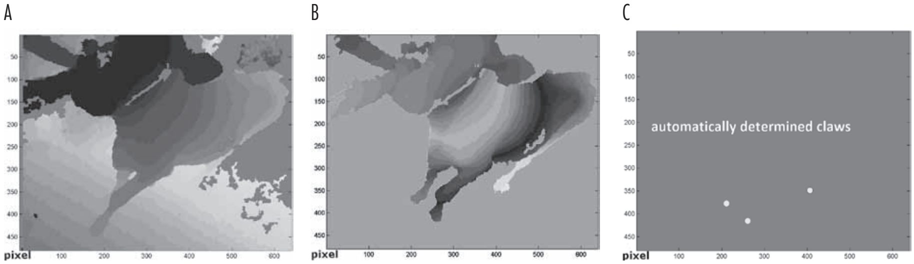

Figure 6. (A) Depth map as recorded by one of the top view cameras, showing a cow led through the framework by rope; (B) Segmented depth map, everything but the cow and the arm of the leading person was set to zero; (C) Automatically determined claws.

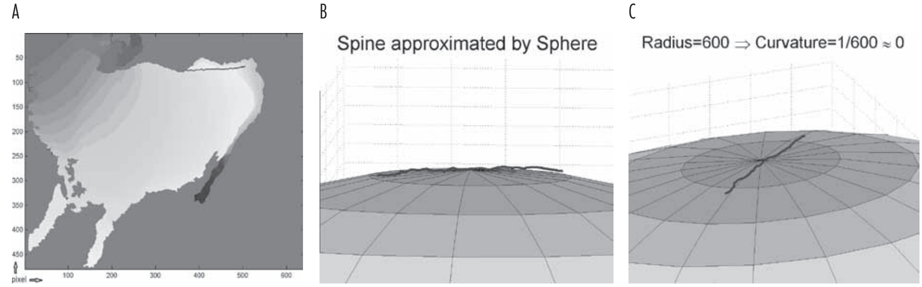

Figure 7. Back posture analysis. (A) Segmented depth map of an approaching cow. The spine was marked. (B, C) 3D-representations of the spine approximated by a sphere. The reciprocal value of the sphere's radius was the curvature of the spine.

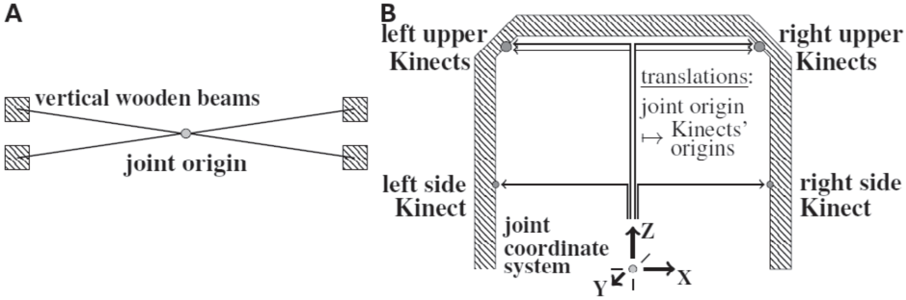

Figure 8. (A) The diagonals between the framework's vertical wooden beams intersected at the origin of the joint coordinate system. (B) Schematic representation of the translations needed to map the joint origin onto Kinect origins. The Kinect cameras' origins within the pairs of upper Kinect cameras differed slightly, as the cameras were mounted topside to topside. The rotations to adapt the Kinect cameras' individual orientations are not presented in this diagram. The joint coordinate system's positive X-axis was directed to the right, the Y-axis to the front and the Z-axis upwards.

directed to the front, and the Z-axis was oriented upwards (Figure 8B). To transform the depth information from the Kinect cameras into these joint XYZ-coordinates, the transformations that mapped the joint coordinate system to the Kinect cameras' coordinate systems had to be reversed for every camera individually. Such transformations consist of a translation (Figure 8B) carried out after a three-dimensional rotation to adapt the individual orientation of the Kinects.

One way of expressing 3D rotations are Tait-Bryan-angles (Berner, 2008); i.e. three angles (φ, θ, ψ) describing three consecutive 2D rotations within the coordinate planes. If φ, θ and ψ are known, the rotation matrix can be calculated. The present study used the YZ'X' convention: The first rotation was carried out around the Y-axis, the second around the Z'-axis – the image of the Z-axis under the first rotation – and the third rotation around the X'-axis, which was the image of the X-axis after the first two rotations. In a left-handed system, clockwise and counter clockwise rotations had positive and negative signs, respectively. Each of the Kinect cameras had three individual Tait-Bryan-angles. The left side view Kinect had the same orientation as the joint coordinate system. All Tait-Bryan-angles were zero. For the right side view Kinect both internal horizontal axes were directed oppositely compared to the joint coordinate system. This led to

Tait-Bryan-angles (0, 180, 0). The rotations of the diagonal top view Kinect cameras were more complicated. The left pair of crossed Kinect cameras was inclined φ = 45° around the Y-axis. Both cameras were subsequently rotated θ = ±28° around the Z'-axis. Within the pair, θ differed in sign to achieve the 56° angle at which the cameras were fixed with regard to one another. To reach its topside down position, one of the Kinect cameras was additionally rotated by ψ = 180° around the X'-axis. This gave Tait-Bryan-angles (45, ±28, 180). For the camera mounted topside up Tait-Bryan-angles would be (45, ±28, 0). The right pair of crossed Kinects was inclined by about φ = -45° around the Y-axis. The cameras were than rotated by θ = ±152° (=180°-28°) around the Z'-axis. Again the camera mounted topside down had to be rotated by ψ = 180° around the X'-axis. The rotation steps for the right pair of upper Kinect cameras are illustrated in Figure 9. The transformations and their reversions were implemented in MATLAB.

Results of preliminary tests

Table 1 presents error rates in both sorting and claw determination. The check was carried out by visual inspection of 30,000 images which were randomly chosen from the recordings taken by all the cameras. Table 2 compares the length of the time window (in milliseconds) specified for synchronisation with the output of synchronous images. The output is given as a percentage of the mean of all images recorded in the period considered for synchronisation.

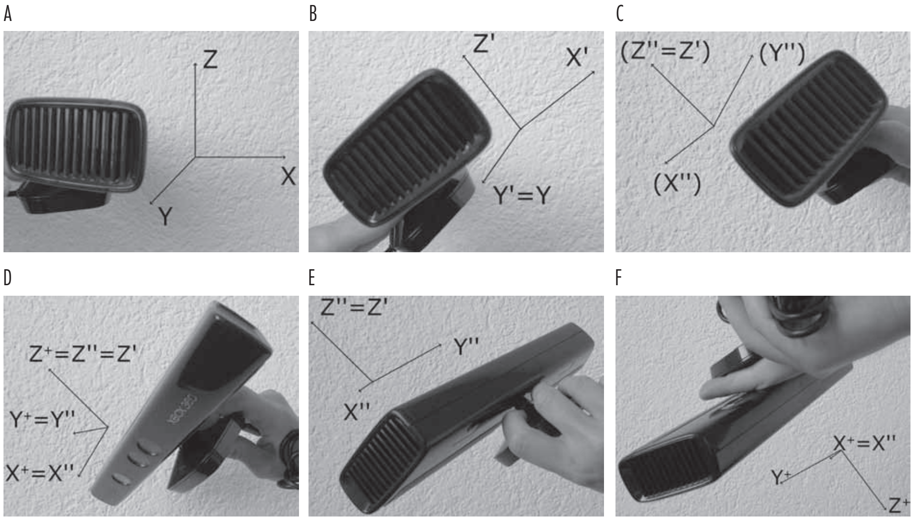

Figure 9. Illustration of the rotations necessary for the right pair of diagonal top view Kinect cameras. (A) The Kinect's orientation coincided with the orientation of the joint coordinate system. (B) Position after a φ = -45° rotation around the Y-axis. This rotation was performed with both Kinects in the pair. (C) Position after an additional 180° rotation around the Z'-axis. This intermediate step is only depicted to illustrate that the Kinects are now facing diagonally downwards, and is not part of the necessary rotation. The required rotations around the Z'-axis are illustrated in subfigures D and E. (D) The Kinect that was mounted topside up needed to be rotated by θ = 152° around the Z'-axis to reach its final position. The final axes were named X^+, Y^+ and Z^+. (E, F) The Kinect that was mounted topside down needed to be rotated by θ = -152° around the Z'-axis (E) and additionally by ψ = 180° around the X'-axis to reach its final position (F). The final axes were named X^-, Y^- and Z^-.

Table 1. Error rates in sorting and claw determination.

Number of tested images	Error rates			
	sorting images into			determination of claws
	cow	parts	empty	
30,000 (randomly chosen)	0%	7.2%	4.8%	1.2%

Table 2. Output of synchronous images compared to the threshold in milliseconds (ms).

ms	<15	15	16	17	18	19	20	23	24	27	31	≥45
%[a]	0	82.0	85.4	87.1	89.9	90.1	90.2	90.4	90.7	90.9	91.0	91.1

[a] 100%: mean of all images recorded in the period considered for synchronisation.

Summary and outlook

Simultaneous recording with six Kinects and synchronization of the images were achieved. The connection between threshold and number of synchronous images was analysed. The larger the time window chosen, the more recorded images could be used. A compromise could be found with a threshold of 20 milliseconds, as 90% was a reasonable number of synchronous images. Distinguishing between image foreground and background was successfully implemented. 'Cow' images were accurately recognised. The relatively high error rates for 'parts of cow' and 'empty' resulted exclusively from wrong distinction between those two categories. No 'cow' images were misplaced. For those the claws were reliably determined with a 1.2% error rate. Software for transformation of depth data into a joint coordinate system was developed. The approximate values of the input parameters are known as a result of construction of the recording unit, but in the final system a calibration geometry will be developed to gather exact camera positions and orientations. They have to be specified accurately, in order to obtain valid results when assembling the depth data and lay a suitable base for point cloud matching algorithms such as the Iterative Closest Point algorithm. Important steps have been made in terms of the necessary groundwork for development of a holistic camera-based solution which provides objective and precise information on the whole animal. A reasonable next step in the development of image processing software would be description of the claws' trajectories. This would give step lengths and heights, standing durations, and additional information, i.e. whether the claws step out of line. For further data collection the construction needs to be firmly installed in a cow barn and equipped with a guidance system so cows can pass the gate freely and straight.

Acknowledgements

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2.4. Hoof lesion detection with manual and automatic locomotion scores in dairy cattle

A. Schlageter-Tello[1], T. van Hertem[2], S. Viazzi[2], E.A.M. Bokkers[3], P.W. Groot Koerkamp[4], C. Machteld Steensels[2], C.E.B. Romanini[2], C. Bahr[2], I. Halachmi[5], D. Berckmans[2] and C. Lokhorst[1]*
[1]Livestock Research Wageningen University, P.O. Box 338, 6700 AH Wageningen, the Netherlands; [2]M3-Biores: Measure, Model & Manage Bioresponses, KU Leuven, P.O. Box 2456, 3001 Leuven, Belgium; [3]Animal Production Systems Group, Wageningen University, P.O. Box 338, 6700 AH Wageningen, the Netherlands; [4]Farm Technology Group, Wageningen University, P.O. Box 317, 6700 AH Wageningen, the Netherlands; [5]ARO. Agricultural Research Organization, P.O. Box 6, Bet-Dagan 50250, Israel; andres.schlagetertello@wur.nl

Abstract

The detection of hoof lesions is an important management practice in dairy farms. Under farm conditions, manual locomotion scoring is often used to detect hoof lesions. Recently, different automatic locomotion scoring systems have been developed. The objective of this study was to determine the capability of a manual (MLS) and an automatic (ALS) locomotion score for hoof lesion detection. The experiment was performed at a dairy farm with 250 milking cows. The presence and severity of hoof lesions were assessed while cows were hoof trimmed. Manual locomotion scoring was performed before hoof trimming. Automatic locomotion scoring was performed with a system based on a 3D camera, positioned in top-down perspective. Both manual and automatic locomotion scoring were performed using a 5-level scale and later transformed into a lame/non-lame classification (lame ≥3). The lame/non-lame classification from MLS and ALS was used to calculate the sensitivity and specificity using as reference hoof lesions and severe hoof lesions. The percentage of cows which had hoof lesions at each level of the 5-level MLS was 72% at level 1, 86% at level 2, 89% at level 3, 96% at level 4, and 50% at level 5. The percentage of cows with severe hoof lesions at each level of the MLS was 34% at level 1, 52% at level 2, 62% at level 3, 82% at level 4 and 50% at level 5. The percentage of cows which had hoof lesions at each level of the 5-level ALS was 89% at level 1, 75% at level 2, 78% at level 3, 82% at level 4 and 100% at level 5. The percentage of cows with severe hoof lesions at each level of the ALS was 37% at level 1, 39% at level 2, 59% at level 3, 45% at level 4 and 100% at level 5. When transformed into a lame/non-lame classification MLS showed a sensitivity of 36% and specificity of 81% when hoof lesions were used as reference and a sensitivity of 43% and specificity of 78% when severe lesions were used as reference. For the ALS, sensitivity for hoof lesions was 47% and for severe hoof lesions was 58%. In conclusion, both manual and automatic locomotion scores demonstrated a poor to moderate capability to detect hoof lesions and severe hoof lesions.

Keywords: back posture, claw, cow, lameness, trimming

Introduction

Hoof lesions are a major problem on dairy farms (Bruijnis *et al.*, 2010). Hoof lesions are common on dairy farms, with prevalence values ranging from 33% (Gitau *et al.*, 1996) to 72% (Manske *et al.*, 2002). Hoof lesions have been associated with a negative effect on milk yield (Amory *et al.*,

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2008) and reproductive performance (Sogstad *et al.*, 2006), and also increase the risk of culling (Barkema *et al.*, 1994, Booth *et al.*, 2004) and production costs on farms (Bruijnis *et al.*, 2010).

One common strategy for detecting hoof lesions is to assign manual locomotion scores (MLSs). With MLSs, human raters look at specific gait and posture traits in order to score the locomotion of a cow on a scale indicating an increasing level of impaired locomotion. In the literature, impaired locomotion is associated with the term 'lameness' (Flower and Weary, 2009; Winckler and Willen, 2001). A cow is classified as lame when it exceeds a predetermined threshold on the scale. A cow classified as lame is commonly assumed to have a painful condition due to hoof lesions or other painful lesions in the limbs (Flower and Weary, 2009; Whay, 2002).

However, as the number of cows per herd increases, farmers are likely to have less time available to assign MLSs. This is one of the main reasons for developing automatic locomotion scoring systems (ALSs). ALSs collect on-farm data from cows using sensors. Data from these sensors is analysed using mathematical algorithms to assess the locomotion of cows (Schlageter-Tello *et al.*, 2014).

ALSs focus on lameness detection (Schlageter-Tello *et al.*, 2014) and use MLSs as a reference for calibration and validation (Schlageter-Tello *et al.*, 2014). Lameness, however, is only a visual indicator of an underlying problem (e.g. hoof lesions) which causes impaired locomotion. In this regard, determining the hoof lesion detection capability of MLSs and ALSs is important in order to evaluate the practical utility of both MLSs and ALSs. Therefore, the aim was to study the usefulness of MLSs and ALSs for detecting hoof lesions in dairy cattle.

Materials and methods

Animals and housing

All data were gathered from a commercial dairy farm in Belgium. The number of cows in the milking herd ranged between 210 and 240. All the cows were Holstein-Friesians and were housed indoors in a cubicle barn with slatted floors all year round. Cows were fed with a total mixed ration based on maize and grass silage. Concentrate was provided by an automatic feeder located in the barn. The cows were milked twice per day (06:00-08:30 h and 18:00-20:15 h) in a 40-stand DeLaval rotary milking parlour. After milking, the cows stepped away from the rotary milking platform and entered a 20 m long corridor that led them back to the cow shed.

Manual and automatic locomotion scoring

Manual locomotion scoring was performed by one experienced rater using a five-level scale as described by Flower and Weary (2006). Cows scored as level 1 exhibited smooth and fluid movement, whereas in cows classified as level 5 the ability to move was severely restricted.

Automatic locomotion scoring was performed with an ALS based on analysis of 3D video records and analysis of the back posture measurement (BPM) described by Viazzi *et al.* (2013) and Van Hertem *et al.*, (2014). Each cow entered the 20 m corridor. They passed a radio frequency antenna (DeLaval AB, Tumba, Sweden) which identified the cows and triggered recording. Video recordings of cows walking were made with a 3D camera (Kinect®, Microsoft Corp., Redmond WA, USA), installed in top-down perspective at a height of 3.45 m above ground level. Videos were analysed by an algorithm which automatically segmented the cow body in the images, extracted the back spine contour line, and calculated the back curvature parameters (Viazzi *et al.*, 2013).

The BPM was calculated as described by Van Hertem *et al.* (2014). BPM values between 0 and 1 were rescaled into a 5-level ordinal scale as MLS.

Hoof trimming and hoof lesion recording

In order to detect hoof lesions, hoof trimming was performed on all milking cows in the herd (n=244). Hoof trimming was carried out by two professional claw trimmers on two consecutive days. Each hoof trimmer treated approximately half the herd. Hoof lesion recording was performed by two experienced raters (not the hoof trimmers), following the instructions from the Alberta Dairy Hoof Health Project (2014). Hoof lesion severity was assessed on a 4-level scale with level 0 indicating absence of lesions, level 1 slight lesion, level 2 moderate lesion and level 3 severe lesion (Winckler and Willen, 2001).

Data gathering schedule

In order to determine the capability of MLS and ALS to detect hoof lesions, manual and automatic locomotion scoring were assessed on 25 November 2013 after morning milking and before hoof trimming (manual locomotion scoring n=216, automatic locomotion scoring n=104). Hoof trimming and hoof lesion recording took place on 25 and 26 November 2013.

Statistical analysis

The manual and automatic locomotion scores were analysed using the 5-level scale and after transformation into a binary lame/non-lame classification (locomotion score ≥3 was considered lame). The hoof lesion severity scale was rescaled into a binary classification using two different thresholds: ≥1 indicating the presence of at least one hoof lesion and ≥2 indicating the presence of at least one severe hoof lesion.

Reliability (expressed as weighted kappa, κw) and agreement (expressed as percentage of agreement, PA) when comparing locomotion scores assigned to the same cow were calculated for MLS and ALS. Agreement indicates the capability of raters to assign identical locomotion scores to a cow (Kottner *et al.*, 2011). Reliability is the capability of raters using MLSs to differentiate between levels within the score (Kottner *et al.*, 2011). Acceptable κw values are ≥0.6 and ≥75% for PA.

The capability to detect hoof lesions was calculated as a percentage of detection of cows with hoof lesions (and severe hoof lesions) for each level of the 5-level scale and calculation of sensitivity (capability of a test to detect true positives) and specificity (capability of a test to detect true negatives) for hoof lesions and severe hoof lesions for the lame/non-lame classification. Reliability and agreement when comparing manual and automatic locomotion scores and sensitivity and specificity for detection of hoof lesions and severe hoof lesions were studied using the FREQ procedure with SAS 9.2 (SAS Institute, Cary, NC, USA).

Results

The lameness prevalence (locomotion score ≥3) within the herd was 32% according to MLS and 47% according to ALS. The prevalence of cows with at least one hoof lesion was 83%, whereas the prevalence of cows with at least one severe hoof lesion was 54%.

The reliability between MLS and ALS for the 5-level scale was κw=0.29, and κ=0.33 for the lame/non-lame classification. Agreement between MLS and ALS was PA = 33.9% for the 5-level scale and 67.2% for the lame/non-lame classification.

The percentage of cows with and without hoof lesions and severe hoof lesions at each level of a 5-level scale for manual and automatic locomotion scores can be found in Table 1. The percentage of cows which had hoof lesions at each level of the 5-level MLS was72% at level 1, 86% at level 2, 89% at level 3, 96% at level 4, and 50% at level 5 (Table 1). The percentage of cows with severe hoof lesions at each level of the MLS was 34% at level 1, 52% at level 2, 62% at level 3, 82% at level 4 and 50% at level 5 (Table 1). The percentage of cows which had hoof lesions at each level of the 5-level ALS was 89% at level 1, 75% at level 2, 78% at level 3, 82% at level 4 and 100% at level 5 (Table 1). The percentage of cows with severe hoof lesions at each level of the ALS was 37% at level 1, 39% at level 2, 59% at level 3, 45% at level 4 and 100% at level 5 (Table 1).

When transformed into a 2-level scale for a lame/non-lame classification, MLS showed a sensitivity of 36% when hoof lesions were used as reference and a sensitivity of 43% when severe hoof lesions were used as reference (Table 2). For the ALS, sensitivity for hoof lesions was 47% and for severe hoof lesions it was 58% (Table 2).

Discussion

Reliability and agreement are useful indicators for the reproducibility and consistency of MLS and ALS. In the current study, reliability and agreement were poor when comparing locomotion scores assigned by MLS and ALS for the 5-level scale and lame/non-lame classification. Maertens *et al.* (2011) reported a percentage of agreement of 84% between an MLS and an ALS using a pressure-sensitive walkway and 3-level scale. The ALS in their study was different from the ALS used in this study. Reliability and agreement for human raters reported in the literature showed high variation (Schlageter-Tello *et al.*, 2014). In this regard, reliability and agreement when comparing MLS and ALS results obtained in the present experiment are similar to those obtained when untrained human raters assess locomotion scoring in cows (Schlageter-Tello *et al.*, 2014).

Table 1. Percentage of cows with and without hoof lesions (lesions) and severe hoof lesions at each level of a 5-level scale for manual and automatic locomotion scores.

	Level 1	Level 2	Level 3	Level 4	Level 5
Manual locomotion score					
n	61	84	47	22	2
Lesions %	72.1	85.7	89.4	95.5	50.0
No lesion %	27.9	14.3	10.6	4.5	50.0
Severe lesions %	34.4	52.4	61.7	81.8	50.0
No severe lesion %	65.6	47.6	38.3	18.2	50.0
Automatic locomotion score					
n	19	36	37	11	1
Lesions %	89.5	75.0	78.4	81.8	100.0
No lesion %	10.5	25.0	21.6	18.2	0.0
Severe lesions %	36.8	38.9	59.5	45.5	100.0
No severe lesion %	63.2	61.1	40.5	54.5	0.0

Table 2. Sensitivity and specificity of manual and automatic locomotion scores for detecting hoof lesions and serious hoof lesions.

	Sensitivity	Specificity
Manual locomotion score		
Hoof lesion	35.6 (28.6-43.0)	80.6 (63.9-91.8)
Severe hoof lesion	42.5 (33.2-52.1)	77.7 (68.4-85.3)
Automatic locomotion score		
Hoof lesion	46.9 (35.9-58.2)	52.4 (29.7-74.3)
Severe hoof lesion	58.0 (43.2-71.8)	62.9 (48.7-75.7)

Both MLS and ALS demonstrated a poor to moderate capability to detect hoof lesions and severe hoof lesions. In the literature, most articles report a moderate hoof lesion detection capability for MLS and ALS. Using a 9-level MLS and a threshold of 3.5 to detect sole ulcers, sensitivity was 54% and specificity was 70% (Chapinal *et al.*, 2009). A comparison between a five-level MLS and an ALS using force plates (Rajkondawar *et al.*, 2002) tested under farm conditions showed a sensitivity = 67% and specificity = 84% for MLS for the capability to detect painful lesions (defined as limb retraction when digital pressure was applied) (Bicalho *et al.*, 2007). For the ALS, sensitivity was 33% and specificity was 90% for painful lesion detection (Bicalho *et al.*, 2007). Van Hertem *et al.* (2013) reported a sensitivity ranging from 74% to 78% and a specificity ranging from 86% to 93% for hoof lesion detection for an ALS based on behaviour and production data analysis. However, the ALS proposed by Van Hertem *et al.* (2013) still needs to be tested under practical farm conditions. A combination of different approaches (e.g. BPM and behaviour date) to create a unique ALSs may improve the accuracy of the system in detecting lameness and hoof lesions.

The aim when using MLSs and ALSs should be to prevent and efficiently manage conditions which induce impaired locomotion. Long-term studies comparing MLSs and ALSs while applying various strategies to prevent and control unfavourable conditions leading to impaired locomotion are required in order to determine the usefulness of MLS and ALS for securing optimal production and animal welfare in practice (Schlageter-Tello *et al.*, 2014).

Conclusions

In conclusion, both manual and automatic locomotion scores showed poor to moderate capability for hoof lesion detection in this practical experimental situation.

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2.5. Discussion: PLF applications of automatic lameness detection

I. Halachmi[1], A. Schlageter Tello[2], A. Peña Fernández[3], T. van Hertem[3], V. Sibony[1], S. Weyl-Feinstein[1], A. Verbrugge[3], M. Bonneau[4] and R. Neilson[4]*
[1]Agricultural Research Organization, P.O. Box 6, Bet-Dagan 50250, Israel; [2]Livestock Research Wageningen University, P.O. Box 338, 6700 AH Wageningen, the Netherlands; [3]M3-Biores: Measure, Model & Manage Bioresponses, KU Leuven, P.O. Box 2456, 3001 Leuven, Belgium; [4]European Federation of Animal Science (EAAP), Via G. Tomassetti 3, 1/A, 00161 Rome, Italy; halachmi@volcani.agri.gov.il

Preface

This chapter documents the questions and the answers that were expressed during the 2014 EU-PLF/EAAP joint-sessions. They were documented verbatim, but each questioner and responder were given the opportunity to rewrite/edit their questions and/or answers for more clarity. This discussion is related to Chapters 2.1 to 2.4, as well as unpublished data by Annelies van Nuffel on 'Gaitwise', a walking-over system for lameness detection in cattle.[5]

Discussion

Question: Kees Lokhorst (Wageningen UR Livestock Research, the Netherlands) – Annelies, you introduced quite some new (gait) variables (for lameness detection); in total more than 30. I'm interested to know if you want to introduce all of them to the farmers. Which of them are of interest to the farmers and have 'agronomical meaning'? Do you have an idea on that?

Answer: Annelies van Nuffel (Institute for Agricultural and Fisheries Research, Belgium) – I realise that we have too many variables to use them all in our lameness detection system. I think we have to focus on maybe 4 or 5 variables to create alerts for the farmer. Asymmetry will be one of them, gait overlap and probably one of the inconsistency variables to improve the detection of mildly lame cows. However, these variables can be shielded from the farmer; then he only sees a list with cows that need special attention regarding lameness. The farmer should be able to look into the changed gait variables if he is interested in them.

Question: Mike Coffey (SRUC, UK) – We have seen different technologies to detect lameness and other things. But my fear to all of this is that this information will be kept locked into the machines that have been developed and perhaps the impact of these devices will come only when the data from all the devices are integrated into a one single system. I would like a comment on the likely of the data to be made available from the devices to be able to be integrated.

Answer: Daniel Berckmans (KU Leuven, Belgium) – It is a very good question. As I said, if there is a rabbit now on the table and if I'm blind, I will still know that there is a rabbit on the table. If I am deaf, I will know it is a rabbit. As I said, a living organism has very specific characteristics.

[5] The unpublished results referred to in this discussion is available on the EAAP website under session 05: http://tinyurl.com/mqv433l.

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It shows its current status in many ways. You can check it in the way it walks, in the way it talks. What I think is that, at the end, we will see a lot of these variables telling the same thing. So I'm not convinced that we, as scientists, have to push to the reality, to the practice, all these things. It is exciting to see that it comes together. But it is only meaningful if it provides additional information and that is the question. What is the focus? In the first system, we want to give an alarm to the farmer without saying what the reason for lameness is. All these researchers are in this trajectory: to see which variables can be measured. But the further we go we will see if we can do it with few variables but we have to do it continuously. In the literature we can see that there are more than 200 causes for lameness. This is not the objective now. Is that an answer to your question?

Question: Mike Coffey (SRUC, UK) – No. I'm afraid not. From my experience, some of these machines that record lameness use their own internal algorithm and create, for an example, a lameness score. It is very difficult to get that information (algorithm) out of the machine. There are other machines to predicting fertility, feed intake, water intake, etc. They are all propriety machines, marketed by their own companies to solve a particular problem. However, the impact of precision livestock farming will not come from these individual machines; it will come from the integration of the individual machines into a farm system.

Answer: Daniel Berckmans (KU Leuven, Belgium) – Sure. But you see the 'Eyenamic system' from Fancom is integrated to the farm management. So this is already happening. Farmers take those data and connect them into production results. And you are right, it has to come together, but at this stage it is normal that individual components are developed.

Answer: Ilan Halachmi (ARO, Israel) – In the ARO, we did a project like this about integrating the data from few sensors together and associate them to different things such as calving disease or lameness. The sensors' data integration depends on the problem, when we work on a health issue we have to integrate them all. When working on oestrus detection, sometimes one sensor is enough. We are also working on lameness (detection) by using a camera. The camera is only a sensor. A camera may be integrated with the behaviour and production sensors that already exist in the commercial dairy farms. You have to integrate the camera with different systems and sensors.

Question: Susanne Klimpel (GEA Farm Technologies GmbH, Germany) – Question for Dr Scheel (Chapter 2.1), you said that taking data and how much data you would like to take is a compromise towards the battery lifetime. How long did your batteries last?

Answer: Christoph Scheel (Kiel University, Germany) – We can now measure for 20 weeks at 10 Hz.

Question: Gerardo Caja (Universitat Autonoma de Barcelona, Spain) – First of all, I want to thank the organizer, Ilan Halachmi, because this session is giving us a little bit more sense about the sensors, because this gives answers to all the measurements that we are doing. At the same time, I am wondering if we are really approaching the problem in the correct way, because we are comparing machines with veterinarians. And veterinarians, when they make the diagnosis of the illness, they put the animals to a challenge, and see how they respond to the challenge. For example for hoof lesion detection, we apply pressure on the hoofs. Camera-based machine are not detecting or capable of doing that. I am asking you, have you really studied also the approach of submitting the animals to a challenge, for instance a walking challenge? I think this is a good question for Andrés Schlageter.

Answer: Andrés Schlageter Tello (Wageningen UR, the Netherlands) – I did not get your point of a walking challenge. What do you mean by that?

Question: Gerardo Caja (Universitat Autonoma de Barcelona, Spain) – This can be, for example, an animal walking over a special surface.

Answer: Andrés Schlageter Tello (Wageningen UR, Netherlands) – This might be good especially for lameness detection, because lameness in that case is only a definition that we have based on an opinion of a person. And this is, as I have shown you during my presentation, causing a lot of variability. Now, if you make the cow walk in different surfaces, it will bring a lot more variability to the system.

Answer: Tom van Hertem (KU Leuven, Belgium) – I want to comment on this. I don't think that PLF technology will replace the veterinarian. It is useful to detect which animals you should bring to the vet. And then the vet can still do his challenges on the animals in order to make his diagnosis. So, PLF can be interesting in the step before the diagnosis of the vet.

Question: Anonymous – My question is on the fifth paper (Chapter 2.5). What criteria did you ask of the automated lameness detection system to flag sole hoof lesions?

Answer: Andrés Schlageter Tello (Wageningen UR, the Netherlands) – Well, the system was actually not validated with the lesions criteria. It was validated on the locomotion criteria. The model was validated with a person, me, going to the farm for one month and checking the locomotion scores of the cows in the herd. And with my locomotion scores, Tom van Hertem and Stefano Viazzi, both designers of the model, made a calibration of the model.

Question: Anonymous – OK. I was still wondering: was the machine turning out some data and were you picking out like ground reaction forces or anything like that?

Answer: Andrés Schlageter Tello (Wageningen UR, the Netherlands) – We went every week to the farm. I don't know if I get your question ...

Question: Anonymous – It might be the way I am saying it. I just wondered, with the automatic detection (system), when you looked at the data it was giving you, what were you looking for to say: 'Yes!! This animal is lame', or 'This animal is not lame'.

Answer: Andrés Schlageter Tello (Wageningen UR, the Netherlands) – I think this question is more for you Tom, since you helped developed the model.

Answer: Tom van Hertem (KU Leuven, Belgium) – The automatic system that Andrés was using was based on video recordings of the cows. What we were measuring was the back curvature of the cow. The algorithm provides us with a value for this curvature, and that is what we related to locomotion scores and to lesions.

Answer: Kees Lokhorst (Wageningen UR Livestock Research, Netherlands) – And the point is that this automatic system is scoring locomotion. Andres was saying that locomotion is translated into lame or not-lame, one way or the other, by human or by an automatic machine by means of classification. And that lameness is still a container issue of all kinds of hoof lesions. And then his conclusion was that between locomotion scoring and hoof lesion detection, there is still a very big gap. Don't trust automatic systems, but don't trust human scores as well!

Answer: Anonymous – I am working with an automated lameness detection system myself, so that is why I was asking you about it.

Question: Peder Nørgaard (Copenhagen University, Denmark) – It is very interesting to see all this new technology. I wonder how far we are from something that is really useful in practice. It is within 1 year or 10 years?

Answer: Annelies van Nuffel (Institute for Agricultural and Fisheries Research, Belgium) – I don't think I have a complete answer to your question yet, but one of the things that we have to investigate in the future, is to point out to the farmers the economic benefit they will have by detecting and treating the cows earlier than they would do without all this technology. To my knowledge, this is not done yet.

Answer: Daniel Berckmans (KU Leuven, Belgium) – A short answer. In EU-PLF we have 20 farmers from poultry, pig and cow farming. They have installed products, in the prototype stage, for cows and in the commercial stage for pigs and poultry. The only objective is to know if they give an added value to the farmer. These are products that are for sale already.

Answer: Tom van Hertem (KU Leuven, Belgium) – I presented results for the installation of a lameness detection system in commercial conditions. The first one is in Israel and the other one in Belgium. We were working together with an industrial partner to see: what does the farmer want and how do we bring the results to the farmer? We had several discussions with the farmers to see how they wanted to see the results of the system. We are on the way for product development, but we are not there yet. It also depends on many other things. For example, the market changes every year and we have to consider that too.

Answer: Jennifer Salau (Kiel University/TiDa Tier und Daten GmbH, Germany) – I cannot tell when my system is going to be installed in a farm. But it is difficult for farmers to adopt this system, because some of them are made to detect lameness or other aspects. So I think it would be easier for the farmer to adopt a system that is more or less holistic. But I really don't know a timeframe when the product is going to be ready.

Answer: Ilan Halachmi (ARO, Israel) – You are all familiar with PLF (Precision Livestock Farming) systems that were developed at ARO (Israel), such as automatic body weight (developed during the 80s), milk analyser (the 90s), body condition scoring, lie-down behaviour and other sensor systems. Some of them are working in commercial farms, while other sensor systems are still under development or will be in the market sooner or later. I assume that our camera based lameness detection can be functioning in the farms within 2-3 years. It also depends on our academic and commercial partners.

Question: Claudia Bahr (KU Leuven, Belgium) – For Miss Salau (Chapter 2.3). You presented a complex system. But the system seems to be able to detect different parameters, such as lameness and body condition score. My question is what do you plan to do? To detect lameness or body condition in your own way or do you want to use the existing knowledge in the literature to develop a system. What is your plan?

Answer: Jennifer Salau (Kiel University/TiDa Tier und Daten GmbH, Germany) – I think it would be a mistake not to use the algorithms and the knowledge present at the moment. But I don't know, maybe our system will give us the opportunity to improve the present algorithms. We will have to see. The first part is to install the system in a cow barn to collect data continuously and to assemble the information from the six cameras to get complete information from the cow. After that we will see how the algorithms present in the literature can be applied to this.

Question: Claudia Bahr (KU Leuven, Belgium) – Mr. Scheel, you show a system using accelerometers for lameness detection (Chapter 2.1). But the information that you get may not only be related to lameness, but also to other diseases. So how could you distinguish lameness from other health problems?

Answer: Christoph Scheel (Kiel University, Germany) – We might not be able to distinguish lameness from other health problems. It might just detect that there is something wrong, that the behaviour of an animal changes. The system is only supposed to emit a warning, telling farm staff that there is something not going well with an animal.

Question: Claudia Bahr (KU Leuven, Belgium) – So, the system should be considered as an early warning for health problems and not as a lameness detector exclusively.

Answer: Christoph Scheel (Kiel University, Germany) – Yes, it could turn out that way.

Question: Vasileios Exadaktylos (KU Leuven, Belgium) – A question to those that presented lameness detection systems. What happens after a cow is detected as lame?

Answer: Annelies van Nuffel (Institute for Agricultural and Fisheries Research, Belgium) – I think, it is a question that not only our research group, but also for a lot of other groups is trying to find an answer to: that is, what to do once lameness is detected? What does the farmer have to do when a cow is detected as lame? To answer this question close collaboration with veterinarians, clawtrimmers, advisors is needed in order to come up with improved Standard Operating Procedures (SOP's) for the treatment of lame cows. We are looking to that, but it is a tricky question. You have to work with a lot of farms, a lot of lame cows and a lot of data to give advice to the farmer.

Answer: Tom van Hertem (KU Leuven, Belgium) – What I can say is that we are working on a tool for the farmer so he can identify the lame cow. But, what he does to the cows is his decision. We are not making this decision for him. Whether a lame cow receives treatment or not depends on the farmer and different factors. For instance, farmers do not treat cows to be culled from the productive systems.

Comment: Pat Dillon (Teagasc, Ireland) – Data are very important for the farm. But it is also important to use this data from a national point of view or even create an international database to help in the 'decision making process'.

Question: Miel Hostens (University of Ghent, Belgium) – We started a project some years ago called 'dairy data warehouse' and we found a new disease: 'dirty data'. That is a real issue. So my question is, instead of using new sensors and new technology, we should have people working on the data. I've heard about genetic databases and we found very low heritability values. We suspect that possibly 'dirty data' is causing the problem. We find low heritability values because we don't have good data. So maybe we should stop working in sensors but start working on data.

Answer: Daniel Berckmans (KU Leuven, Belgium) – That is a very good point. What I think is that by collaborating with different disciplines this problem would be solved. Because people, like in our group, who don't like to be in livestock houses, we do not have a single project in which we don't have collaboration, because our people like to be behind a computer. And several of them are focused in finding the data to obtain good sensitivities, specificities and accuracy values. To give an example, we did a motion monitoring with a football team, AC Milan, in a normal training session. There was 45 minutes of data, but the data was good enough to create the system in only 10 minutes of the data. The other point was also interesting; to make databases that are big and store them to have value; and from there you can have high quality data. You'll always have a lot of noise but if you focus you can get the information. Another important point is that farmers don't know that they own the data. It is a really interesting point that is solved by collaboration I think.

Answer: Jennifer Salau (Kiel University/TiDa Tier und Daten GmbH, Germany) – You said that maybe we should not spend time in sensors. But the sensors are already there. We only try to use them in a proper way. Of course, there is a lot of noise in data, but this has to be technically addressed. Because they just deliver signals for the famer that something can be wrong.

Question: Anders Herlin (Swedish University of Agricultural Sciences, Sweden) – Does PLF have a role in prevention of problems and animal disorders or does it only detect them?

Answer: Tom van Hertem (KU Leuven, Belgium) – It is true; we are all working on detecting a problem. But with these systems the farmer can know how big the problem is and take actions later. He can use the sensors to see the effect of the actions that he took. So prevention is not just using the sensors but also taking action from data given by the sensors.

Answer: Daniel Berckmans (KU Leuven, Belgium) – We need accurate data. When you have accurate data you can predict and that is the key to prevention. Early warning is one thing, but prediction is the key and maybe society is not ready for that. In our lab we can make insects move wherever we like, so we can control it. It will go in that way. Look to the medical world, technology is there, but the business model is not. In our country a doctor is only paid when you are sick, not to keep you healthy. Prevention is on the way to come.

Answer: Annelies van Nuffel (Institute for Agricultural and Fisheries Research, Belgium) – Another way of ensuring prevention is looking at lameness at the herd level. If you see that more than the average amount of cows is becoming lame, you can take actions to prevent that (e.g. take care of the floor). On the individual level, Gaitwise f.e. could detect the size of the contact area of the claw with the measurement zone. This contact area might be useful to alert for possible overgrowth of claws and hence, alert the farmer to those cows in need for claw trimming.

Part 3. How precision livestock farming delivers added value to the farmers

3.1. Use of sensor systems on Dutch dairy farms

W. Steeneveld[1] and H. Hogeveen[1,2]*
[1]Business Economics Group, Wageningen University, Hollandseweg 1, 6706 KN Wageningen, the Netherlands; [2]Department of Farm Animal Health, Faculty of Veterinary Medicine, Yalelaan 7, Utrecht University, 3584 CL Utrecht, the Netherlands; wilma.steeneveld@wur.nl

Abstract

A survey was developed to investigate the reasons for investing or not in sensor systems on dairy farms, and to investigate how sensor systems are used in daily cow management. This survey was sent to 1,672 Dutch dairy farmers. The final dataset consisted of 512 dairy farms (response rate of 30.6%); 202 farms indicated that they have one or more sensor systems and 310 farms indicated that they do not have any sensor systems. In total, for 95 dairy farms with oestrus detection sensor systems, information about the average calving interval for the years 2003 to 2013 was available. In addition, for 30 dairy farms with oestrus detection sensor systems for young stock, information about the average first calving age was available for the years 2003 to 2013. The most common sensors on farms with an automatic milking system are sensor systems to measure the colour and electrical conductivity of milk. In total, 41% of farms with an automatic milking system had activity meters/pedometers for dairy cows, and 70% of farms with a conventional milking system and sensor systems also had activity meters/pedometers for dairy cows. The main reasons for investing in activity meters/pedometers for dairy cows were to improve detection, improve the profitability of the farm and to gain insight into the fertility level of the farm. The most important reasons for not investing in sensor systems were economic. Having an oestrus detection sensor system was not linked with the average calving interval of the farm. Furthermore, having an oestrus detection sensor system for young stock was not linked with the average first calving age. These results suggest that the farmers use the same rules on when to start inseminating as without oestrus detection sensor systems, and as a result there is no change in first calving age and calving interval.

Keywords: sensor systems, dairy, reproduction, investment

Introduction

In recent years, many sensor systems have been developed for cow management. For instance, there are sensors that measure milk, fat and protein yield (Katz *et al.*, 2007) and milk components to monitor cow fertility (Friggens and Chagunda, 2005; Posthuma-Trumpie *et al.*, 2009) and udder health (e.g. Kamphuis *et al.*, 2008; Whyte *et al.*, 2004). Activity meters, pedometers and 3D accelerometers have also been developed to improve and automate the detection of oestrus (e.g. Firk *et al.*, 2002; Holman *et al.*, 2011) and lameness (Chapinal *et al.*, 2010; Miekley *et al.*, 2012; Pastell *et al.*, 2009). Recently, sensor systems have also been developed to measure the weight of cows (Van der Tol and Van der Kamp, 2010) and the rumination time (Büchel and Sundrum, 2014). Most certainly, other sensor systems are under development right now.

So far, research on sensor systems has focused on development of the sensors and the detection performance (Rutten *et al.*, 2013a). It is, however, not known which sensor systems are used on dairy farms, and which sensor systems are hardly ever used. Moreover, the reasons why farmers invest or not in sensor systems are not known. So far, studies on reasons for investing in new

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technologies on dairy farms have focused in particular on investing in an automatic milking system (AMS). Labour reduction and more flexible labour time were the most important reasons for investing in an AMS (Mathijs, 2004). Only Russell and Bewley (2013) have investigated the reasons for not investing in sensor systems on US dairy farms, and they found that the most important reasons for not investing were that farmers are not familiar with the technologies that are available. It is also not known whether the use of sensor systems for oestrus detection results in a lower average calving interval (CI) in the herd. Inchaisri *et al.* (2010) investigated the effect of higher oestrus detection performance on the CI. This was, however, a normative study and was not based on a higher oestrus detection rate due to the use of sensor systems.

This study has several objectives relating to the use of sensor systems on Dutch dairy farms. The first objective is to provide an overview of the sensor systems currently used in the Netherlands on both AMS and conventional milking system (CMS) farms. The second objective is to investigate the reasons for investing in oestrus detection sensor systems. The third objective is to investigate the reasons for not investing in sensor systems. The final objective is to investigate the effect of using oestrus detection sensor systems on CI and first calving age.

Material and methods

Data collection

A survey was developed to investigate the reasons for investing and not investing in sensor systems, and to investigate how the sensor systems are used in daily cow management. The first question was whether the farm has sensor systems, and subsequently there were different questions for farms with and without sensor systems. The number of questions for farms with sensor systems was dependent on the number of sensor systems at the farm. For each different sensor system there were questions about whether the sensor system was part of an AMS, year of investment, reason for investment, whether the investment was made in conjunction with another major change on the farm and the extent of use of the sensor system.

The survey was developed in Qualtrics software (Qualtrics, Provo, UT, USA). A link to the survey was sent by email to 1,672 Dutch dairy farmers. The list of email addresses was provided by a Dutch accounting agency (Accon AVM, Leeuwarden, the Netherlands). This agency is one of the largest farm accounting agencies in the Netherlands. The farms are located all over the Netherlands. The email with the link to the survey was sent on 18 October 2013, and farmers were able to fill in the survey until 17 November 2013. During that time, two reminders were sent to farmers who had not yet filled in the survey.

In total, 532 farmers filled in the survey. Twenty farms were deleted because they indicated that they had no dairy cows any more (n=15) or because they indicated that they wrongly stated that they had sensor systems (n=5). The final dataset consisted of 512 dairy farms (response rate of 30.6%); 202 farms indicated that they had one or more sensor systems and 310 farms indicated that they did not have any sensor systems.

In total, information about the average CI for the years 2003 to 2013 was available for 95 dairy farms with oestrus detection sensor systems. In addition, information about the average first calving age was available for the years 2003 to 2013 for 30 dairy farms with oestrus detection sensor systems for young stock. This information was provided by CRV (Cattle Improvement Cooperative, Arnhem, the Netherlands).

Data editing and analysis

Data were transferred from Qualtrics into SAS version 9.3 (SAS Institute Inc., Cary, NC, USA). Two farm types were defined for the analyses (AMS farms with sensor systems and CMS farms with sensor systems). This classification was made because it was expected that CMS farms with sensor systems would have different reasons for investing in and using sensor systems from AMS farms because CMS farms make a deliberate choice to invest in sensor systems, while on AMS farms the sensor system may become available with the investment in the AMS.

To investigate the effect of using oestrus detection sensor systems, the year of investment was excluded, and all years before and after the investment were selected. The final dataset for the analyses of the effect of oestrus detection sensor systems for dairy cows consisted of 836 farm years, and the final dataset for the analyses of the effect of oestrus detection sensor systems for young stock consisted of 287 farm years.

In the analysis of the effect of oestrus detection sensor systems for dairy cows on CI, the average CI was the dependent variable and year, percentage growth in herd size and whether the farm had a sensor system for oestrus detection in dairy cows were included as independent variables. Growth in herd size was defined as the percentage increase or decrease in number of cows in comparison with two years earlier. Whether the farm had an oestrus detection sensor system for the years in the data was defined as follows: 1=years before investment in the sensor system on AMS farms, 2=years after investment in the sensor system on AMS farms, 3=years before investment in the sensor system on CMS farms, 4=years after investment in the sensor system on CMS farms. In the analysis of the effect of having sensor systems for oestrus detection for young stock on the average first calving age, the average first calving age was the dependent variable and year and whether the farm had a sensor system for oestrus detection for young stock were included as independent variables. In both analyses, herd was included as a random effect. All variables were analysed using a backward stepwise procedure. Only variables at $P \leq 0.05$ in the Wald test were retained in the model. All data editing and all analyses were performed with SAS (PROC MIXED).

Results

The average herd size on AMS farms with sensor systems was 104 dairy cows, and CMS farms with sensor systems had on average 123 cows. The average yield on both types of farm was almost the same (7,982 and 7,986 kg per cow per year).

An overview of the available sensor systems on both AMS and CMS farms is presented in Table 1. The most common sensors on AMS farms were sensor systems to measure the colour and electrical conductivity of the milk (Table 1). A weighing platform, fat/protein sensors, SCC sensor and milk temperature sensors were predominantly present at AMS farms (Table 1). In total, 41% of the AMS farms had activity meters/pedometers for dairy cows, and 70% of the CMS farms with sensor systems had activity meters/pedometers for dairy cows (Table 1).

The main reasons for investing in activity meters/pedometers for dairy cows were to improve detection, improve the profitability of the farm and gain insight into the fertility level of the farm. The farmers gave the same reasons for investing in activity meters/pedometers for young stock (Table 2). The output from activity meters/pedometers for dairy cows and young stock is intensively used (Table 3).

Table 1. Overview of sensor systems used on farms with an automatic milking system (AMS) and a conventional milking system (CMS).

Type of sensor system on the farm	AMS farms (n=121)	CMS farms (n=81)
Colour sensor	72 (60%)	1 (1%)
Somatic cell count sensor	21 (17%)	1 (1%)
Electrical conductivity sensor	112 (93%)	28 (35%)
Weighing platform	33 (27%)	4 (5%)
Rumination activity sensor	11 (9%)	10 (12%)
Activity meters/pedometers for young stock	14 (12%)	23 (28%)
Activity meters/pedometers for dairy cows	50 (41%)	57 (70%)
Fat/protein sensor	24 (20%)	0 (0%)
Temperature sensor	7 (6%)	11 (14%)
Milk temperature sensor	56 (46%)	4 (5%)
Progesterone sensor	2 (2%)	1 (1%)
Urea sensor	2 (2%)	1 (1%)
Lactate dehydrogenase (LDH) sensor	3 (2%)	1 (1%)
Beta-hydroxybutyrate (BHB) sensor	3 (2%)	1 (1%)
Other sensor systems	4 (3%)	8 (10%)

Table 2. Reasons for investing in activity meters/pedometers for young stock and dairy cows for farms with an automatic milking system (AMS) and a conventional milking system (CMS).

	Young stock (n=14 farms)		Dairy cows (n=50 farms)	
Reasons for investing on AMS farms	No.	%	No.	%
It was standard with the AMS	0	0	9	18
Bought for a reduced tariff with the AMS	4	29	15	30
Reducing labour	0	0	3	6
Improving oestrus detection rates	9	64	36	72
Insights into fertility level of the farm	5	36	21	42
Improving profitability of the farm	9	64	24	48
Other reasons	1	7	0	0
	Young stock (n=23 farms)		Dairy cows (n=57 farms)	
Reasons for investing on CMS farms	No.	%	No.	%
Reducing labour	12	52	22	39
Improving oestrus detection rates	21	91	46	81
Insights into fertility level of the farm	8	35	26	46
It was not a conscious decision to invest	0	0	2	4
Improving profitability of the farm	12	52	27	47
Other reasons	2	9	3	5

Table 3. Extent of use of activity meters/pedometers for young stock and dairy cows for farms with an automatic milking system (AMS) and a conventional milking system (CMS).

	Young stock (n=14 farms)		Dairy cows (n=50 farms)	
Extent of use on AMS farms	No.	%	No.	%
Never	1	7	0	0
Sometimes	2	14	3	6
Regularly	0	0	3	6
Frequently	0	0	7	14
Daily	11	79	37	74
	Young stock (n=23 farms)		Dairy cows (n=57 farms)	
Extent of use on CMS farms	No.	%	No.	%
Never	2	9	1	2
Sometimes	1	4	2	4
Regularly	2	9	2	4
Frequently	2	9	10	18
Daily	16	70	42	74

The most important reasons for not investing in sensor systems were economic, with 'prefer to invest money in other things for the farm' and 'uncertainty about the profitability of the investment' as the most frequently mentioned reasons (Table 4).

Having an oestrus detection sensor system was not associated with the average CI of the farm. Only year and growth in herd size were associated with the average CI of the farm. Having an oestrus detection sensor system for young stock was not associated with the average first calving age.

Discussion

This study presents the reasons for investing in and the extent of use of oestrus detection sensor systems only. This information was also available for other sensor systems but was not presented in the current study.

Improving the profitability of the farm was frequently mentioned as a reason to invest, and the main reasons for not investing were also related to economics. These results emphasize the importance of research into the economic consequences of investment in sensor systems. Dairy farmers will only invest in sensor systems if the benefits are clear. So far, only the economic consequences of investing in automated oestrus detection and concentrate feeding (Van Asseldonk *et al.*, 1999), automated body condition scoring systems (Bewley *et al.*, 2010) and activity meters for oestrus detection (Rutten *et al.*, 2013b) have been investigated using normative models. It will be interesting to also determine the economic consequences of investing in sensor systems by analysing actual farm data, for instance farm accounting data. On most farms, the reasons for investing in sensor systems were related to reducing labour and making herd management easier.

Table 4. Reasons for not investing in sensor systems indicated by 310 Dutch dairy farmers.

Reasons for not investing	No.	%
Prefer to invest money in other things for the farm	149	48
Uncertainty about the profitability of the investment	119	38
Poor integration with other farm systems and software	40	13
Waiting for improved versions of sensor systems	29	9
There are better alternatives to improve daily management	24	8
There is too much information provided without knowing what to do with it	24	8
Not familiar with sensor systems that are available	20	6
Not enough time to work with sensor systems	11	4
Poor technical support or training	6	2
Too difficult or complex to use	6	2
Sensor systems are not reliable	4	1
Sensor systems are not useful	3	1

This means that using sensor systems can have a positive economic effect on the farm, especially by reducing the labour costs. Further investigation must therefore focus on whether substitution of capital for labour occurred on farms which invested in sensor systems, and whether the capital/labour ratio of farms is different before and after investment in sensor systems.

The reasons for not investing in sensor systems are in agreement with Russell and Bewley (2013), who also found that uncertainty about the profitability of the investment was an important reason for not investing in automated monitoring technologies on dairy farms. Russell and Bewley (2013) found that the most important reason for not investing was that farmers are not familiar with the technologies that are available. This reason was only mentioned by 6% of the farmers in the current study. It is likely that Dutch farmers are more informed about new technologies through farming magazines and meetings.

Having oestrus detection sensor systems did not influence the first calving age and CI. Having oestrus detection sensor systems for cows also had no effect on milk yield (results not shown). It is, however, not surprising that there is no effect on milk yield when there is no effect on CI because a higher milk yield can be achieved by a shorter CI (Auldist *et al.*, 2007). Furthermore, having oestrus detection sensor systems did not affect the interval in days from birth to first insemination and the interval in days from calving to first insemination (results not shown). It is frequently reported that using oestrus detection sensor systems results in improved oestrus detection (e.g. Hockey *et al.*, 2010; Kamphuis *et al.*, 2012), but current results show that heifers and dairy cows are not inseminated earlier. It is possible that farmers detect oestrus more effectively but still use the same rules on when to start inseminating as without oestrus detection sensor systems, thus resulting in no change in first calving age and CI. These rules include, for instance, starting to inseminate heifers from a certain BW or age onwards, or starting to inseminate cows after a specific period of time. Most farmers invested in sensor systems for oestrus detection in order to improve the oestrus detection rate and to reduce labour. This means that farmers are investing in sensor systems to make farm management easier, and are thus less focused on improving the technical parameters of the herd. Another reason for not finding an effect on first calving age and CI might be that most investment in oestrus detection sensor systems has taken place in recent years and it was difficult to observe an effect.

Conclusions

Sensor systems for mastitis detection and oestrus detection were the most used sensor systems. Reasons for investing in sensor systems were different for different sensor systems. For sensor systems attached to the AMS the farmers made no conscious decision to invest as they answered that the sensors were standard at the AMS or were bought for reduced costs with the AMS. Main reasons for investing in oestrus detection sensor systems were improving detection rates, insights in fertility level of the herd, improving profitability of the farm and reducing labour. The main reasons for not investing in sensor systems were economically related. Having an oestrus detection sensor system was not associated with the average CI of the farm. Having an oestrus detection sensor system for young stock was not associated with the average first calving age.

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3.2. Economic modelling to evaluate the benefits of precision livestock farming technologies

C. Kamphuis[1], W. Steeneveld[1] and H. Hogeveen[1,2]*
[1]Chair group Business Economics, Wageningen University, Hollandseweg 1, 6706 KN Wageningen, the Netherlands; [2]Department of Farm Animal Health, Faculty of Veterinary Medicine, Utrecht University, Yalelaan 7, 3584 CL Utrecht, the Netherlands; claudia.kamphuis@wur.nl

Abstract

'Precision Livestock Farming' (PLF) technology is an emerging research field which develops management tools aimed at continuous automatic monitoring of animal production, including real-time monitoring of growth, health and welfare. The purpose of PLF is to support farmers in making daily management decisions by providing extra 'senses', and to make farmers less dependent on human labour. Many PLF concepts have been developed in recent years, but the uptake of most of these technologies on commercial farms has been slow. Reasons for this slow uptake include the fact that these PLF technologies generate substantial amounts of data but this data is not converted into useful information for decision management. Another reason is that the investment in PLF technologies can be significant, whereas the economic benefits of the investment are unknown. Insight into the on-farm economics of PLF is therefore important. The objective of the study was to develop a value creation tool that models the economic impact of PLF technologies on dairy, fattening pig and broiler farms. The tool uses technical parameters, and the economic impact of PLF implementation can be estimated at farm level by estimating the impact of PLF technologies on these technical parameters. Twenty key global suppliers of PLF technologies were approached in order to gain insight into their views on which of these technical parameters are affected by their PLF technology and to what extent. The knowledge acquired will be used to validate the tool and to gain insight into the costs and benefits of PLF technologies. This current paper specifically reports on the value creation tool developed for dairy farms. Automated heat detection (Nedap N.V., Groenlo, the Netherlands) is used to demonstrate how this tool works and to calculate the potential added value of this PLF technology. The value creation tool will assist, ultimately, in the development of PLF technologies that add value to on-farm decision-making processes.

Keywords: livestock production, automatic monitoring techniques, economic impact

Introduction

'Precision Livestock Farming' (PLF) technology is an emerging research field that develops management tools aimed at automatic and continuous real-time monitoring of animal production, and animal health and welfare. By means of continuous monitoring, PLF seeks to support farmers in making better daily management decisions based on information from additional 'senses', and to make farmers less dependent on human labour. There is extensive development of new PLF concepts (sensors and/or other hardware) that are potentially interesting for on-farm application: 126 peer-reviewed studies on 139 PLF technologies were published for the dairy cattle industry alone (Rutten *et al.*, 2013b) from January 2002 to June 2012. Projects such as All-Smart-Pigs (www.all-smart-pigs.com), and the Dutch Smart Dairy Farming project (www.smartdairyfarming.nl),

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together with conferences (e.g. European Conference on Precision Livestock Farming (ECPLF) 2013 and Smart Agrimatics 2014) that focus on the collection, storage and use of sensor data are also proof of the growing interest in, and demand for, on-farm PLF technologies.

Despite the growing need for PLF technologies for decision support management, the uptake of most PLF concepts on commercial farms has been slow. There are several explanations for these modest adoption rates. Explanations that are often heard include the fact that PLF technologies (1) generate substantial amounts of data but provide little or no information for decision management; (2) have an unfavourable cost-benefit ratio; and (3) have a lack of perceived economic value (Russel and Bewley, 2013). For example, continuous monitoring of the weight of fattening pigs and generating alarms when the actual weight deviates from expected values is interesting data for farmers to have. However, as long as farmers are unable to translate data and/or alarms into clear actions, monitoring weight will have limited added value for decision making processes.

The net economic benefit of PLF technology when applied on farm is one of three key characteristics which determine the potential value of a PLF technology (Hogeveen and Steeneveld, 2013). The absence of clear cost-benefit data on PLF technologies, however, is one of the most important limiting factors for commercialisation of PLF technologies (Banhazi *et al.*, 2012). Economic analyses are therefore important and it logically follows that a PLF technology is more likely to become successful when information on its potential economic value is available. In recent years, several studies have attempted to model the economic impact of PLF technologies. These models can be straightforward partial budget models (e.g. Jago *et al.*, 2011) which are particularly useful for farmers in making better-informed purchase decisions, but the potential economic value of PLF technologies should be identified earlier, during the development phase, to increase the likelihood that that they will become accepted. There are also more complex bio-economic models (e.g. Bewley *et al.*, 2010; Rutten *et al.*, 2013a) which use simulation techniques to accurately estimate the economic impact of PLF implementation on-farm. However, these bio-economic models require a lot of modelling skills and knowledge from experts or literature and are, thus, time-consuming and expensive to develop. Moreover, bio-economic models are specific to the PLF technology they were developed for.

The current study reports on preliminary results for a value creation tool which will help suppliers to estimate the on-farm economic impact of PLF concepts. The study is part of the EU-PLF Project (www.eu-plf.eu) which aims to develop a blueprint that will help current and emerging suppliers with the development of PLF concepts that add value to decision-making processes on dairy, fattening pig or broiler farms.

A tool to evaluate the economic impact of PLF technologies

Because dairy farms, fattening pig farms and broiler farms differ in many respects (e.g. labour, investment and (volatile) market prices), three value creation tools were developed, one for each of the three animal groups. All three tools use technical parameters (e.g. farm size, labour) and data on investment, costs and prices that are easily obtained by drawing on farmer and/or expert knowledge or by searching national databases which report official annual statistics. The economic impact of PLF implementation can be estimated at farm level by estimating the impact of PLF technologies on these input parameters. For example, an automated fattening pig sorter is likely to reduce the size of the penalty which abattoirs impose on fattening pig producers if too many pigs fall outside the weight range specified by the abattoir. Another example, an automated mastitis detection system, will reduce health costs as cows with mastitis are detected earlier (when their mastitis is less severe), with increased recovery rates. This paper reports on the tool that has been developed for the dairy industry, and uses the example of automated heat detection in dairy cows to demonstrate in more detail how the tool actually works. Value creation tools for fattening pig and broiler farms are available, but are outside the scope of this paper.

Whether or not PLF technologies will bring benefits at farm level depends on many factors, including the default situation of the farm for which the PLF technology is bought. To gain a better insight into the range of the economic impact of PLF technologies, it was decided to create farm situations based on two economic factors: labour and capital (Figure 1). Input parameter values for the value creation tool will differ between scenarios, resulting in four different economic 'default' situations. These default farm scenarios will be useful in discussing the extent to which PLF technologies have an impact on input parameters and therefore on farm economics.

Input and output of the value creation tool for dairy farms

Table 1 lists the technical input parameters used by the value creation tool. Values for these input parameters can be relatively easily obtained from farmers, accountancy data or experts, or retrieved from handbooks or national databases reporting official annual statistics for the dairy industry. Input parameters are used by the value creation tool to calculate two output parameters:

1. Net farm income (NFI), which is calculated by subtracting the total costs from the total revenues of a dairy farm. Total revenues are from milk production and sales of animals or, for example, forage. Total costs include the cost of feed, cost of rearing heifers, cost of buildings, machinery and equipment, cost of land, cost of the interest rate for livestock and other costs.
2. Labour income (LI). The LI adjusts the NFI for labour costs by adding the number of hours worked times the hourly rate.

Table 1 reports the values for the input parameters for a capital and labour intensive farm (Scenario 2; Figure 1). This type of dairy farm, characterised by high labour costs, a large number of animals per full time equivalent, and high investments in advanced milking parlours or automated milking systems, can typically be found in countries such as the Netherlands.

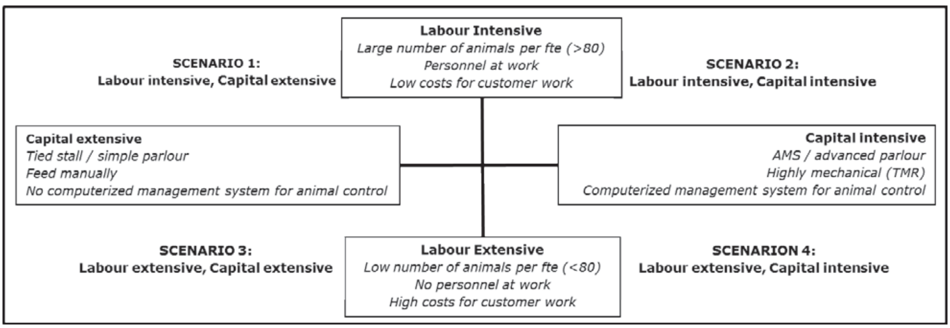

Figure 1. Two economic factors (labour and capital) are used to distinguish between four farm scenarios. Input parameter values will differ between these four farm scenarios and can be used to support estimates of the economic impact of PLF technologies.

Table 1. Input parameters and their units that are used to estimate the economic impact of precision lifestock farming (PLF) technologies on dairy farms. The values presented are for a labour and capital intensive dairy farm (LEI, 2014, unless otherwise stated) without technology (no PLF) and for the same farm when automated heat detection (PLF) is implemented. Values for parameters which change due to the implementation of PLF are coloured grey.

Input parameters	Unit	No PLF	PLF
Technical parameters			
Labour	FTE	1	1
Labour hours	Hours/year	2,080	2,080
Farm size	Dairy cows	80	80
Replacement heifers	% of dairy cows	38	30
Mortality replacement heifers	% of replacement heifers	10	10
Land	Ha	49	49
Milk production	Kg milk/cow/year	8,100	8,222
Buildings, machinery, and equipment			
Value of land	€/ha	27,000	27,000
Interest rate land	%	2	2
Nominal interest rate	%	5	5
Replacement value of buildings [a]	€[b]	800,000	800,000
Depreciation buildings	% of total investment	4	4
Maintenance buildings	% of total investment	1.5	1.5
Replacement value machinery and equipment	€	126,000	126,000
Depreciation machinery and equipment	% of total investment	10	10
Maintenance machinery and equipment	% of total investment	5	5
Replacement value PLF	€	-	10,000
Depreciation PLF	% of total investment	-	10
Maintenance PLF	% of total investment	-	1[c]
Prices			
Dairy cow	€/dairy cow	1,200	1,200
Heifer (1-2 years)	€/heifer	835	835
Calf	€/calf[b]	100	100
Milk	€/kg milk	0.39	0.39
Labour	€/hour[d]	18	18
Rearing costs	€/heifer/year	770[e]	770[e]
Other revenues			
Livestock revenues	€/dairy cow	259	259
Miscellaneous revenues	€/dairy cow	166	166
Other costs			
Concentrates, milk products, minerals	€/dairy cow	680	690
Roughage	€/dairy cow	121	121
Land lease	€/dairy cow	0	0
Fertilizer and pesticides	€/ha	87	87
Customer work	€/dairy cow[b]	200	200
Health care (preventive)	€/dairy cow[b]	50	50
Health care (curative)	€/dairy cow[b]	150	150

Table 1. Continued

Input parameters	Unit	No PLF	PLF
Other costs			
Artificial insemination and breeding	€/dairy cow	80[b]	70
Miscellaneous costs	€/dairy cow[b]	200	200
Other variable costs for PLF	€/dairy cow	-	-

[a] Includes milking parlour.
[b] Expert knowledge.
[c] Lammers, Nedap N.V., personal communication, 2014.
[d] Huijps *et al.*, 2008.
[e] Based on Mohd Nor *et al.*, 2012.

The default values listed in Table 1 were, therefore, retrieved from a Dutch national database (LEI, 2014) using the figures reported for 2011. Based on these default values (no PLF; Table 1) for the technical input parameters, the value creation tool estimates NFI at -€9,657 and LI at €27,783 for a labour and capital intensive farm where no PLF technologies are applied.

Validating the value creation tool with input from suppliers

To validate the value creation tool and to analyse the economic impact of PLF technologies when implemented on-farm, 25 key-suppliers of PLF technologies which are already commercially available were approached by email with a request to collaborate with the EU-PLF project and to help in developing the blueprint. The primary goal was to get their view of the impact of their PLF technology on the technical input parameters of the value creation tool. Six suppliers (24%) agreed to collaborate. This included two companies selling commercial PLF technologies for the dairy industry (GEA Farm Technologies, Düsseldorf, Germany; eCow Ltd., Exeter, UK), one supplier selling commercial PLF products for the pig and dairy industry (Nedap N.V., Groenlo, the Netherlands), one for the pig and broiler industry (Fancom B.V., Panningen, the Netherlands), and two for the pig industry (Roxell bvba, Maldegem, Belgium; SoundTalks N.V., Leuven, Belgium). To date, two of these suppliers have been contacted in person to work with the tool and to obtain input for those parameters affected by their PLF technology on a labour intensive and capital intensive dairy farm (Scenario 2; Figure 1).

The automated heat detection system for dairy cows is used in the current study to serve as an example of how the value creation tool can assist in estimating the economic impact of this PLF technology when used on a capital-intensive and labour-intensive dairy farm. The PLF supplier (Nedap N.V., Groenlo, the Netherlands) indicated the input parameters affected (grey cells in Table 1): automated heat detection will reduce the costs of artificial insemination and breeding, and increase the cost of concentrates, which affects the costs for concentrates, milk products and minerals. It will also increase the milk yield per cow per year due to the reduced calving interval and the large proportion of older cows in the herd. Moreover, fewer replacement heifers will be needed as there will be less involuntary culling of cows that do not become pregnant. This reduction in replacement heifers will reduce heifer rearing costs. In collaboration with the supplier, values for the input parameters affected were changed (Column PLF, Table 1). In addition to these effects on input parameters, the farmer has to invest in this PLF technology and, thus, costs for PLF technology have to be accounted for. The supplier mentioned investment costs of €10,000 with a depreciation period of 10 years and maintenance costs of 1% of the investment. Using these new values for input parameters, the value creation tool estimated an NFI of -€2,295 and an LI of €35,145. In other words, investing in automated heat detection for dairy cows has an estimated positive economic impact of €7,362 per annum for this capital and labour intensive dairy farm.

To estimate the economic impact of automated heat detection system for dairy cows in another situation, e.g. a labour intensive but capital extensive dairy farm (Scenario 1, Figure 1), is a straightforward exercise. Labour intensive but capital extensive farms can typically be found in countries like Ireland, where pasture-based dairying is common. The default values can therefore be changed to values which are more appropriate for this scenario. Input parameters which may change include the lower cost of investment in buildings, machinery and equipment, and lower feed costs as these dairying systems have low inputs of concentrates. Reducing the default values for buildings to €200,000 and for machinery and equipment to €75,000, reducing the feed costs to €300, reducing the value of land to €11,000 per ha, changing the milk price to €0.34 per kg of milk, reducing the milk yield per cow to 5,500 kg per cow per year, and reducing the values of animals (€700 for a dairy cow, €300 for a heifer and €50 for a calf) and the rearing costs of heifers (€400) changes the NFI and LI for a labour intensive and capital extensive dairy farm to €3,415 and €40,855, respectively. Assuming that the impact of automated heat detection remains similar to that in Scenario 2, implementation of this PLF technology on this type of farm results in an NFI of €7,230 and an LI of €44.670. The economic benefit of €3,815 per year is less than was estimated for a labour intensive and capital intensive dairy farm, but investing in automated heat detection systems for dairy cows still produces an economic benefit.

The collaboration with Nedap demonstrated that the economic tool was easy to use. Input parameter values are easily changed and the tool calculates new values for the output parameters accordingly. Moreover, the output parameters from the value creation tools are expressed at farm level. This may help to identify the areas that have most impact on NFI and LI and, thus, to identify areas where PLF concepts are likely to have most influence.

A potential downside is that, for the value creation tool to be useful, suppliers must have a clear picture of which input parameters are affected by their PLF technology and to what extent. Moreover, the economic value of a PLF technology depends on many different aspects of the PLF application (Hogeveen and Steeneveld, 2013). Many new PLF concepts aim to improve the health status of animals. The costs arising from disease are then a key-element as these costs represent the potential economic value of the PLF technology. However, improvements in animal health (and thus a reduction in the costs incurred because of disease) are not the only factors that can be influenced by PLF technology: improved management and production efficiency and reduced labour are other areas that can be affected (Hogeveen and Steeneveld, 2013). The social impact is yet another area that can be affected by PLF technology. This social impact is hard to estimate and even harder to express as a value, but must not be underestimated in terms of its influence on whether a PLF technology becomes successful. One of the clearest examples is automated milking systems (AMS). Today, more than 10,000 farms worldwide have adopted AMS (Rodenburg, 2013). This figure suggests that AMS is probably the most widely accepted PLF technology at present, despite the fact that several studies have concluded that AMS has negative effects on economic performance at farm level when compared with conventional milking (Hogeveen and Steeneveld, 2013). However, the two most important motivators for farmers to invest in AMS were a reduction in heavy labour and flexibility of working hours (Hogeveen *et al.*, 2004). Both motivators have a significant influence on the social life of dairy farmers. Future work should focus on how social benefits can be modelled in order to estimate the added value of PLF technologies on-farm.

Conclusions

To increase the likelihood that a PLF technology becomes widely accepted by farmers, information on its on-farm economic value forms a key element. This study reported preliminary results on a value creation tool which may help suppliers to estimate the on-farm economic impact of PLF concepts. The tool used technical parameters and data on investment, costs and prices to estimate the economic impact at farm level. Automated heat detection with dairy cows was used as illustrative example of this tool. Implementing automated heat detection resulted in an estimated positive economic impact of €7,362 per annum for a capital and labour intensive dairy farm. The tool appeared to be easy to use by the supplier of automated heat detection, but requires clear understanding which input parameters are affected and to what extent. Potential social value is not (yet) included in this tool.

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3.3. Developing SmartFarming entrepreneurship – II preparing precision lifestock farming spin-offs

H. Lehr[1], J. van den Bossche[2], M. Mergeay[3] and D. Rosés[4]*
[1]Syntesa Partners & Associates, Rambla Exposició 89 1r 1a, 08800 Vilanova i la Geltrú, Spain; [2]SO Kwadraat, Technologielaan 9, 3001 Leuven, Belgium; [3]M&M Corporation, Technologielaan 3, 3001 Leuven, Belgium; [3]Abrox, c/Valencia 229, 08009 Barcelona, Spain; heiner@syntesa.eu

Abstract

One of the main challenges in modern livestock farming is the lack of well-trained and market-savvy high-tech innovators. The EU-PLF project aims to help by developing a blueprint for a Smart Farming service sector that is driven by high-tech entrepreneurs in conjunction with market leaders. The blueprint will look at service and business models and value creation from Smart Farming technologies, and will in particular investigate the relationship between high-tech start-ups and established market players in the innovation process in the Smart Farming sector. The blueprint will be validated by early stage companies or start-ups which will be trained in the blueprint and coached using the SO Kwadraat coaching methodology. This methodology is based on individual coaching by an experienced high-tech entrepreneur. A competition will be held between these entrepreneurs and the best will receive funding to demonstrate their technology on-farm. Within the EU-PLF project this is known as the SME Drive. In this contribution we will look at the livestock service sector and its analysis from the BrightAnimal project, lay out the foundations for the SME Drive, justify the methodology that we have chosen for selection of teams, report the results from the selection process and give an overview of the first year's activities and results.

Keywords: entrepreneurship, EU-PLF, high-tech start-ups

Introduction

The EU-funded coordination and support action BrightAnimal (Smith and Lehr, 2011) analysed the precision livestock farming (PLF) sector (Banhazi *et al.*, 2012; Cox, 2003, 2005, 2007; Lehr *et al.*, 2013a,b; Lockhorst and Berckmans, 2011; Lokhorst and Groot Koerkamp, 2009) in Europe and worldwide. The BrightAnimal project identified a number of reasons why a service sector of this nature has not yet been established. The reasons cited included:

- There seems to be a certain reluctance on the part of farmers to invest in non-conventional farm technology, i.e. technology that is not related to traditional farm hardware such as tractors, ploughs, etc.
- A large number of existing farm technology providers do not focus on high-tech SmartFarming solutions.
- There is a clear lack of successful cases which demonstrate (1) a return on investment in SmartFarming technology for farmers and (2) successful providers of SmartFarming technology.

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Based on this analysis, the EU-PLF project set out to assist in the creation of a SmartFarming service sector by:

- Selecting a number of key indicators for animal health, welfare and productivity that can be measured with PLF technology and that would be commercially important to farmers.
- Carrying out a socio-economic evaluation of a number of chosen technologies on 25 commercial farms for different species (fattening pigs, broilers, dairy cows and calves).
- Investigating and evaluating possible SmartFarming business models.
- Collecting the findings together in a 'blueprint' which should help companies to get involved in SmartFarming.
- Validating the blueprint by creating four spin-offs (see below) on the basis of the blueprint.

This is shown schematically in Figure 1.

The role of work package 5 'Innovation through high-tech SMEs' is to validate the blueprint by identifying a number of potential SmartFarming spin-offs or start-ups, coaching them using the blueprint, demonstrating the best solutions/products on the farm and feeding back the experience into the blueprint in order to validate (and/or improve) it.

In particular, the work package has the following four objectives:

1. Identification of opportunities for valorisation of additional promising PLF technologies in SMEs and research labs.
2. Coaching teams in valorisation of existing technology in the field of PLF by creating spin-offs.
3. Demonstration of valuable PLF applications through developed prototypes.
4. Creation of four spin-offs.

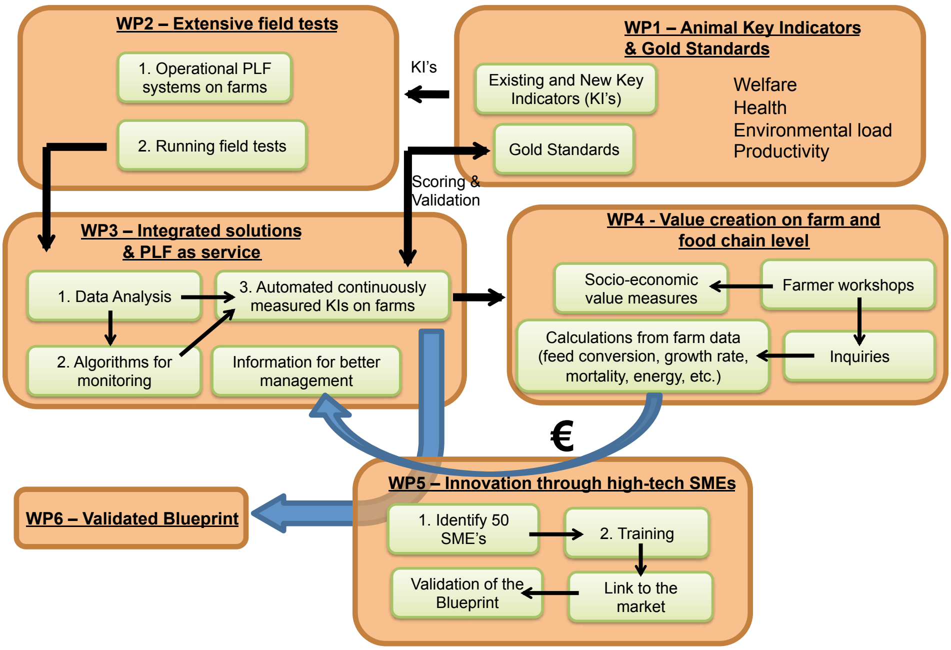

Figure 1. Collaborative model of EU-PLF.

To this end, the team made up from experienced initial stage coaches (idea → start-up) and innovation managers (start-up → business success) identified a number of teams in Europe with SmartFarming technologies that seem to be commercially viable. These teams have entered or will enter a competition and the best will be awarded a total of €100,000 in funding for on-farm demonstrations of their technology. The aim is to start four spin-offs/start-ups or spin-outs. The basic timeline is:

- team selection (Nov 2012-Oct 2013);
- coaching and prototype development (Nov 2013-April 2015);
- creation and valorisation of start-ups (Nov 2013-Oct 2015).

This contribution provides insight into the activity and reports our initial findings from the selection of teams throughout Europe.

Identification of opportunities for valorisation of additional promising PLF technologies in SMEs and research labs by organising local innovation days

Four major university cities were selected, based on (1) the presence of a large group of PhD students in different technology domains, and (2) the presence of a project partner in the region. Wageningen, Leuven, Barcelona and Milan were selected to organise SmartFarming Innovation days.

The schedule for the innovation day was:

1. About 2 hours of presentations covering:
   - introduction to SmartFarming and examples of available technologies;
   - the coaching methodology;
   - case study of a successful SmartFarming spin-off;
   - requirements for participation in EU-PLF;
   - questions and answers.
2. Buffet lunch to break the ice. Coaches approach participants directly to engage in conversations about the participants' work.
3. Dedicated in-depth conversations with groups that would like to participate (about 20 min for each group).

The information gained was used for preliminary selection of the teams. The events were held exclusively in English for two reasons: (1) a team that wishes to be coached had to speak good enough English to communicate with the coaches and (2) a SmartFarming offering that does not target at least the European market is not considered to be viable[6].

The target audience was selected using a general mailing campaign directed at PhD students at the university. A project brochure and an application form were distributed. Based on the application forms received, the teams that were eligible for the coaching process and related funding for breadboard construction were invited to the innovation day.

The first event was held in Barcelona and on 7 March 2013. We made contact with Barcelona Activa, a government-run incubator in Barcelona, which allowed us to use their facilities for the

[6] However, the initial information to Technology Transfer offices and similar institutions was delivered in local languages because we felt that the same conditions did not apply to these gatekeepers.

event. An intensive market search was carried out in order to find potential participants from the farming industry, the academic world and the technology industry. This was done through telephone calls, personal visits and the internet. The following groups/people were contacted:

- 12 technology transfer offices at universities all over Spain, local government and research organisations;
- 250 direct e-mails to researchers in ICT, mechatronics, sensor technology, biotechnology, agriculture, targeting PhD students in particular;
- 150 high-tech start-ups through Barcelona Activa;
- 5,000 technological entrepreneurs (through Barcelona Activa);
- 1000 technological SMEs (through Barcelona Activa).

In total, 20 highly interested participants attended the seminar. They were all very motivated and had ideas or worked in areas related to SmartFarming. Following the individual interviews, 9 out of the 20 participants filed a project information document, including basic information on potential projects they would like to work on. This produced the following outcome after the first event:

- 2 direct coaching team candidates;
- 3 possible coaching cases, under investigation;
- 2 projects not assessed as a target for SmartFarming;
- 2 possible teams to conduct further analysis and send more information.

In general, our team regarded the evaluation of the Barcelona event and the results obtained as very positive.

Through the University of Wageningen, a partner in the EU-PLF project, a second event was organised in Wageningen at the end of May 2013. There were 13 participants, resulting in 2 direct coaching team candidates, 1 strong candidate from whom more information is required and a number of possible coaching cases, which are under investtigation.

Through the University of Milan, a partner in the EU-PLF project, a third event was organised in Milan in mid-June 2013. There were 21 participants, resulting in 1 direct coaching team candidate, 2 strong candidates from whom more information is required and a number of possible coaching cases, which are being explored.

The event in Leuven brought 20 participants together and resulted in 7 additional candidates for coaching.

In conclusion, we can state that more than 2,000 potentially interested people were contacted by holding local innovation days. Of this group, 74 participated in one of our innovation days and more than 20 participants filed a project information document, each of which was evaluated to determine whether it was eligible for coaching.

In addition, the SME drive also received direct applications from interested people who had not attended an innovation day but had heard about the EU-PLF project though different communication channels.

Currently, a total of 17 projects are being coached, with different levels of activity. The ultimate goal of progressing four selected teams to technology valorisation through spin-off creation looks achievable.

Coaching teams in valorisation of existing technology in the field of PLF through spin-off creation

The methodology that will be used for the coaching process is based on a successful formula developed by SO Kwadraat (Spin-Off Kwadraat vzw). This not-for-profit organisation has coached 200 teams over the last 8 years, 70 of which have started their own high-tech company. Most of these start-ups are based on a team of PhD students. All companies are active in Europe, and 50% are active worldwide. This underlines the importance of high-tech companies in export and internationalisation.

Coaching potential spin-offs is a sensitive business. Coaches from SO Kwadraat follow a written code of conduct (available on the website) which guarantees clear and transparent behaviour on the part of the coaches. The objective is to help create sustainable, new, high-tech companies, and to maximise the survival chances of the new companies. This also maximises the number of newly created employment opportunities and hence the return on investment for society.

The coaching methodology starts with an evaluation of the team. Is there a motivated dream team present? The team's motivation to start up a company is the most important non-scientific criterion that is evaluated. In the second phase, detailed screening of the technology is carried out. Is it a mature and proven technology or is there still a long way to go to productise the technology? An initial business concept is drafted, taking into account the capabilities of the team and the potential of the technology. This business concept is evaluated in the market through presentations to potential customers. Feedback from these presentations is then brought back into the coaching process and the initial business concept is revised. In some cases the business concept is completely reconsidered. In most cases, however, the business concept undergoes an evolution towards a market validated concept. This is an iterative process and lasts until the point where all involved are comfortable about feasibility, market and finances. This comfort level is monitored through a risk assessment procedure and an evaluation matrix. If the comfort level is high for both team and coach, business and financial plans are written, with the financial plan setting out the capital required. If there is a clear business concept, strong market interest (optimally expressed in the form of a first customer order), and a strong team, it will be relatively easy to find money on the market (FFF: Family, Fools and Friends, Business Angels or VCs). Our experience indicates that if a company can be started with relatively little money (<250,000 euros), its survival rate increases dramatically compared with capital-intensive start-ups (Table 1).

The evaluation matrix (Figure 2) indicates the readiness of the pre-starters to set up their own company. A number of topics are evaluated here, such as the situation with regard to relevant intellectual property (IP) and product status. The IP may be patented, resulting in a high score (10),

Table 1. Funding of high-tech starters versus survivors and drop-outs.

Funding at start-up (in €)	Survivors	Drop-out
0-100,000	30	0
100,000 and 250,000	20	1
250,000 and 1,000,000	12	1
1,000,000 and 5,000,000	8	5
Total	70	7

EVALUATIEMATRIX Dossier:	
Klasse	**Item**
Team	Management competenties ?
Team	Commerciële competenties ?
Team	Technische competenties ?
Product	Is het product gedefinieerd ?
Product	Intellectuele eigendom ?
Product	Technologisch haalbaar ?

Enkel een idee	2	Het product is beschreven	5	Gedetailleerde specificatie beschikbaar
Onbekend	2	Draft patenttekst beschikbaar	4	Patenttekst OK
Niet onderzocht	2	Onderzoek lopende	4	Preliminaire resultaten ok
Ontwerp beschikbaar	2	Eerste prototype beschikbaar	5	In huis getest prototype beschikbaar
		Berekeningen lopende	5	
Onbekend	2	Toepassingen worden onderzocht	5	Toepassingen beschreven
Draft beschikbaar	2	Overzicht beschikbaar	4	Activiteiten gekend
zwak	-20	voldoende	5	redelijk goed
				Beschrijving beschikbaar

Is het product beschikbaar ?	2	Neen
Kostprijs beschikbaar ?	1	Neen
Commerciële toepassingen ?	2	Geen
Concurrentie analyze ?	2	Onbekend
Positie tov concurrentie ?	2	Onbekend
Unique Selling Proposition ?	2	Onbekend
Actuele industriële contacten ?	2	Geen
Actuele industriële contracten ?	2	Geen
Marktgrootte ?	2	Geen markt
Sales & marketing plan ?	2	Geen
After sales plan?	1	Geen

Figure 2. Evaluation matrix for different criteria (extracts; in Dutch).

or a freedom to operate investigation may be ongoing, resulting in a low score (4). In order for the coach to give a green light for the creation of the high-tech company, on average 80% of the top scores must be achieved.

In addition to tracking the status of a project through the evaluation matrix, a risk assessment is performed. This risk assessment evaluates the financial, IP, market, technology and human resources risk of the project. The overall company risk index is obtained by multiplying all these risk factors. This risk index should be higher than 80%, indicating that the 3-year survival chances of the company will be higher than 80%.

The coach makes another final evaluation: he or she tries to answer the question: 'under the given conditions would I personally start up this company?' If the answer is yes, the risk assessment is positive and the evaluation matrix scores higher than 80%, the coach will suggest that the team should start up the company.

The objective within the framework of the EU-PLF project is to coach 10 teams, and to support the creation of 4 new high-tech ventures. Coaching of the different teams has already started. Since March 2013 a large number of coaching sessions have been conducted with variable results.

As a first step in the coaching process, the teams are asked to fill in a detailed project description sheet. This is a detailed project description, relating to all the different aspects of business creation: (1) project description; (2) market and sector data; (3) status of development; (4) intellectual property; (5) business model; (6) currently invested effort; (7) estimated effort to realise project; (8) team; (9) SWOT analysis of strengths and weaknesses (internal), opportunities and risks (external) and finally; and (10) references.

Based upon this document, the coach can evaluate the weak points of the project and direct his coaching in these directions.

The coaching projects can be classified into three categories:
1. Projects on hold: for different reasons, projects where coaching has started may be temporarily put on hold. The most common reasons are:
   - a change in focus of the strategy, change in priorities;
   - lack of confidence in a viable business model, after initial business analysis;
   - lack of a strong and motivated team willing to risk the start-up.
   - once these roadblocks are removed, active coaching can restart;
2. Projects with one star: these projects are in the pipeline, but currently need more concrete information or more focus by the team. These projects are subject to further technical, commercial or financial information gathering.
3. Projects with two stars: these projects have all the elements needed to get started. They are thus also intensively coached by the SMEDrive.

Of the 17 projects on the coaching list, 4 are on hold, 8 have one star and 5 have two stars.

Demonstration of valuable PLF application through prototypes developed

As explained above, the EU-PLF project has reserved a certain amount of funding for the selection of about four on-farm demonstration activities for spin-offs that are coached by EU-PLF.

The winners are selected by an independent jury of technicians, researchers and experienced business people who have expertise in evaluating companies and projects working on agriculture. The president of the jury is the director of the Agri Venture Capital Fund in Belgium, and the decision is taken based on expert advice from the organisation. The jury is completely independent of the SMEDrive team and therefore a possible conflict of interest between coaches and jurors is avoided. The jury gives a green light (fund the project) or a red light (do not fund the project) in two major areas: technical and economic/financial viability. Only projects where both areas obtain a green light are funded.

To date, three projects have entered the competition. Two of them were given a green light in both areas. In addition, the jury provided very valuable feedback to strengthen the projects.

One project was rejected, not because of its technical potential but for economic/financial reasons. After discussion with the team concerned, the project was put on hold.

Creation of four spin-offs

The two projects which passed the jury evaluation are on their way to forming a new spin-off. The creation of a spin-off involves a number of steps and thus close follow-up by the SMEDrive team will be required.

The most important steps are:
- creation of an entrepreneurial team;
- evaluation of the technology developed;
- business concept definition;
- evaluation of the concept in the real-world marketplace;
- iteration of the concept;
- preparation of the necessary documents;
- start-up and continued coaching.

The most important risk factors are related to the team (human resources). If (1) a team is composed of people who do not know each other very well, or (2) if the team is composed of people of significantly different ages, or (3) if the team is composed of people with a different educational background, then the survival chances of the company are reduced.

It is important for team members to have worked together for some time (preferably a number of years) before setting up a technology company, because they then know each other's strengths and weaknesses. In the event of an operational incident and a related stress situation, this helps them to make the right decisions, distribute the work correctly and define an optimal trajectory to escape from a difficult situation.

It is advisable to form a team with people of more or less the same age. This means that time horizons are aligned and that there is a higher chance of having an aligned vision for the company. It also helps to avoid generation conflicts.

Looking at the different educational levels of team members, we recommend that start-ups should have a team with similar educational profiles. This helps to align the strategy and enables clearer communication. The founders will find it easier to understand each other and know what they are talking about.

So far, 23 teams have been identified as coachable, of which 2 have started a company, and 16 are currently in a coaching process. Twelve teams are working on sensor development for applications such as position tracking and different health monitoring tasks. Other teams are working on automation applications, animal model parameter identification, and feeding applications.

For 5 teams, the coaching process has stopped. The main reasons were (1) a lack of market opportunities to transform an existing technology into viable applications in the smart farming markets, and (2) a lack of interest in this specific market on the part of the teams. Teams are now being coached in different cities, such as Barcelona, Wageningen, Leuven, Milan and Athens.

Conclusions

After holding the SmartFarming innovations days, we can conclude that bringing technology to farms is not per se an attractive proposition for PhD students or other potential entrepreneurs associated with universities and research centres. Heavy direct and indirect marketing of the events in the four different cities resulted in lower attendances than expected. We assume that the main reason for this behaviour is the lack of role models, i.e. the lack of successful start-ups or spin-offs in the SmartFarming sector. Quite understandably, some candidates needed convincing that animal farming is a potentially interesting sector to engage in compared to other uses of their technology.

However, for our purposes the resulting projects were very successful, because the people that do show up at the events are highly focussed, usually quite knowledgeable already, and very motivated to enter a business coaching process. Entrepreneurs with potential SmartFarming applications are generally in need of a better understanding of how to prepare and start a successful business. Most, if not all, candidates came from the engineering side and had had no business training during their education.

It is important to note that, as a result of the innovation days, we could observe some teams starting to cooperate, in particular for the commercial exploitation of research results. Being able to access the participants in the EU-PLF project and their knowledge is clearly perceived as a benefit, since most university teams feel quite removed from actual farms and from the farming economy.

The coaching process is known to be quite intensive and involves ups and downs, sometimes resulting in projects being put on hold. The obvious solution, in order to meet the EU-PLF project's target of creating at least four companies, is to have a large enough portfolio of interesting projects. The SMEDrive teams are convinced that our pipeline of one-star and two-star projects is more than sufficient to meet the target.

The positive reaction of the independent jury to two of the projects is the best proof that the methodology used by the SMEDrive team leads to results.

Taking into account (1) the limited budget for announcing the coaching programmes, and (2) the restriction to smart farming applications, it is clear that coaching programmes for valorising university research have tremendous potential. Bridging the gap between research and industrial value creation is a significant challenge but the first phase of this EU-PLF project has demonstrated that it is feasible.

Acknowledgements

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3.4. Word of caution for technology providers: practical problems associated with large scale deployment of PLF technologies on commercial farms

T. Banhazi[1], E. Vranken[2,3], D. Berckmans[4], L. Rooijakkers[2] and D. Berckmans[3]*
[1]PLF Agritech EU, 3b Ormiston Terrace, Edinburgh EH127SJ, United Kingdom; [2]FANCOM B.V., Research Department, P.O. Box 7131, 5980 AC Panningen, the Netherlands; [3]KU Leuven, M3-BIORES: Measure, Model & Manage Bioresponses, Kasteelpark Arenberg 30, 3000 Leuven, Belgium; [4]SoundTalks, Kapeldreef 60, 3001 Heverlee, Belgium; thomas.banhazi@plfag.com

Abstract

'Precision Livestock Farming' (PLF) technologies are described as usually hi-tech management tools aimed at continuously and automatically monitoring different aspects of animal production, including production efficiency, environmental sustainability of the farming operation and the health and welfare of animals. Quite a few PLF technologies have been developed by different research organizations in recent years, but large-scale field trials of these technologies have never been attempted before. Thus, the main objectives of the European Union funded EU-PLF and All-Smart-Pigs projects were to (1) deploy selected PLF technologies on commercial farms and (2) evaluate the benefits derived by producers and other stakeholders from the information provided by these technologies. In addition, the EU-PLF project is aimed at developing a 'blue-print' for SMEs and other stakeholders so that they are aware of the challenges associated with managing these technologies on farms. It is believed that, ultimately, such a blue-print will allow future SMEs and technology providers to learn from past mistakes and thus better be able to serve the needs of farming communities in the future. Both projects started with the deployment of a large number of technologies on farms, which was both inspiring and of course challenging. The four suppliers of PLF technologies within these two projects were approached to obtain a list of 'problematic issues' encountered on farms during the deployment phase of the projects. This article will list and discuss the practical difficulties associated with deploying these technologies on farms and the solutions that were invented to overcome these challenging problems. Approximately 30 main issues were identified, including (1) rats/mice damaging the electric cables, (2) working in buildings with very high ceilings, (3) flies and dirt obscuring camera lenses, (4) setting-up wireless network connections in remote areas and (5) unstable/fluctuating power on farms – to name but a few. The authors hope that the acquired knowledge will be used by future technology developers to avoid making the same mistakes.

Keywords: installations, trouble shooting, occupational health and safety risks, water damage, electricity

Introduction

Livestock producers globally are facing an increasing range of issues and pressures from (1) increasing feed costs (between 50 and 70% of operational costs for pig producers, for example); (2) increasing social awareness of animal welfare and environmental impacts and therefore subsequent consumer demands; (3) increasing costs involved in compliance with farm-related

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legislation; and (4) the increasing demand for protein from an ever-increasing population and changed eating habits. These issues are all clearly prevalent in an industry environment which lacks the various mechanisms and tools to control or gauge these issues in an effective and efficient manner. As a result, there is a lack of feedback and thus the ability to optimize livestock production is generally limited (Berckmans, 2008).

European Union (EU) livestock production is regulated by directives which contain significant legislative controls in relation to animal welfare and environmental sustainability (Banhazi *et al.*, 2012a,b; Berckmans, 2011; Kashiha *et al.*, 2013; Wathes *et al.*, 2008). Market response to PLF technologies will be constrained by the government and producers' ability to (1) identify the need for change; (2) accept that technology is a key component in the process of change; and (3) allocate or obtain the appropriate funding required to upgrade and standardise facilities (Gregersen, 2011). The need for livestock producers to decrease their costs via improvements in production effectiveness is very real due to the factors summarised below:
- increased cost of feed and increase in regulations;
- increase in cost of energy and stress on land and water resources;
- increasing demand for production but lack of skilled and technically able staff;
- increasing worldwide competition in countries with better climate conditions and lower salary costs.

The EU-PLF project offers a solution to the industry to enable livestock producers to navigate the increasingly complex problems they are facing (Lehr, 2011a). Important considerations include the degree to which industry will adopt and support PLF solutions, and specifically, the commercial grounds for industry to react positively to the technology. There is general agreement that production methods within the livestock industries need to change and that these industries need to be far more productive than current practices allow (Banhazi and Black, 2009). These pressures stem from the consolidation of smaller producers and increasing costs for large producers. The projected potential room for improvement within the pig industry, for example, has been estimated at between 10 and 30% of production related costs (Black and Banhazi, 2013).

Therefore, solutions which can function automatically and optimise the production environment in an animal-centric approach will be sought after (Aerts *et al.*, 2001). This can be achieved by (1) optimising the amount of feed per kilogram of meat produced; (2) assisting in the detection and prevention of disease, injuries or sickness (Chedad *et al.*, 2001; Ferrari *et al.*, 2008); and (3) monitoring and controlling environmental factors (Banhazi, 2009). This would be considered highly valuable by the industry, and as such will allow animals to grow to their full market potential with minimal issues.

Globally, livestock industries are facing the above mentioned challenges which drive the industry to become more productive and innovative. Producers which remain in the marketplace will face a future where the demand for protein will increase due to increased wealth. Therefore, remaining producers will enjoy better profitability due to their ability to service a growing market using fewer resources, and will have greater bargaining power (Lehr, 2011b).

However, before this can happen, it is necessary to undertake a large-scale evaluation of the proposed PLF technologies. This article reports on the large-scale utilisation of five different PLF technologies (SoundTalk's Cough-monitor, Fancom's eYeNamic, PLF Agritech's Weight-Detect™, PLF Agritech's Feed-Detect™ and PLF Agritech's Enviro-Detect™) and problems associated with the deployment, use and maintenance of these PLF tools. It is hoped that this systematic review of issues encountered and the practical knowledge gained will be used to good effect by future technology developers.

Methodology

Many PLF technologies have been developed by different research organizations in recent years, but large-scale field trials of these technologies under commercial farm conditions have never been attempted before. Thus, the main objectives of the European Union funded EU-PLF and All-Smart-Pigs projects were to (1) deploy selected PLF technologies on commercial farms and (2) evaluate the benefits derived by producers from the information provided by these technologies. Both projects started with the deployment of a large number of technologies on farms, which was both inspiring and of course challenging. The four suppliers of PLF technologies within these two projects (SoundTalks, Fancom, PLF Agritech EU and Nema) were asked to provide an exhaustive list of 'problematic issues' encountered on farms during the initial phase of the projects. In essence, information about problems encountered while installing, maintaining and using the technologies on farms was collected systematically.

Results and discussion

Table 1 presents the problems encountered during installation, use and maintenance and some of the solutions developed.

Table 1 lists the practical difficulties associated with deployment, use and maintenance of PLF technologies on farms and the solutions that were invented to overcome these challenging problems. Approximately 30 main issues were identified, including (1) rats/mice damaging the electric cables, (2) working in buildings with very high ceilings, (3) flies and dirt obscuring camera lenses (Figure 1), (4) setting-up wireless network connections in remote areas, (5) unstable/fluctuating power on farms – to name but a few.

Challenges associated with rodents (rats and mice) are real in intensive livestock buildings. Protecting cables from rodents is not a simple task and definitely needs ongoing vigilance. Damage to cables and instruments by livestock is also a real problem in all livestock building, but especially in piggeries.

Flies caused unexpected problems for the camera based systems. For some reason, flies were attracted to the lenses and quite quickly covered the instruments with dirt, reducing the visibility considerably in some cases (Figure 1). A regular cleaning regime was implemented and helped to overcome this problem quite effectively. The need to make the instruments both water- and air-tight often conflicted with the need to ventilate the instruments at the same time so that any heat generated can be easily dissipated.

Social issues are also real and need to be taken into consideration when dealing with the installation of PLF technologies on farms. Some of the negative results (less growth and more health problems than expected) had to be communicated to farmers sensitively.

Installing PLF technologies on farms is an inherently dangerous activity, so the occupational health and safety aspects of installation also had to be considered very carefully. Potential encounters with asbestos (especially on older farms), heights and interference by animals during installation all

Table 1. Sample list of problems encountered during installation, use and maintenance of PLF tools (only the key issues encountered are presented).

Problem	Solution	Comments/suggestions
Maintenance issues		
Damage to cables by rats and mice	Protection of cables with hard plastic tubes and spraying cables with chilli concentrate.	Be careful when applying spray as the concentrate is very strong, but safe/food grade. Make sure that sufficient hard plastic tubes and equipment for wall-mounting are available on site.
Damage to cables by pigs during and after installation	Move pigs away if possible or install with sufficient people when not possible. Spray cables with paprika/chilli concentrate. Make sure the pigs cannot reach cables.	Be very careful when applying spray as the concentrate is very strong, but food grade. Could cause damage to skin, if touching cables and then sensitive skin and eyes.
Flies cover lenses with dirt	Apply fly-repellent, institute regular maintenance schedule to clean lenses, potentially use transparent film in front of the lenses, air-flow over lenses.	Treat lenses with fly-repellent, create schedule to clean lenses regularly.
Damage to equipment during cleaning between batches	Order replacement units and install ASAP.	Prepare instruction manual for farm staff to explain proper use and care of equipment.
Water damage to the equipment	Ensure that the equipment used is water resistant and/or installed in a watertight box.	Carry out thorough testing of the equipment before installing it on farms and make sure watertight seal is intact. Use silicone for additional sealing. Make sure that all equipment is waterproof.
Damage to equipment by dust and ammonia	Ensure that the equipment used is enclosed in an air-tight box.	Carry out thorough testing of the equipment before installing it on farms and make sure air-tight seal is intact.
Overheating of equipment	Install cooling fans in the equipment box. Please note the contradiction between the need to enclose the equipment in an air and water tight box and the need for cooling.	Test all equipment in harsh conditions (climate room if possible) to ensure that the equipment can withstand high temperatures.
Social issues		
Different expectations in relation to result	Results have to be presented positively and technology suppliers have to acknowledge potential errors.	If negative results are presented end users might reject the technologies used.
Farmer reluctant to give access to (part of) the house	Make sure that appropriate (written) agreements have been made before starting installation.	Make clear agreements in advance (>1 month) and confirm the agreement just before installation (<1 week).
Language problems in Europe	Use interpreter.	Use interpreter appropriately.
Installation issues		
Different power-points are used in different countries	Use travel plug converter for temporary use during installation and use correct plugs for permanent installation.	Find out the correct plug configuration in advance.
Heating elements and electricity cables in ceiling	Ask farmer to put on heating, to find out where hot pipes are located. Be aware of electrical cables as they pose OH&S risk.	Place all equipment at least a few metres away from hot water pipes. Make sure no equipment is placed close to the hot pipes as it would overheat.
Very high ceilings	Use cherry pickers or very long ladders when possible. Be aware of the OH&S implications of these arrangements.	Make sure that cherry pickers or ladders are definitely long enough and make sure all equipment used is secured.
Asbestos in houses	Do not drill holes in asbestos.	Be careful with asbestos! Make sure no holes are drilled in asbestos and the material is not disturbed in any way. Be aware of the serious OH&S implications.

Table 1. Continued

Problem	Solution	Comments/suggestions
Technical issues		
Problems when setting-up wireless network connection	Use IT-personnel on-site during installation.	Get advice from local IT specialist who knows the farm.
Unreliable internet connection	If possible install 3G (or 4G) antennas. Test the internet connection that is available on the farm, check if the farm area is covered by 3G or 4G.	Only use 3G or 4G if cable connection is not available.
Unstable power and abrupt power-off	Make sure all equipment can withstand sudden power-off, or install UPS with safe shutdown. Test whether equipment can withstand multiple sudden power-off situations.	Also test whether the power-off during start-up of the system is tolerable.
Business issues		
Loss of key staff	Makes sure that replacement staff are available.	Ensure that damage inflicted on the company can be minimised.
Limited resources available	Collaboration between SMEs helped better resource allocation.	Maintenance of research sites required considerable human and financial resources.

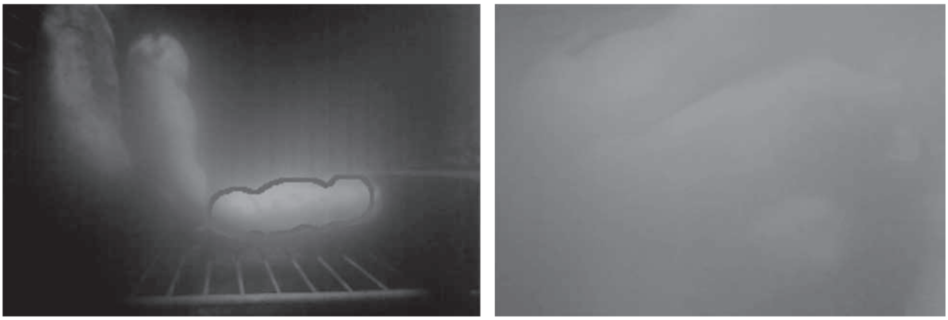

Figure 1. Example of dirt on camera lenses resulting in poor image quality (later on regular cleaning procedures were implemented to counter the problem).

posed a significant danger to installers, but especially when these danger factors were combined. For example, work undertaken using high ladders while pigs were bumping into the ladder made some of the installation sites extremely dangerous. Human health and safety was obviously a very high priority, so installation of the equipment had to be planned and executed very carefully.

Internet reliability was again a major issue on many farms throughout the project. Long-term solutions must be found to improve the reliability of the internet on sites and/or fund other/alternative communication strategies to transfer data to users. This again highlighted the fact that the whole livestock sector needs to be transformed into a high-tech sector with innovative products and services associated with it.

Business issues, such as loss of staff during the initial phase of the project, also provided challenges for SMEs. Given the reliance of SMEs on staff, especially during the initial phase of the project, some of the staff were tempted to take advantage of their position and attempted to exert undue influence within the SMEs. This obviously created problems for the companies as they had to deal with the extra pressure during the project. SMEs have to be aware of these issues and plans must be in place to deal with such eventualities. The plan must include readily available replacement staff and careful documentation of existing knowledge within the company so that corporate knowledge is not lost in the event of unplanned staff departures.

These issues need to be dealt with during and after installation, and ongoing maintenance of these PLF tools must also be undertaken by technology suppliers on farms. These issues create extra challenges for SMEs involved in the development and delivery of PLF tools for livestock producers. PLF tools will definitely increase the labour efficiency of staff on farms and this is a very important issue, as increasing demand will require farms to do more with less labour. Livestock industries are not regarded as attractive industries to work in and so there are limited skilled personnel available to provide individual animal care and husbandry. As farm sizes grow, traditional husbandry methods become a highly impractical method of caring for animals in general. Typically, the labour force is unskilled as the working environment does not offer a large degree of job satisfaction. This limits the ability of farm managers to supervise farm practices effectively, often resulting in great variances in growth performance, with an adverse effect on profitability. The installation of PLF tools on farms will surely assist livestock producers to be more efficient with the available labour.

Conclusions

There are external and environmental factors which determine the output (market weight of animals and their products), and therefore the ultimate profitability. As domesticated animals are living and sociable organisms, they are affected by their environment, which can have either a positive or a negative impact on their production efficiency. If their environment causes them to become sick, diseased or stressed, their consumption of feed and nutritional requirements will change. To really understand the context of the commercial realities of livestock farming, it is essential to understand the animals. The core of PLF solutions is to enhance the ability of livestock producers to manage animals more effectively (Banhazi *et al.*, 2012b).

PLF technologies installed on 10 farms as part of the European Union funded EU-PLF and ALL-Smart-Pigs projects provided some excellent information, but ensuring that these technologies will provide useful information continuously and reliably under farm condition is a challenge. The main objective is to ensure that these technologies will increase the profitability and sustainability of livestock farms, while improving animal health, welfare and production efficiency. Further R&D will be required to ensure that the data and information provided by these technologies are validated. In addition, further work must address improvements in the reliability of the communication aspects of the instruments, advanced design of housings (to facilitate heat transfer but ensure that the equipment is water dust, and gas proof) and the development of remote self-diagnostic capacity.

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3.5. Discussion: how PLF delivers added value to farmers

I. Halachmi[1], A. Schlageter Tello[2], A. Peña Fernández[3], T. van Hertem[3], V. Sibony[1], S. Weyl-Feinstein[1], A. Verbrugge[3], M. Bonneau[4] and R. Neilson[4]*
[1]Agricultural Research Organization, P.O. Box 6, Bet-Dagan 50250, Israel; [2]Livestock Research Wageningen University, P.O. Box 338, 6700 AH Wageningen, the Netherlands; [3]M3-Biores: Measure, Model & Manage Bioresponses, KU Leuven, P.O. Box 2456, 3001 Leuven, Belgium; [4]European Federation of Animal Science (EAAP), Via G. Tomassetti 3, 1/A, 00161 Rome, Italy; halachmi@volcani.agri.gov.il

Preface

This chapter documents the questions and the answers that were expressed during the 2014 EU-PLF/EAAP joint-sessions. They were documented verbatim, but each questioner and responder were given the opportunity to rewrite/edit their questions and/or answers for more clarity. This discussion is related to Chapters 3.1 to 3.4.

Discussion

Question: Erik Vranken (Fancom, the Netherlands) – A question to Claudia Kamphuis (Chapter 3.2). You presented a very interesting model that calculated the economic advantage of the applied technology in the farm. There is a lot of technology available and farmers have or use many different technologies in their farms. My first question is: you used data or results provided by the technology provider. How reliable are these results if they are coming from the people that sell the technology? And my second question: now that in the EU-PLF project sensors are installed in several commercial farms, can the data obtained by these sensors prove the added value to the farmer? At the moment, nobody knows what or where the benefit is, and as long as we keep on guessing what the benefits of the technology for the farmer are, it will always seem profitable.

Answer: Claudia Kamphuis (Wageningen University, the Netherlands) – I understand your concern about the reliability of the data when coming from the technology providers and we need to keep this fact in our minds when interpreting the results of this study. I also believe that when technology providers make-up these numbers, they will receive negative feedback from the farmers that use his system in the future. From the technology providers' point of view, you will cut your own fingers, so to speak, when presenting wrong information because farmers will disagree with this information in the end and will lose trust in the system. In case of the technology I used as an example in my presentation, it was rather easy to fill in the value creation tool since there is a clear action linked with the output of the technology. This clear link will make it easier for the technology provider to realistically estimate the effect of the system on model parameters. I understand that this is more difficult for technologies that are not associated with clear management actions. However, your technology is installed on a number of farms now and the tool does use data that should be easy to retrieve from the farmers. You could use the data from the farms before you installed your tools and compare it with the data after installation to see if the technology provides economic benefit and if so, where this benefit comes from.

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Question: Daniel Berckmans (KU Leuven, Belgium) – Maybe related to that … Would it be realistic to include in the blueprint of the EU-PLF project a tool for farmers so that every farmer can use the tool to do that calculation?

Answer: Claudia Kamphuis (Wageningen University, the Netherlands) – This would be very valuable and I believe that the tool that we have today is easy to use by farmers too.

Question: Jenny Gibbons (DairyCo, UK) – I heard a very interesting set of talks today. Thanks to everybody for that. In some of the studies and surveys that were conducted, were farmers asked how they use available information to decide which technology to purchase and install on their farm? Also, whether or not there was a desire or a need for independent advice on these technologies? And the third part to my question relates to this, if there is a desire for independent advice, how is the scientific community going to ensure that the evidence or relevant information is readily available to farmers and associated bodies?

Question: Daniel Berckmans (KU Leuven, Belgium) – How can somebody who is looking for information get independent advice on all these systems, or where to go for this information?

Answer: Jeffrey Bewley (University of Kentucky, USA) – We did not ask in our survey where they got their advice from, and we did not put up this particular question in these surveys. In the second survey that I presented here today, done by Borchers *et al.*, which results will be published soon, the surveyor did ask whether or not third party information was interesting or not, and it came out as number four in the list of factors affecting their decision to buy the system. This shows that they wanted independent third party verification that the technology is actually doing what it is supposed to do. If there is a third party involved, it gives the end-user a little bit more the feeling that what they are working with is real. There is a real challenge in that, from a realistic perspective though, and I can only speak from the US model. In the USA, it is very difficult to get third party verification work funded from a federal or outside entity or funding source. For instance, if I submit a proposal to the USDA to check the sensitivity and specificity of a heat detection system, they would say it looks like interesting work, but that is not something that they fund, that is something that should be funded by the company. But if the company is funding the research, the question on the reliability of the results arises. I think that from a scientific and integrity perspective, that it can't be trusted. We work with a lot of different companies, but the challenge is still there. Often there is a written agreement between a research institute and the company that the results will be published regardless of the outcome. That can be from both sides a nervous proposition, because if I, the researcher, show that the technology is not doing so great as it was supposed to do, than the company does not want me to publish that. But it is our goal to do this work, although it is still a real challenge. I think that there is an opportunity for the companies, and the best companies take that risk, because they are confident in their product and they want to know when the product is not doing what it supposed to do, and the farmer is going to find that out anyway. They use this knowledge to make their products better. A lot of companies do have that attitude. And that's where we, academia and industry, need to work together.

Question: Ilan Halachmi (ARO, Israel) – I invited Dr Jeffrey Bewley all the way from the US to answer this question: all the Israeli sensor companies are looking at the American market. But the American market is slow in adopting PLF technology compared to some other countries. Why is the American market this slow in adopting the PLF technology? And I am wondering if the other people like Heiner Lehr and Dries Berckmans can answer this question from a commercial company point of view.

Answer: Jeffrey Bewley (University of Kentucky, USA) – (joking) Maybe we are not as smart as Europeans, and we don't understand computers ... I don't think that that is the issue, obviously. This was actually one of the other questions that Borchers *et al.* asked the farmers. Apparently, I picked the wrong slides in my presentation, but it did show clearly more interest from the European and Israeli farmers who answered our survey on technologies. I think there are a few reasons for that. One of them is labour costs. The labour situation in the USA is, as I understand, different from a lot of Europe's and the Israeli situation, so that changes the dynamics somewhat. I think some of it is herd size related, because some of the issues, say for example an oestrus detection technology for a 3,000 cow dairy, are different. We have farms that use an outside service that comes to the farm and tail check every morning and they breed the cows. Maybe that is a more economical way to breed cows than an automated system. A calving detection tool for example, some farms have people 24 hours a day in the calving pen, so they do not need an automated solution to identify that particular behaviour or action. So some of it is size related. I also think that some of it is a general lack of focus on the social side of farming that Claudia Kamphuis has mentioned. When visiting farms with automatic milking systems in Europe, the economics were always borderline, but the quality of life they gain was one of the main reasons why they invested in the system. I am not saying that our farmers do not value quality of life, but I think that sometimes they just work more. Their answer to cost savings perspective issue is often work more instead of investing in technology that makes their lives or the lives of their employers easier. I am sure that there are also some other reasons that we haven't thought of.

Answer: Claudia Kamphuis (Wageningen University, the Netherlands) – I think there are many reasons why adoption can be slower than expected. One reason can be that expectations and demands differ between countries in which technologies are developed and those in which they are implemented. As an example, I went for a few years to New Zealand, where they have a pasture-based dairy system. We did some work on automated oestrus detection systems, with systems that were developed for a dairying system where cows are housed and, thus, outside New Zealand. I just did not realise how important it is for New Zealand farmers to get their cows pregnant in just six weeks' time. This meant that they have to invest in systems for the entire herd (500 cows) and only benefit from these systems during 6 weeks. Moreover, they really expect a high sensitivity of these systems as they cannot afford to miss too many oestrus events, taking into account the pasture based dairying situation. This difference in expectation and demands is something suppliers from abroad in this situation didn't realise enough.

Answer: Heiner Lehr (Syntesa, Spain) – Thank you for that question. Unfortunately, I cannot answer for the US market, but I certainly have some thoughts on why adoption in general is a bit slow. If I were a farmer, I would certainly need some more convincing why I should adopt these technologies. We are running a project called *AllSmartPigs*, which just works on fattening pigs, and we were convinced that we had a set of working technologies that we just needed to demonstrate the value of, and everybody would start buying it afterwards. It has turned out to be a little bit more complicated than that. We are still at the start. We are still trying to find out where the exact value is, and how large it is. And what kind of keys we need to press to sell it to the farmer. We have seen some economic things presented today; some examples where an investment that seems to provide a clear economic benefit. But I am sure this is only part of the answer. All farmers, like everybody else in this room, are complex beings, and our purchasing decision is made in part on economic arguments, but in part also on other arguments. We still need to find those other arguments and create a desire in the farming industry to buy that. Until we do that, I don't think it will kick off. Most of technologies that we see are still not reliable enough to be used out-of-the-box in a farm, and we still haven't found the socio-economic framework in which we need to sell those technologies. Thank you.

Answer: Dries Berckmans (SoundTalks, Belgium) – Thank you, Ilan, for the question. I think it is a really interesting question. On top of what has been said already, I think that one of the surprising things is also that to start a SME, for example, it is much easier to do that in the US and it is easier to find the money to do that, compared to the situation here in Europe. And still, the adoption is slow. I am afraid I cannot give the full answer, but maybe part of the answer, which was already touched by Heiner Lehr, is that we are, for PLF in general, lacking some very good examples. I think that if you have some very good examples, farms where the technology works well, then it will go much faster. People will also start to adopt when it becomes clearer, when there is more evidence on what the cost-benefit can be for the farmer. And I agree with you that the US market should suit PLF quite well, because the size of the farms creates a lot of the problems that you want to address with PLF technology.

Question: Arjen van der Kamp (Lely International, the Netherlands) – I saw a lot of interesting PLF techniques today, and some of them probably require some farm management changes. Jeffrey showed a nice picture of a farmer lying totally relaxed in his chair, completely adapted to his new technology. But you also mentioned the case when technology went wrong, and the farmer went totally the wrong direction. How can we make sure that the farmer changes his management strategy in the correct way when he adopts to the technology? Do you have some ideas about this? And are we not giving too much information to the farmer at some point?

Answer: Dries Berckmans (SoundTalks, Belgium) – There is always a risk. It is a question that we also ask ourselves a lot. Earlier (Chapter 2.5 Discussion), there was a question about which of the lameness detection systems will solve the lameness problem in dairy farming. The reaction was that at this point, none of the systems will solve it. It is only a monitoring tool, and then it depends on what the farmer does with it afterwards that will solve the problem and determine if the system is beneficial for him or not. The system itself will not solve the problem. In the example of the cough monitor, we monitor the number of coughs in a fattening pig house, and we try to give an early warning when there is an infection or a disease. Also here it is the action of the farmer that will make the difference. Just knowing that there is a problem will not solve the problem. I always compare to what the situation is today, and common practice nowadays in farms is not the best solution. So we try to improve on that. How to be sure the farmer takes the correct decision, is by educating him and giving him trust that when using PLF technologies and a change in management, he can have better results. I think that is the only thing you can do.

Answer: Heiner Lehr (Syntesa, Spain) – Again, part of the answer to that question is to point in the direction of the infant stage of what we are trying to do here. So far, the sector has been characterised by looking mostly at the hardware issues: how can we measure it, what kind of algorithms do we need, etc. Now we start to expose ourselves to the real world, the commercial business, and we need to learn, together with the farmer, what that means. I am sure that most of you own a weighing scale at home for which there is no direct return, so from an investment point of view, that does not make any sense. However, we have learned from years and years of experience to relate weight to health aspects, and we use a simple number as an indicator. We need to undergo a similar process with farm animals. We need to reduce the amount of information that we currently collect and condense that information into a few indicators or some kind of simplified warning elements, such as red, yellow and green that would then help the farmer make better management decisions. We don't know yet how that works. Is it by showing real data? Is it by showing early warnings? We are now like a blind man going into a room trying to find out what the room looks like.

Answer: Jeffrey Bewley (University of Kentucky, USA) – Education and training go a long way, and I think those will help. And not just education and training of the farmers, but also education and training for the consultants, nutritionists, veterinarians, etc. that work with those farmers. I think that user-groups can help a lot in creating a network of people that are using the technology. That can be of tremendous value. In our situation, we have tried that with David, our role-model farmer, and other farmers and he finally just said: 'They just don't get it! It is not going to work for them'. He realised there was a management issue. At some point we have to be realistic about human nature. There is always going to be a variation between people that succeed and don't succeed. One of the things that we do as humans is that, as part of our mentality, we want a solution in a bottle or in a package. If we look to any health store, you will see a whole aisle of pills that you can take to lose weight. And there is a huge industry related to it, because everybody wants that solution. It is a lot easier than changing my lifestyle or changing the management of how I live my life. But it doesn't work that way. So I think that sometimes it is by nature that people who are going to buy technology are looking for a solution to a management problem, in a package. So we are going to have some failures because of the nature of people.

Part 4. Precision livestock farming in genetics, health of beef and cattle

4.1. The effect of gradual weaning on haematological profiles and leukocyte relative gene expression levels of Holstein-Friesian and Jersey bull calves

D. Johnston[1,2], D.A. Kenny[1], S.M. Waters[1], M. McCabe[1], A.K. Kelly[2], M. McGee[1] and B. Earley[1]*
[1]Animal & Grassland Research and Innovation Centre, Teagasc, Dunsany, Co. Meath., Ireland;
[2]University College Dublin, Belfield, Dublin 4, Ireland; dayle.johnston@teagasc.ie

Abstract

The objectives of the study were (1) to examine the effect of breed and plane of nutrition on haematological profiles of artificially reared Holstein-Friesian and Jersey calves in response to gradual weaning, and (2) to examine the effect of breed on the immune response genes in bovine leukocytes using real-time qPCR. Holstein-Friesian and Jersey bulls were group housed indoors and fed using an automatic feeder. They were allocated to a high, medium or low plane of nutrition, based on milk replacer (MR) and concentrate. During the weaning phase MR was gradually reduced over a 14-day period. On day -14, -6, -3, 0, 1, 3, 8, and 14 relative to weaning (day 0), calves were blood sampled for subsequent haematological analysis. On day -14, 1 and 8, a subset of calves from each breed, consuming equal amounts of MR and concentrate, were blood sampled for examination of gene expression levels. Breed × time interactions were observed for lymphocytes, monocytes, red blood cells (RBC) and haemoglobin ($P \leq 0.05$). Relative gene expression levels were greater ($P \leq 0.05$) in Jersey calves compared with Holstein-Friesian for the pro-inflammatory cytokine *CXCL8* and the glucocorticoid receptor, *GRα*. An effect of time was observed for *Fas* ($P \leq 0.05$) with increased relative gene expression on day 1 relative to day -14. Plane of nutrition had no effect on haematological profiles or relative gene expression. An immune response to gradual weaning was observed as the expression pattern of the pro-apoptotic gene, *Fas*, changed over time. Gradual weaning produced differential biological responses in the two breeds, evidenced by breed × time interactions for lymphocyte, monocyte, and RBC number and plasma haemoglobin concentration, and the increased levels of transcripts for *CXCL8* and *GRα* suggests that Jersey calves may have a more sensitive immune system.

Keywords: bovine, breed, plane of nutrition, weaning

Introduction

The two dairy sire breeds used predominantly in Ireland are Holstein-Friesian and Jersey (AIM, 2012). Our group has previously reported that weaning exerts an acute stress response in single-suckled beef calves, characterised by changes in the distribution of haematological cells (Lynch *et al.*, 2010; O'Loughlin *et al.*, 2011) and up-regulation in expression of genes involved in the pro-inflammatory response (O'Loughlin *et al.*, 2011). However, this response has not yet been examined in artificially reared dairy calves.

Breed can influence immune responses. For example, compared with Jersey calves, tumour necrosis factor-α was secreted in greater quantities from mononuclear cells isolated from Holstein-Friesian calves, and additionally, blood from Holstein-Friesian calves had more cytotoxic potential (Ballou,

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2012). However, the effect of plane of nutrition on health parameters is less clear. Feeding a higher plane of nutrition improved neutrophil oxidative burst intensities after co-culture with *Escherichia coli* in one study (Ballou, 2012), while in another study the authors found increased oxidative burst intensities from calves on a low plane of nutrition (Obeidat *et al.*, 2013). More nitric oxide, which can cause tissue damage when produced in excess, was secreted from mononuclear leukocytes from calves fed greater quantities of milk replacer (MR) to achieve a high growth rate. Furthermore, viabilities of specific T cell subsets were lower in cells cultured from these calves (Foote *et al.*, 2007).

The objectives of the present study were (1) to examine the effect of breed and plane of nutrition on the haematological profiles of artificially reared Holstein-Friesian and Jersey calves in response to gradual weaning, and (2) to examine the effect of breed on the immune response in bovine leukocytes using real-time qPCR.

Materials and methods

Animal management

The study was structured as a factorial design with two breeds Holstein-Friesian and J, and three planes of nutrition (High (H), Medium (M) and Low (L)) within breed. 44 Holstein-Friesian and 29 Jersey clinically healthy bull calves were purchased at approximately 2.7 weeks of age and group housed indoors at Teagasc, Grange Beef Research Centre on sawdust floored pens (balanced for breed) from day -56 to 28 of the study. All Holstein-Friesian calves came from a single farm and Jersey calves were sourced from three farms. Calves were immunised against Infectious Bovine Rhinotracheitis (IBR), PI-3-virus, BRS-Virus *Mannheimia haemolytica* serotypes A1 and A6 and *Salmonella dublin* and *Salmonella typhimurium* using Rispoval IBR-Marker live, Bovipast RSP and Bovivac S vaccines, respectively.

Calves were blocked, within breed, to nutrition treatment on the basis of live-weight, age and sire. Holstein-Friesian and Jersey calves were allocated to either a H, M or L plane of nutrition (Holstein-Friesian (H): n=14, (mean age ± standard deviation (SD)) 21±5 days, (mean weight ± SD) 49±6 kg; Jersey (H): n=11, 35±8 days, 33±5 kg; Holstein-Friesian (M): n=16, 22±7 days, 46±5 kg; Jersey (M): n=9, 35±9 days, 34±4 kg; Holstein-Friesian (L): n=20, 20±4 days, 45±5 kg; Jersey (L): n=9, 35±8 days, 33±5 kg). Calves were fed a 23% crude protein (CP) MR (Blossom Easymix; Volac, Co. Cavan, Ireland) and concentrate (26.5% barley, 25% soya, 15% maize, 12.5% beet pulp, 12.5% soya hulls, 5% molasses, 2.5% minerals, 1% vegetable oil (18.8% CP, 22.4% neutral detergent fibre)) using an electronic feeding system (Foster-Tecknik SA 2000, Engen, Germany). The pre-weaning, weaning and post-weaning periods were defined as days -56 to -14, -13 to 0 (milk feeding ceased), and 1 to 14 respectively. Holstein-Friesian calves on H, M and L nutrition levels were offered 8, 6 or 4 litres MR daily, and *ad libitum*, a maximum of 1.5 kg or 1 kg concentrate daily, respectively, pre-weaning. Jersey calves on H, M and L nutrition levels were offered 6 l, 4 l or 3.5 l MR daily, and *ad libitum*, a maximum of 1.5 kg or 1 kg concentrate daily, respectively, pre-weaning.

Weaning was initiated when calves were consuming 1 kg of concentrate per day for three consecutive days. During the weaning phase MR was gradually reduced from its previous allocation to 0 l over 14 days (day -13 to 0). After weaning, the maximum concentrate allowance was maintained at *ad libitum* for H and increased to 2 and 1.7 kg, for Holstein-Friesian calves for M and L groups, respectively, and 1.7 and 1.4 kg, for Jersey calves on the M and L planes of nutrition, respectively. Throughout the trial period, calves were weighed on a weekly basis.

Blood sample collection

On day -14, -6, -3, 0, 1, 3, 8, and 14 relative to weaning (day 0), calves were blood sampled via jugular venepuncture for subsequent haematological analysis. Blood samples were collected in 6 ml K_3Ethylenediaminetetraacetic acid (K_3EDTA) tubes (Vacuette, Cruinn Diagnostics, Ireland). Serum was collected at arrival for the zinc sulphate turbidity test.

A subset of calves from each breed consuming 6 l MR and *ad libitum* concentrate were randomly selected for gene expression profiling of selected genes previously found to be affected by weaning (O'Loughlin *et al.*, 2011). Eight Holstein-Friesian ((mean age ± SD) 23±7 days, (mean weight ± SD) 46±6 kg) and eight Jersey bull calves (37±8 days, 34±5 kg), were blood sampled via jugular venipuncture on day -14, 1 and 8, relative to weaning, day 0. Three ml blood samples were collected in Tempus Blood RNA Tubes containing RNA stabilisation solution (Applied Biosystems, Foster City, CA, USA). These blood samples were shaken vigorously for 20 seconds immediately after collection and were stored at -80 °C until analysis.

Zinc sulphate turbidity test

The zinc sulphate turbidity test (ZST) was performed at 20 °C on serum samples collected from the calves at arrival with the turbidity subsequently measured at 520 nm using a spectrophotometer (McEwan *et al.*, 1970).

Haematology

Whole K_3EDTA blood samples were analysed immediately after collection using an ADVIA 2120 analyser (AV ADVIA 2120, Bayer Healthcare, Siemens, UK) which contained software necessary for the analysis of bovine blood.

RNA Extraction and cDNA synthesis

RNA was extracted from whole blood using the Tempus Spin RNA Isolation Reagent Kit (Applied Biosystems) with the methods described in the manufacturer's instructions, utilising the optional DNase step. A Nanodrop spectrophotometer (NanoDrop Technologies, Wilmington, DE, USA) was used to quantify the RNA. The quality of the RNA was assessed with an Agilent 2100 Bioanalyser (Agilent Technologies Ireland Ltd., Dublin, Ireland). All samples had an RNA Integrity Number (RIN) of between 8.9 and 10. cDNA was synthesised in a 20 µl reaction, according to the manufacturer's instructions, from one µg of total RNA per sample, utilising the High Capacity cDNA Reverse Transcription kit (Applied Biosystems). The cDNA was stored at -80 °C until analysis.

Real-time qPCR

Primer sequences for the candidate and reference genes were obtained from the literature (Table 1) and were commercially synthesised (Sigma-Aldrich Ireland Ltd., Dublin, Ireland). Serial dilutions of pooled cDNA samples were used to determine amplification efficiencies using the equation $E = -1 + 10^{(-1/slope)}$. The slope was calculated by plotting the linear curve of cycle threshold (Cq) values against the log dilutions (Pfaffl, 2001). Primers had PCR efficiencies of between 88 and 107%.

Three reference genes, β-actin (*ACTβ*), glyceraldehyde-3-phosphate dehydrogenase (*GAPDH*) and tyrosine 3-monooxygenase/tryptophan 5-monooxygenase activation protein, zeta polypeptide

Table 1. Primer sequences for candidate and reference genes.

Gene		Sequence 5′ → 3′	Amplicon size (bp)	Reference source
YWHAZ	F	GCATCCCACAGACTATTTCC	120	Goossens *et al.*, 2005
	R	GCAAAGACAATGACAGACCA		
IL 8	F	TGGGCCACACTGTGAAAATTC	92	O'Loughlin *et al.*, 2011
	R	CCTTCTGCACCCACTTTTCC		
TNFα	F	TGGAGGGAGAAGGGATTCTT	140	O'Loughlin *et al.*, 2011
	R	CCAGGAACTCGCTGAAACTC		
TLR4	F	TGGTAAACCCCAGAGTCCAG	164	O'Loughlin *et al.*, 2011
	R	GCACAATGCTTGGTACATGG		
GRα	F	CCATTTCTGTTCACGGTGTG	132	O'Loughlin *et al.*, 2011
	R	CTGAACCGACAGGAATTGGT		
Fas	F	AGTTGGGGAGATGAATGCTG	171	O'Loughlin *et al.*, 2011
	R	CCTGTGGATAGGCATGTGTG		
ACTB	F	ACTTGCGCAGAAAACGAGAT	123	O'Loughlin *et al.*, 2011
	R	CACCTTCACCGTTCCAGTTT		
GAPDH	F	GGGTCATCATCTCTGCACCT	176	O'Loughlin *et al.*, 2011
	R	GGTCATAAGTCCCTCCACGA		

(*YWHAZ*) were used in this study. An average stability M value of 0.21 was calculated for these genes based on average pairwise variations. The geometric mean of the reference genes was used to calculate a normalisation factor and this was subsequently used to normalise expression of each gene of interest.

Two µl of the optimised concentration of cDNA was added to 18 µl of master mix (10 µl Fast SYBR Green 1 master mix (Applied Biosystems), 7 µl nuclease-free water and 0.5 µl each of forward and reverse primers at individually optimised concentrations). Real-time qPCR was used to measure gene expression of the reference genes and the pro-inflammatory cytokine (*CXCL8*), the glucocorticoid receptor (*GRα*), the pro-apoptotic gene, *Fas*, toll-like receptor 4 (*TLR4*) and tumour necrosis factor (*TNF)α*, according to MIQE guidelines (Bustin *et al.*, 2009). Applied Biosystems 7500 FAST RT-PCR equipment v2.0.1 was used (Applied Biosystems). The conditions applied were as follows: 95 °C for 20 s followed by 40 cycles of 95 °C for 3 s and 60 °C for 30 s, finishing with amplicon dissociation at 95 °C for 15 s, 60 °C for 1 min increasing 1 °C per cycle until 95 °C was reached for 15 s followed by 60 °C for 15 s.

The Cq values were imported into GenEx Software v.5.2.7.44 (2010) (MultiD Analyses AB, Göteborg, Sweden). A modified Grubbs test was used to remove outliers from replicate wells at a $P<0.05$ confidence interval for replicates differing from the replicate mean by a standard deviation of greater than 0.25 cycles. Adjustments were performed to account for inter-plate variation using the inter-plate calibrator sample included on all plates. The Cq values were adjusted for amplification efficiencies and replicates were averaged. The resulting values were normalised to the reference genes and relative quantities were calculated to the highest Cq value.

Statistical analysis

All data were examined for adherence to a normal distribution (PROC UNIVARIATE, SAS v 9.3, Cary, NC, USA). Neutrophil data were not normally distributed and were transformed by raising the variable, as appropriate, to the power of lambda. The required lambda value was calculated by conducting a Box-Cox transformation analysis using the TRANSREG procedure of SAS. Data subjected to transformations were used for *P*-values. However, the corresponding non-transformed least squares means (Lsmeans) and standard error of the mean (sem) are presented to facilitate interpretation of results. Relative gene expression values were all log2 transformed prior to statistical analysis.

Haematological data were analysed in accordance with the factorial nature of the design using repeated measures mixed models ANOVA (PROC MIXED, SAS v 9.3) with breed, plane of nutrition, sampling time and their interactions included as fixed effects. Non-statistically significant interactions were sequentially removed from the model.

Relative gene expression data were analysed using repeated measures mixed models ANOVA (PROC MIXED, SAS v 9.3) with breed, sampling time and the breed by sampling time interaction included as fixed effects.

The covariance matrix was determined for each variable by examining the Sawa's Bayesian Information Criteria (BIC) value. Animal was the experimental unit. Sampling time was included in the models as a repeated measure. Differences between the means were tested using the PDIFF option within the PROC MIXED model of SAS. Means were considered statistically significantly difference at a probability level of $P \leq 0.05$. Values are expressed as least square means (Lsmeans) ± sem.

Results

The ZST (McEwan *et al.*, 1970) performed on serum collected on arrival of the calves showed a greater level of maternally derived passive immunity in Jersey compared with Holstein-Friesian.

Leukocyte haematological profiles

No breed × plane of nutrition × sampling time interactions or plane of nutrition × sampling time interactions were observed for the distribution of leukocyte haematological variables ($P>0.05$). However, a number of breed × time interactions were detected ($P \leq 0.01$) (Table 2). There was a breed × time interaction for lymphocyte number ($P \leq 0.01$) where the breeds did not initially differ but following the onset of gradual weaning Jersey calves had a greater number of lymphocytes throughout both the weaning and post-weaning periods (Figure 1). A breed × time interaction was also observed for monocyte number ($P \leq 0.01$). Holstein-Friesian and Jersey monocyte profiles differed initially and throughout the weaning period with Holstein-Friesian having approximately 19% greater monocytes. However, monocyte number converged between the breeds from day 1 post-weaning (Figure 2).

A breed effect was observed for neutrophil number ($P \leq 0.05$) with Holstein-Friesian having a greater number of neutrophils (Table 2). There was a sample time effect in all calves ($P \leq 0.0001$) with neutrophil number decreasing over time post weaning, from the initial day -14 baseline value. Time effects for all calves were also evident in white blood cell (WBC) count ($P \leq 0.0001$) and in basophil number ($P \leq 0.0001$) (Table 2). The WBC count was elevated relative to baseline number at each time point during the weaning and post-weaning periods except at day -3. Basophil number increased from baseline level at day -3 relative to weaning and remained elevated throughout both the weaning and post-weaning periods. Plane of nutrition did not affect leukocyte haematological profiles ($P>0.05$).

Table 2. Effect of breed and plane of nutrition on white blood cells (WBC), lymphocyte, monocyte, neutrophil and basophil number, during gradual weaning in Holstein-Friesian (H-F) and Jersey (J) calves.[1]

Variable	Breed (B)		sem	Plane of nutrition (N)[2]			sem	Time (T)[3]								sem	*P* values[4]			
	H-F	J		H	M	L		-14	-6	-3	0	1	3	8	14		B	N	T	T×B
WBC ($\times 10^3$ cells/µl)	9.6	9.8	0.33	10.0	9.1	10.1	0.39	9.1	9.8^{a}	9.2	9.9^{b}	9.6^{a}	9.9^{c}	9.9^{b}	10.4^{c}	0.28	NS	NS	***	NS
Lymphocytes ($\times 10^3$ cells/µl)	6.0	6.8	0.22	6.9	6.1	6.3	0.27	6.0	6.2	6.2	6.5^{c}	6.5^{c}	6.6^{c}	6.6^{c}	6.8^{c}	0.17	**	NS	***	**
Monocytes ($\times 10^3$ cells/µl)	1.0	0.9	0.04	1.0	0.9	1.0	0.04	0.9	1.0^{b}	1.0	1.0	0.9	0.9	0.9	1.1^{c}	0.04	NS	NS	***	**
Neutrophils ($\times 10^3$ cells/µl)	1.2	0.9	0.14	1.0	1.2	1.1	0.17	1.2	1.3	1.1	1.2	1.0^{c}	0.9^{c}	0.9^{c}	0.9^{c}	0.12	*	NS	***	NS
Basophils ($\times 10^3$ cells/µl)	0.2	0.2	0.01	0.2	0.2	0.2	0.01	0.1	0.1	0.2^{c}	0.2^{c}	0.2^{b}	0.2^{b}	0.2^{c}	0.2^{c}	0.01	NS	NS	***	NS

[1] The values are expressed as least square means (Lsmeans) and standard error of the mean (sem).

[2] H = high; M = medium; L = low plane of nutrition.

[3] Within rows, Lsmeans differ from pre-weaning baseline by ^{a} $P \leq 0.05$, ^{b} $P \leq 0.01$, and ^{c} $P \leq 0.001$, respectively.

[4] * = $P \leq 0.05$, ** = $P \leq 0.01$, *** = $P \leq 0.001$, NS = not significant ($P > 0.05$).

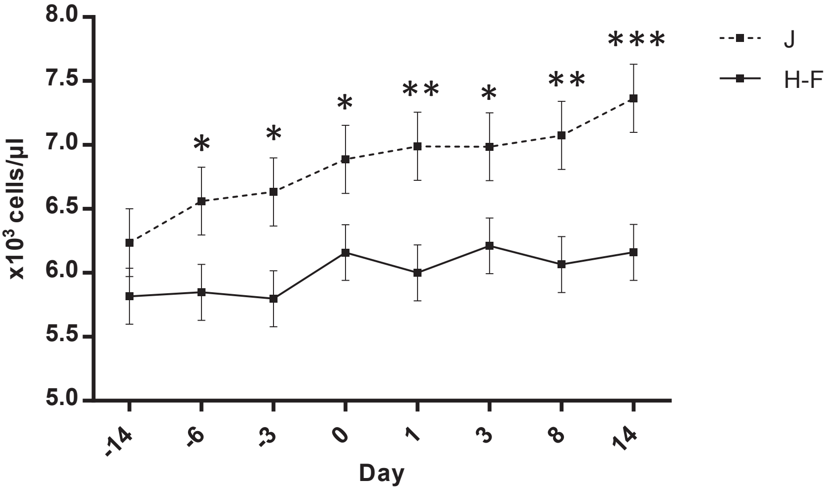

Figure 1. Effect of gradual weaning on lymphocyte number in Holstein-Friesian (H-F) and Jersey (J) calves. Initially there was no difference between breeds, but following the onset of gradual weaning, Jersey calves had greater lymphocyte numbers. *$P \leq 0.05$, ** $P \leq 0.01$, *** $P \leq 0.001$.

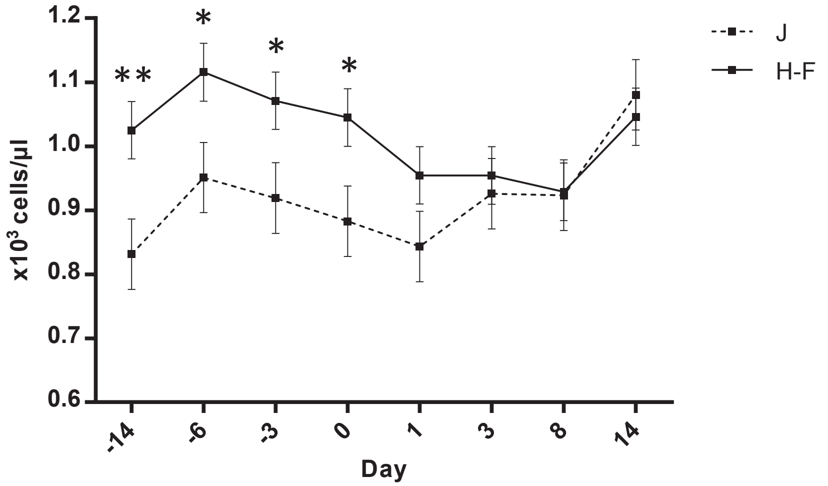

Figure 2. Effect of gradual weaning on monocyte number in Holstein-Friesian (H-J) and Jersey (J) calves. Holstein-Friesian had a greater monocyte number during the weaning period but monocyte number converged between the breeds post-weaning. *$P \leq 0.05$, ** $P \leq 0.01$.

Red blood cell number, haematocrit percentage, haemoglobin concentration, and platelet number

There were no breed × plane of nutrition × time interactions or plane of nutrition × time interactions for these haematological variables ($P>0.05$). Breed × time interactions were detected for red blood cell (RBC) count and haemoglobin (HGB) percentage ($P \leq 0.05$) (Table 3). Holstein-

Table 3. Effect of breed and plane of nutrition on red blood cell (RBC) count, haematocrit (HCT) percentage, plasma haemoglobin (HGB) concentration and platelet number, during gradual weaning in Holstein-Friesian (H-F) and Jersey (J) calves.[1]

Variable	Breed (B)		sem	Plane of Nutrition (N)[2]			sem	Time (T)[3]								sem	*P* values[4]			
	H-F	J		H	M	L		-14	-6	-3	0	1	3	8	14		B	N	T	T×B
RBC ($\times 10^6$ cells/μl)	11.0	10.2	0.18	10.8	10.4	10.6	0.22	10.5	10.5	10.6[a]	10.8[c]	10.8[c]	10.9[c]	10.5	10.2[b]	0.14	**	NS	***	**
HCT (%)	29.8	31.0	0.37	30.4	30.2	30.7	0.44	29.9	30.2	30.6[b]	31.2[c]	31.0[c]	31.3[c]	30.2	29.2[a]	0.32	*	NS	***	NS
HGB (g/dl)	11.1	11.6	0.14	11.3	11.3	11.4	0.16	10.9	11.2[c]	11.5[c]	11.6[c]	11.5[c]	11.5[b]	11.4[c]	11.1	0.11	**	NS	***	*
Platelets ($\times 10^3$ cells/μl)	903.4	974.8	31.45	985.9	896.1	935.5	37.88	903.7	859.5	957.1	959.2	927.5	945.0	951.9	1,009.4[b]	31.55	NS	NS	**	NS

[1] The values are expressed as least square means (Lsmeans) and standard error of the mean (sem).

[2] H = high; M = medium; L = low plane of nutrition.

[3] Within rows, Lsmeans differ from pre-weaning baseline by [a] $P \leq 0.05$, [b] $P \leq 0.01$, and [c] $P \leq 0.001$, respectively.

[4] * = $P \leq 0.05$, ** = $P \leq 0.01$, *** = $P \leq 0.001$, NS = not significant ($P > 0.05$).

Friesian calves had greater RBC numbers throughout the gradual weaning period and during the post-weaning period up to day 8 with no difference at day 14 between breeds (Figure 3). Jersey calves had greater concentrations of haemoglobin throughout, except day -6 in the weaning period, and at day 3 post-weaning where there was no difference between breeds (Figure 4).

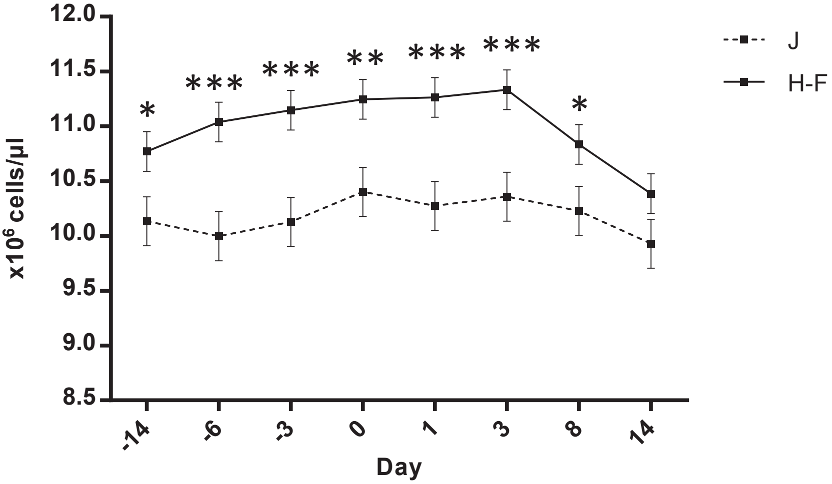

Figure 3. Effect of gradual weaning on red blood cell (RBC) number in Holstein-Friesian (H-J) and Jersey (J) calves. Holstein-Friesian calves had a greater RBC number up until day 8 post-weaning. At 14 days post-weaning, there was no difference between breeds. **P*≤0.05, ** *P*≤0.01, *** *P*≤0.001.

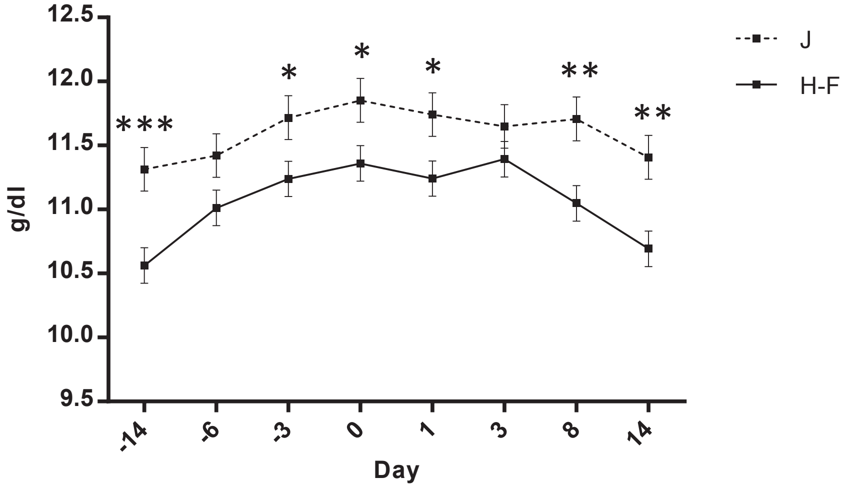

Figure 4. Effect of gradual weaning on plasma haemoglobin concentration in Holstein-Friesian (H-J) and Jersey (J) calves. Plasma haemoglobin (HGB) concentrations were greater in Jersey calves at each sampling day except day -6 and 3 where there were no differences between breeds. * *P*≤0.05, ** *P*≤0.01, *** *P*≤0.001.

The haematocrit (HCT) percentage was greater in Jersey compared with Holstein-Friesian calves ($P \leq 0.05$) (Table 3). Time affected both HCT percentage ($P \leq 0001$) and platelet number ($P \leq 0.01$) (Table 3). HCT percentage in all calves increased during the pre-weaning period and was different ($P \leq 0.01$) from baseline levels at day -3. The HCT percentage remained elevated compared with the baseline until 3 days post-weaning and it subsequently decreased after this time-point. From day -3 pre-weaning, the platelet count was numerically elevated in all calves compared with the pre-weaning baseline but it was only significantly increased from baseline values on day 14 during the post-weaning period. Plane of nutrition did not affect RBC number, HCT percentage, plasma HGB concentration or platelet number ($P > 0.05$).

Leukocyte gene expression

No breed × sampling time interaction was observed for any of the immunological genes examined ($P > 0.05$). Relative gene expression levels were greater ($P \leq 0.05$) in Jersey calves compared with Holstein-Friesian for the pro-inflammatory cytokine *CXCL8* (Jersey 8.53 vs Holstein-Friesian 5.47 (±1.17)) and the glucocorticoid receptor *GRα* (Jersey 2.34 vs Holstein-Friesian 1.27 (±0.26)) (Figure 5). Gene expression differences ($P > 0.05$) were not observed between the two breeds for the pro-apoptotic gene *Fas,* the toll-like receptor *TLR4* and the tumour necrosis factor *TNF-α*. An effect of time was observed for *Fas* ($P \leq 0.05$) with increased relative gene expression between day -14 (1.44±0.09) and day 1 (1.68±0.09) (Figure 6). There were no changes ($P > 0.05$) over time in the expression levels of *TNF-α, TLR4, CXCL8* and *GRα.*

Discussion

This study characterised the haematological profiles and leukocyte gene expression in Holstein-Friesian and Jersey bull calves during the gradual weaning and immediate post-weaning periods. It also examined the effect of plane of nutrition on haematological profiles. There have been limited studies on haematological distributions in dairy calves. This paper provides an in-depth

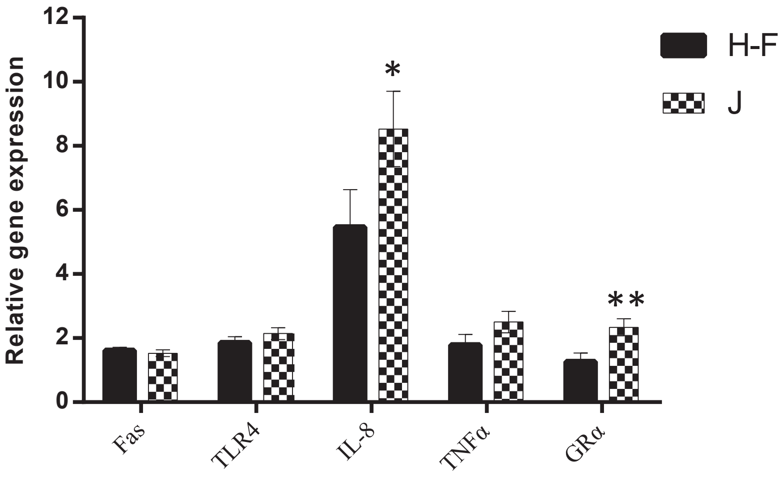

Figure 5. Effect of breed on immunological gene expression levels. Relative gene expression levels of both *CXCL8* and *GRa* were greater in Jersey calves. *$P \leq 0.05$, ** $P \leq 0.01$.

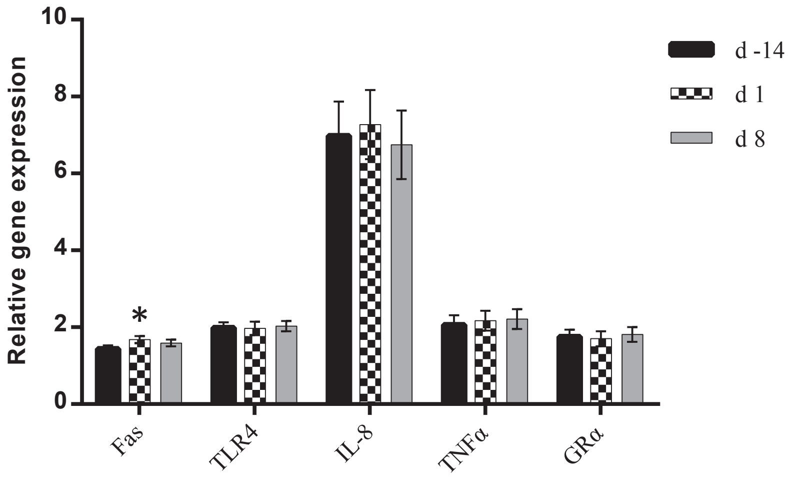

Figure 6. Effect of gradual weaning on immunological gene expression levels. The relative gene expression of *Fas* increased on day 1 from the baseline level at day -14. *$P \leq 0.05$.

description of haematological profiles in two different dairy breeds. To the authors' knowledge, this is the first study to examine the leukocyte relative gene expression levels in Holstein-Friesian and Jersey calves in response to gradual weaning.

Weaning is typically a stressful event for calves. The effects of this stressful period have previously been demonstrated in the haematological profiles of abruptly weaned suckled calves through an increase in neutrophil number, known as neutrophilia, and a decrease in lymphocyte number (lymphopaenia) (Hickey *et al.*, 2003; Lynch *et al.*, 2010; O'Loughlin *et al.*, 2011). However, suckled calves undergo additional stresses around weaning which dairy calves are not subjected to, such as the breaking of the maternal bond and social rearrangement. Weaning in dairy calves involves the complete removal of milk from the diet and we have shown in the present study that this affects markers of immune function including haematological profiles and relative gene expression levels. However, the typical neutrophilia and lymphopaenia responses observed in abruptly weaned beef calves were not observed in these dairy calves. The haematological distributions observed here demonstrate a much less pronounced stress response to weaning by dairy calves, compared with the suckled calf response. Another study, however, did observe a decrease in lymphocyte number and a corresponding increase in the neutrophil:lymphocyte (N:L) ratio after weaning in dairy calves (Kim *et al.*, 2011). However, the calves in that study were weaned at 6 weeks of age and, consequently, weaning may have been harder on them as they were on average 41 days younger than the calves in the present study.

The observed changes in haematological profiles suggest a differential stress response to gradual weaning between Holstein-Friesian and Jersey calves. Weaning differentially affected monocyte profiles by causing an increase in monocyte number post-weaning in Jersey calves which brought their monocyte number in line with the Holstein-Friesian monocyte number. This may indicate a larger stress response in the Jersey breed as their monocyte number rose disproportionately after weaning. Similarly, in support of this conclusion, lymphocyte number also increased more rapidly in Jersey calves throughout both the weaning and post-weaning periods. Although the RBC count was greater in Holstein-Friesian calves at all but one time-point, Jersey calves had higher

HGB concentrations. This could indicate slight regenerative anaemia in the Holstein-Friesian calves as immature RBCs contain less HGB (Jones and Allison, 2007). However, the plasma HGB concentrations within both breeds were within normal reference ranges (Jones and Allison, 2007). While the distribution of haematological variables was affected by breed, no changes were elicited due to plane of nutrition.

We found that relative gene expression levels for several selected biomarkers of immunological competence were influenced by either weaning or breed, but plane of nutrition had no effect. An immune response to gradual weaning was observed in Holstein-Friesian and Jersey calves as the expression pattern of the pro-apoptotic gene, *Fas*, was changed over time. The differences in relative gene expression between the breeds may suggest that the Jersey innate immune system is constantly more stimulated, demonstrated by increased levels of the pro-inflammatory cytokine, *CXCL8*, and of the glucocorticoid receptor, *GRα*.

Gradual weaning produced differential biological responses in the two breeds, evidenced by breed × time interactions for lymphocytes, monocytes, RBCs and HGB. The more pronounced increase in lymphocyte number throughout weaning and during post-weaning and the disproportionate elevation in monocyte number post weaning along with greater levels of transcripts for *CXCL8* and *GRα* suggests that Jersey calves may have a more sensitive immune system.

Acknowledgements

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4.2. Monitoring of the physiological and behavioural stress response of Holstein bulls following group mixing

S. Weyl-Feinstein[1,2], A. Orlov[1], M. Yishay[1], R. Agmon[1], M. Steensels[3], V. Sibony[1], I. Halachmi[3], I. Izhaki[2] and A. Shabtay[1]*

[1]Department of Ruminant Science, Institute of Animal Science, Newe Ya'ar Research Center, Agricultural Research Organization, P.O. Box 1021, Ramat Yishay 30095, Israel; [2]Department of Evolutionary and Environmental Biology, Faculty of Sciences, University of Haifa, 3498838 Haifa, Israel; [3]Institute of Agricultural Engineering, Agricultural Research Organization (ARO), the Volcani Center, P.O. Box 6, Bet-Dagan 50250, Israel; sarah@volcani.agri.gov.il

Abstract

Holstein bulls destined for beef production which are unfamiliar with each other are routinely mixed prior to marketing. This practice constitutes a stressful event which affects both animal welfare and meat quality. We questioned whether mixing 34 days before marketing could induce a stress response that would affect the animal performance and pH of meat. For the experiment, 22 Holstein bulls (at a mean age of 7.35±0.07 months and mean weight of 285.5±90 kg) were raised in groups of three and were mixed 34 days prior to marketing to form two groups (n_1=13, n_2=9). The daily rumination and activity of the bulls were monitored for 20 days before and 33 days post mixing (DPM) and bulls were weighed 1 day before mixing (DBM), 3 and 33 days DPM. Plasma concentrations of non-esterified fatty acid (NEFA), and anti-oxidative capacity in bulls were measured pre- and post-mixing (PM). After slaughter, pH measurements were taken at the *m. longissimus thoracis* et *lumborum* (LTL) 24 h after the carcasses were chilled. The results demonstrated that mixing had significantly decreased the calves' weight gain by 6.2±2 kg at 3 DPM. Daily rumination decreased twofold 24 h PM *(P<0.0001)*. The daily number of steps taken by calves was 3 times higher, and did not return to PM values even 25 DPM *(P<0.0001)*. The mean plasma NEFA concentrations increased from 120±13 to 428±40 µmol/l, 24h PM *(P<0.0001)*, and the anti-oxidative capacity of the serum 24 h PM decreased significantly (*P=0.01*). Finally, the mean pH value of LTL in meat was 6.5±0.02, greater than what is required for proper acidification. The data collected using precise livestock farming monitoring methods demonstrated the physiological and behavioural outcome of mixing 34 days prior to marketing, which resulted in elevated pH levels in the meat. However, further investigations are required in order to assess the additional impact on meat quality and determine the optimal time needed to recover from mixing in order to maintain good meat quality.

Keywords: Holstein bulls, group-mixing, anti-oxidative capacity, non-esterified fatty acids

Introduction

Animal handling practices prior to marketing are a growing concern in many countries around the world, as they have an impact on animal welfare (Adzitey, 2011). During handling, animals are exposed to physical and psychological stresses, such as the breakdown of social groupings and mixing with unfamiliar animals (Warriss, 2000). Mixing of unfamiliar bulls causes injuries,

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bruises and body weight losses (Grandin, 1980), with a significant economic impact (D'Eath, 2002). Lawrie and Ledward (2006) reported that poorer meat quality is evident when stress levels are higher. Pre-slaughter handling can affect both carcass and meat quality. The major influence of pre-slaughter handling on lean meat quality is through the potential effect on muscle glycogen stores. If these stores are depleted by chronic stress, the extent of post-mortem acidification is reduced, leading to the production of dark cutting beef (DCB) which is prone to spoilage and has poor organoleptic qualities. The major cause of DCB is mixing unfamiliar animals, thus promoting agonistic behaviour, particularly in young bulls. Therefore pre-slaughter handling practices which encourage mixing increase the incidence of DCB (Warriss, 1990), with negative economic implications. DCB is a condition in which the ultimate pH post mortem measured after 12-48 h is ≥6. This can occur when animals are exposed to chronic or long-term stress before slaughtering (Adzitey and Nurul, 2011). The mixing policy is an integral part of beef cattle production; therefore, methods for reducing the stress associated with mixing are increasingly being explored. Evidence in the literature for the recommended period between group mixing and slaughter is not unequivocal; when seeking methods to prevent DCB, Warriss *et al.* (1984) found that unfamiliar young bulls required two days to recover from mixing stress by sufficiently replenishing muscle glycogen stores and achieving a pH<6. Similarly, Tennessen *et al.* (1985) observed that bulls showed very little aggressive behaviour 10 days post-mixing. Yet the process of creating a new social hierarchy for stranger bulls can take at least 12 weeks (Tennessen and Price, 1980). In the light of the above, we questioned whether mixing 34 days before marketing may still induce a stress response which could affect the productivity and pH of meat.

Materials and methods

Animal husbandry and nutrition

Twenty-two young horned Holstein bulls, not castrated, were included in this experiment. The bulls were maintained in 9 m^2 pens (n=3 animals/pen), from the age of 7.3±0.07 months until the age of 15.7±0.07 months. The bulls were fed a total mixed ration (Table 1).

Following a request by the abattoir, thirty-four days before marketing the bulls were mixed to form two groups (n_1=13, n_2=9). Bulls were weighed on the day before mixing (DBM) and at 3 and 33 days post mixing (DPM). Mixing was performed in the same paddock by removing the barriers between the bulls. The bulls were slaughtered in a commercial abattoir at a mean age of 523±0.34 days.

Rumination and activity measurements

In order to examine the behavioural changes associated with group mixing, all bulls were equipped with rumination tags (HR-Tag, SCR Engineers, Netanya, Israel) that measured the duration of daily rumination in minutes (min/day). The rumination tags were hung around the neck of each bull throughout the trial period. The rumination data were logged in 2 h blocks which were transferred to the computer and analysed using Matlab software (Matlab 6.1, MathWorks, Natick, MA, USA). Activity evaluation included the total number of steps, number of rest-bouts (number of times an animal lies down and stands up again) and rest-time (duration of rest in minutes). These data were recorded by a behaviour sensor tag (Pedometer Plus™, AfiFarm® Dairy Herd Management software) that was fitted to the forelimb of each bull. Daily activity is presented for a 24 h period. Day-time activity was considered as the activity during daylight hours, hence from 04:00 until 18:00, and night-time activity was defined as the period between 18:00 and 04:00. The

Table 1. Ingredient and chemical composition of the total mixed ration fed to experimental bulls.

Components (g/kg of dry matter (DM))	Amount
Ingredients composition	
Barley grain	402
Ground maize grain	264
Soybean meal (solvent-extracted)	27.06
Wheat barn	51.6
Gluten feed	35.8
Vetch hay (Vicia)	81
Wheat silage	89
Broiler litter silage	33
Minerals and vitamins	2.56
NaCl	3.8
Limestone	10.15
Chemical components	
Metabolisable energy, MJ/kg of DM	2.83
Crude protein, g/kg of DM	132
Organic matter, g/kg of DM	950
Neutral detergent fibres, g/kg of DM	240
Ether extract, g/kg of DM	28
Soluble carbohydrates (g/kg)	461
Roughage (g/kg)	170
Ash (g/kg)	50
Ca (g/kg)	8
P (g/kg)	4.68
Vitamin A (IU)	7,000

variables that were collected were analysed in the following form: sum of daily (24 h), daytime and night-time number of steps, sum of daily, day-time and night-time lying time in minutes, and sum of the number of daily, day-time and night-time rest-bouts. Average values for every parameter were obtained for each group for the different periods: 20 DBM, 24 h post-mixing (PM), 2, 3-14 and 15-25 DPM.

Blood sampling

Blood was sampled 1 DBM and 1 and 3 DPM, from the caudal vein, using tubes containing EDTA, heparinised tubes and serum clot activator tubes. The blood was centrifuged at 1,500×*g* at 4 °C to separate the cells from plasma and to collect serum. These samples were frozen in liquid nitrogen and kept at -20 °C until use.

Determination of serum anti-oxidant capacity

Two methods were used to evaluate total antioxidant capacity, namely the ferric reducing antioxidant power (FRAP) assay (Benzie and Strain, 1999) and the chemiluminescence-inducing cocktail method (Ginsburg *et al.*, 2004a,b). The FRAP assay uses antioxidants as reluctant in a redox-linked colorimetric method, employing an easily reduced oxidant system. Analyses were performed in duplicates on 1 DBM, 1 and 3 DPM heparinised plasma samples, and data were presented as µM ascorbic acid equivalents.

For the chemiluminescence-inducing cocktail method we used serum samples. This method is based on the generation of light-conjugated free radicals. The anti-oxidant capacity of a sample is evaluated by its potential to quench the light generated by the system. Thus, lower luminol-dependent chemiluminescence (LDCL) values reflect samples with a higher anti-oxidant capacity. The reaction cocktail was comprised of Hank's buffer (cat #02-016-1A; Biological Industries, Kibbutz Beit Haemek, Israel), H_2O_2 and 1 mM of Cobalt Chlorine, sodium selenite, and luminol. A volume of 20 µl serum was added to the reaction mixture and analysed immediately in a Lumac type 2500 M luminometer for LDCL generation. The samples were measured for 6.5 min and values were calculated as the sum counts of the entire measurement period.

Analysis of plasma non-esterified fatty acids

We used a two reaction, enzymatic-based assay that was adapted and validated to quantify non-esterified fatty acids (NEFA) in bovine heparinised plasma, using microtitre plates (Buege and Aust, 1978). The analysis was performed in duplicate samples on 1 DBM, 1 and 3 DPM using the commercial kit NEFA-HR (2) R1 set, (cat #434-91795; Wako chemicals GmbH, Neuss, Germany).

Measurement of meat pH levels

The bulls were slaughtered at a commercial abattoir one day after arrival. The pH of the *m. longissimus thoracis et lumborum* (LTL) was measured using a glass electrode 24h after the carcasses were chilled.

Statistical analysis

All means are presented ± standard error of the means and analysed with the use of SPSS for Windows (version 17.0; Chicago, IL, USA). The differences in weight gain, activity, rumination, FRAP and anti-oxidative activity, were tested using a repeated measurement analysis of variance (ANOVA). Comparison of meat pH distribution was tested using a Chi-square test. Statistical significance was declared at a probability level of $P \leq 0.05$.

Results

Mixing of the groups had a significant impact on the live weight gain (P=0.04; Figure 1). Following mixing, weight gain of bulls decreased by 6.2±2 kg at 3 DPM. Moreover, even at 33 DPM, the average weight gain had not returned to the values obtained before mixing. Additionally, one bull suffered from a broken leg on the day following mixing and had to be excluded from the experiment. In response to mixing, plasma NEFA levels increased significantly (P<0.0001; Figure 2). Nevertheless, 20 DBM and NEFA levels at 1 DPM were positively correlated (r_s= 0.59, P=0.006, n=17).

The total antioxidant capacity evaluated by the FRAP method was not affected by mixing. However, the anti-oxidative capacity of the serum measured by the chemiluminescence method revealed a significant decrease in anti-oxidant capacity following mixing (P=0.01).

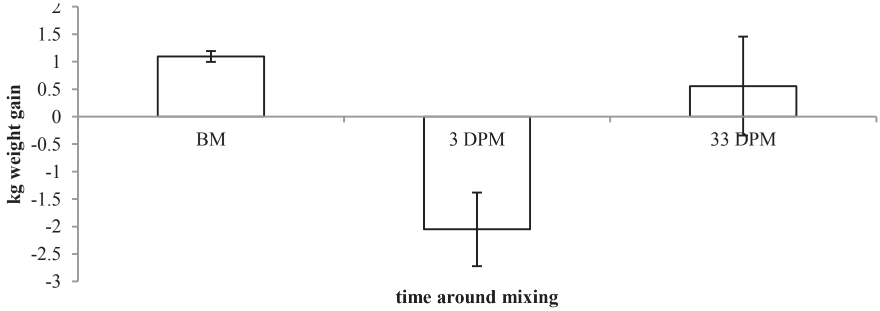

Figure 1. Effect of group mixing on weight gain of Holstein bull calves (P=0.04). BM = before mixing; DPM = days post mixing; values are presented as mean ± standard error of the mean.

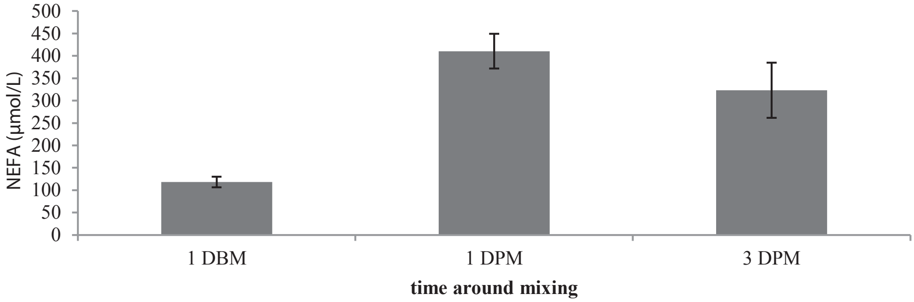

Figure 2. Effect of group mixing on plasma non-esterified fatty acids (NEFA) of Holstein bull calves (P<0.0001). BM = before mixing; DPM = days post mixing; values are presented as mean ± standard error of the mean.

Mixing had a significant effect on bulls' activity: the number of daily steps at 20 DBM, 24 h, 2, 3-14 and 15-25 DPM was 3,508±445, 10,305±783, 4,062±638, 4,913±657 and 6,391±1,167 steps/day, respectively (P<0.0001; Figure 3A). The daily number of rest-bouts was also affected by group mixing, being 19.1±0.8, 10.4±0.7, 16.4±1.1, 17±0.5 and 19.7±0.9 rest-bouts/day, respectively (P<0.0001), for 20 DBM, 24 h, 2, 3-14 and 15-25 DPM. Daily rest-time differed significantly between the periods around mixing: on 20 DBM, 24 h, 2, 3-14 and 15-25 DPM the bulls rested a total of 702±12, 384±17, 609±20, 580±12 and 701±19 min/d, respectively (P<0.0001). The impact of mixing on the rest-bouts was clearly noticeable (P<0.0001). Rest-bouts, which are positively correlated with rest-time (Mattachini *et al.*, 2013) decreased at 24 h PM and then calves gradually regained their pre-mixing values at 15-25 DPM.

The average daily rumination duration was negatively affected by mixing since the differences between 20 DBM and 24 h, 2, 3-14 and 15-25 DPM were significant (P<0.0001; Figure 3B). Prior to mixing, bulls ruminated for 318.5±20 min/day, whereas 24 h PM, rumination activity took place for only 166.6±17 min/day. Rumination duration increased to regain initial pre-mixing values at 2 DPM (293.3±15 min/day).

The average pH value for all meat samples was 6.5±0.02. These values are higher than the LTL of other Holstein bulls reared, handled and slaughtered under the same conditions, without being

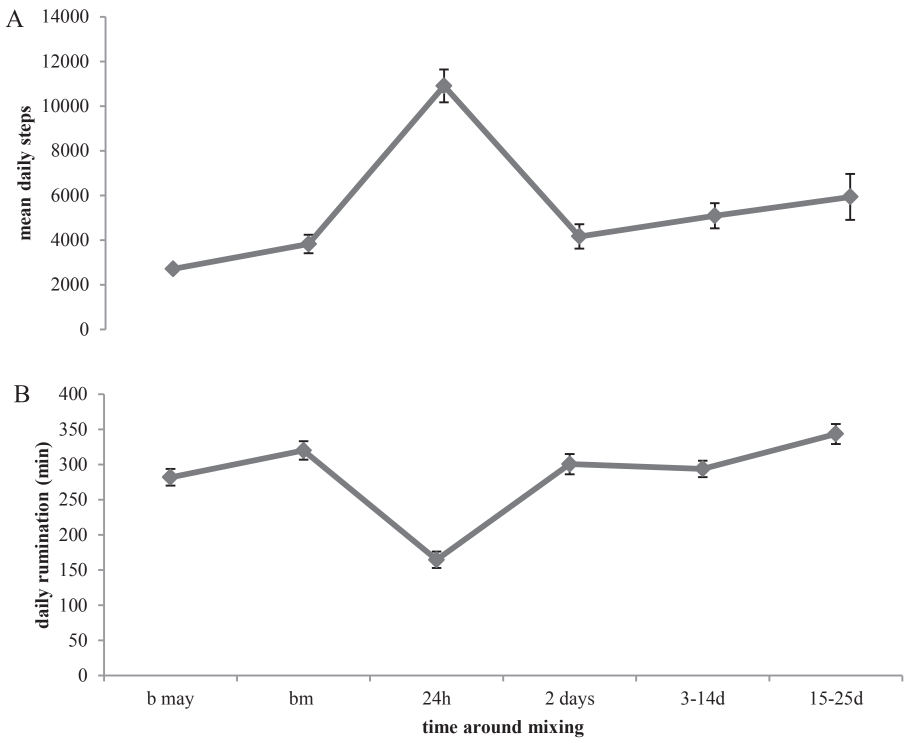

Figure 3. The differences in daily steps (A) and daily rumination (B) of calves (n=20) throughout the pre- and post-mixing period (*P*<0.0001). Values are presented as mean ± standard error of the mean, and the pre-mixing (b may) represent the mean of the 20 days before mixing. The differences between periods were tested using ANOVA repeated measurements.

mixed, where 60% of carcasses had a pH<6 as opposed to 21% of carcasses in the current trial (*P*=0.009).

Discussion

Group mixing was clearly accompanied by a high degree of physical activity, which gradually decreased during the post-mixing period. The social and environmental changes which are associated with the establishment of group social hierarchy (Bouissou *et al.*, 2001) were behaviourally characterized by aggressive butting, pushing, frequent mounting and increased vocalization (data not shown). Warriss *et al.* (1984) reported that behavioural interactions and associated physical activity occurring during group mixing had led to a considerable rise in plasma creatine phosphokinase activity and free fatty acid concentration. In the present study we observed that mixing had a noticeable effect on activity as judged by the increased number of steps along with a decreased rest-time. This stressful stimulus was further evidenced by increased plasma NEFA levels and decreased rumination and weight gain, which we assume were a result of decreased feed intake. Non-esterified fatty acids (NEFA) are released from lipid stores and oxidized in the liver as an alternative energy source. Thus, their concentration in the plasma is an indication for lipid mobilization to overcome the current demand for energy (Drackley, 1999). The meat pH measurements in the current study are considered higher than recommended (mean ± standard error of the mean; 6.5±0.02), and we assume that this might be related to the mixing that had occurred 34 days pre-slaughter. Based on the precise activity data monitored in the present study, bulls do not re-establish their pre-mixing behaviour even 25 days post mixing and their pH levels after slaughter were greater than 6, even when slaughter occurred 34 days post mixing. These discrepancies might be explained by differences in breeds, rearing and slaughter practices, but further investigations are required to explore this issue.

Conclusions

Mixing of unfamiliar calves has strong behavioural and physiological implications. This was demonstrated by the increase in number of steps, NEFA levels and anti-oxidative activity and the decrease in rest, rumination and weight gain. In terms of meat quality characteristics, the consequences of mixing may have further led to elevated pH levels in the meat after slaughter. From this point of view, the activity and rumination monitoring systems utilized in this study may serve as a predictive tool for the recovery period needed from mixing to marketing.

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4.3. Investigating the use of rumination sensors during the peripartum period in dairy cows

D.N. Liboreiro, K.S. Machado, M.I. Endres and R.C. Chebel*
University of Minnesota, Department of Animal Science, 225C Haecker Hall, 1364 Eckles Avenue, St. Paul, MN 55108-6118, USA; miendres@umn.edu

Abstract

The objective of the current study was to determine the accuracy of disease detection based on daily rumination time (DRT) and activity of periparturient dairy cows. All animals were fitted with rumination/activity monitors from -21 to 21 days relative to calving. Cows that were within the lowest 25th percentile of milk yield in the first 90 d postpartum had reduced DRT, but there was no association between milk yield and activity during the periparturient period. Based on criterion created using DRT, stillbirth could be diagnosed with sensitivity and specificity of 50 and 79.7%, respectively. Two criteria could be used for diagnosis of sub-clinical hypocalcemia on the day of calving; one resulted in 66.7 and 61.3% sensitivity and specificity, and the other sensitivity and specificity of 82.7 and 49.6%, respectively. Metritis could be diagnosed 72 h after calving with a sensitivity and specificity of 75 and 93.1%, respectively. Among cows that were diagnosed with retained placenta within 24 h after calving, the DRT criterion resulted in sensitivity and specificity of 70.8 and 75%, respectively. In conclusion, automated monitoring of DRT could possibly be used as a tool for diagnosis of periparturient diseases; however, the use of DRT data to select individuals for treatment without additional diagnostic exams is likely to results in erroneous treatment of periparturient cows.

Keywords: rumination time, periparturient cows, disease detection, transition period

Introduction

Periparturient diseases, metabolic and infectious, have a profound impact on well-being of dairy cows and profitability of dairy herds. The development of on-farm diagnostic methods for metabolic and infectious peripartum diseases presents a significant opportunity for early treatment of cows, which could reduce the impact of such diseases on longevity of animals and contribute to profitability and sustainability of dairy herds. Dry matter intake (DMI) during the periparturient period is important for health and performance of dairy cows. Rumination is influenced by feed intake. The Hi-Tag rumination monitoring system (SCR Engineers Ltd., Netanya, Israel) has been validated for measuring daily rumination time (DRT) of cows compared with visual observation (Schirmann *et al.*, 2009). Although associations between health disorders and rumination time may be observed, more research is needed to investigate whether rumination time and activity may be used as accurate diagnostic tools.

The objectives of the current study were to determine the accuracy of disease (infectious and metabolic) detection based on DRT and activity of periparturient dairy cows. Furthermore, the current study aimed to determine the accuracy of using peripartum DRT and activity data to identify cows that present subpar milk yield in the first 90 days postpartum.

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Material and methods

Cows

Holstein animals (nulliparous = 77, parous = 219) were enrolled in this experiment at 260±3 days of gestation. All animals were fitted with rumination/activity monitors (SCR Engineers Ltd., Netanya, Israel) from -21 to 21 days relative to calving.

Metabolites and calcium

Blood was sampled weekly from -17 to 17±3 days relative to calving to determine non-esterified fatty acid (NEFA) concentrations. Blood sampled weekly from day 3 to 17±3 relative to calving was used to determine beta-hydroxy butyrate (BHBA) concentration. From a subgroup of animals (n=249), total calcium concentration was determined 0 to 72 h after calving.

Body condition and locomotion score

Cows were scored for body condition (1 = thin, 5 = obese) and locomotion (1 = normal, 5 = severely lame) at enrolment, respectively 3±3 and 24±3 days postpartum. Cows were classified as lame when the locomotion score was ≥3 and severely lame when the locomotion score was ≥4.

Health disorders

Cows were examined daily from calving to 14 days postpartum for diagnosis of retained foetal membranes and metritis. Sub-clinical hypocalcaemia was defined as serum Ca <8.55 mg/dl. Sub-clinical ketosis was defined as BHBA >1000 µmol/l. Occurrences of twin birth and dystocia (calving ease >3) were recorded for each individual.

Milk production

Cows were milked three times daily. Daily milk yield from calving to 21 days postpartum was used to evaluate the correlation between milk yield and DRT and activity. Furthermore, average milk yield in the first 90 days postpartum was calculated for each cow. Cows were then classified as being within the lowest 25th percentile milk yield in the first 90 days postpartum or above the lowest 25th percentile milk yield within parity (primiparous vs multiparous).

Statistical analysis

Statistical analyses were conducted using SAS (SAS Institute Inc., Cary, NC, USA) and MedCalc (Ostend, Belgium). Continuous data were analysed by ANOVA for repeated measures using the MIXED procedure. Univariate analysis was used to determine the association between health disorders and milk yield and DRT and activity. The results of the univariate analysis were used to identify when differences in DRT and activity between cows that had health disorders and healthy cows were greatest. The raw DRT and activity data and the algorithms created based on the raw DRT and activity of each individual cow were tested as diagnostic tools using the receiver operating characteristic procedure. The test was only considered to be useful as a diagnostic tool if it could be used to identify health disorders before or on the day when the disorder would be diagnosed on farm.

Results

The percentages of male calves and twin births were 54.4 and 7.4%, respectively. Incidences of retained foetal membranes, metritis, sub-clinical hypocalcaemia, and sub-clinical ketosis were 13.2, 21.2, 37.8 and 12.7%, respectively.

There was a correlation between DRT prepartum and postpartum (P<0.01; Figure 1) and between activity prepartum and postpartum (P<0.01; Figure 2). There was no correlation between prepartum DRT and activity (P=0.20), but postpartum DRT and activity were correlated (r=0.14 (0.02, 0.25); P=0.02). Milk yield was correlated with DRT (P<0.01; Figure 3) and activity (P<0.01; Figure 4).

Cows that were within the lowest 25th percentile of milk yield in the first 90 days postpartum had (P<0.01) reduced DRT (Figure 5), but there was no association (P=0.14) between milk yield and activity (Figure 6) during the periparturient period.

Based on a criterion created using DRT, stillbirth could be diagnosed with sensitivity and specificity of 50 and 79.7%, respectively.

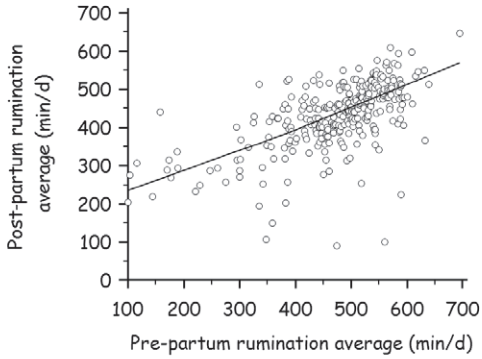

Figure 1. Correlation between daily rumination time postpartum and prepartum (r=0.63 (95% CI=0.53, 0.67); P<0.01). Partial correlation: r=0.65; P<0.01.

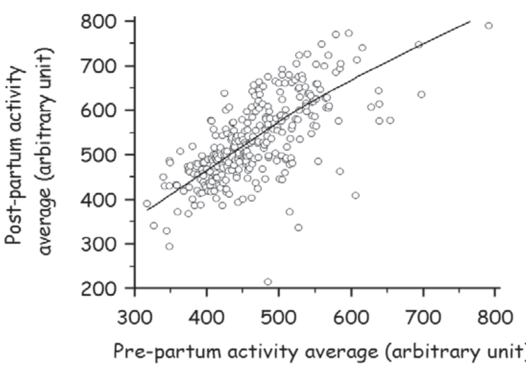

Figure 2. Correlation between activity postpartum and prepartum (r=0.68 (95% CI=0.62, 0.74); P<0.01). Partial correlation: r=0.71; P<0.01.

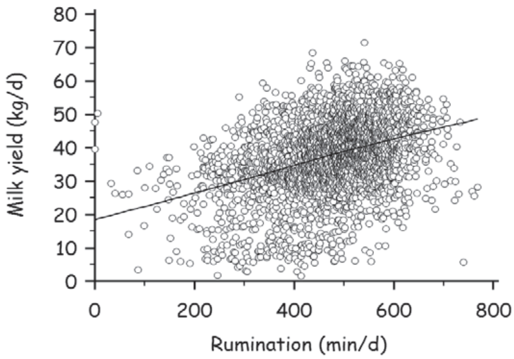

Figure 3. Correlation between milk yield and daily rumination time (r=0.37 (95% CI=0.34, 0.40); *P*<0.01). Partial correlation: r=0.28; *P*<0.01.

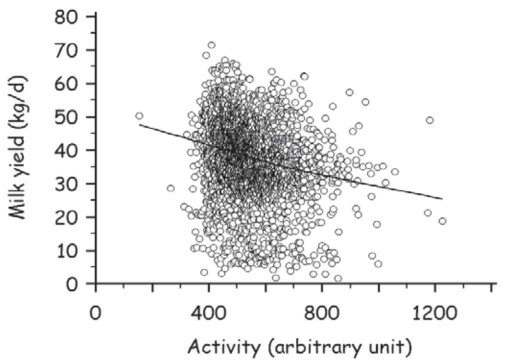

Figure 4. Correlation between milk yield and daily activity (r=-0.21 (95% CI=-0.24, -0.18); *P*<0.01). Partial correlation: r=-0.10; *P*<0.01.

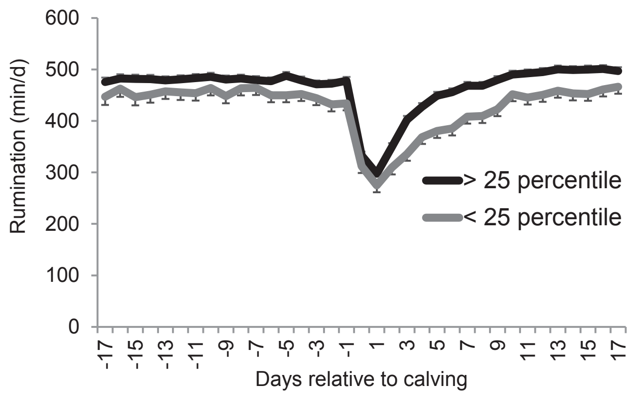

Figure 5. Association between milk yield in the first 90 d postpartum and rumination. Effect of milk yield (*P*<0.01); day (*P*<0.01); and milk yield by day (*P*=0.28).

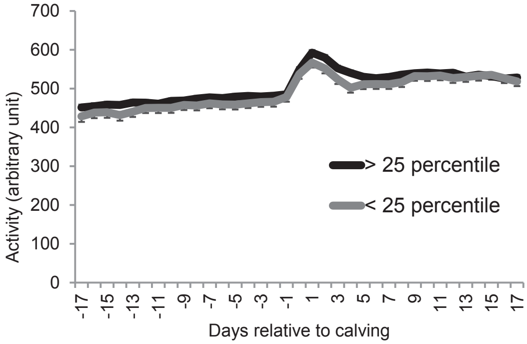

Figure 6. Association between milk yield in the first 90 days postpartum and activity. Effect of milk yield (P=0.14); day (P<0.01); and milk yield by day (P=0.91).

Daily rumination time and activity could not be used for the diagnosis of retained placenta (RP) before the day of calving. Two criteria could be used for diagnosis of sub-clinical hypocalcaemia on the day of calving. One of the criteria resulted in 66.7 and 61.3% sensitivity and specificity, respectively. The second criterion resulted in sensitivity and specificity of 82.7 and 49.6%, respectively.

Metritis could be diagnosed 72 h after calving with a sensitivity and specificity of 75 and 93.1%, respectively. Among cows that were diagnosed with RP within 24 h after calving, the DRT criterion resulted in sensitivity and specificity of 70.8 and 75%, respectively.

Conclusions

Automated systems that allow for continued monitoring of rumination and activity have been characterized as possible tools for diagnosis of periparturient diseases. Criteria created based on actual DRT resulted in moderate sensitivity and specificity for diagnosis of stillbirth, metritis, sub-clinical ketosis, sub-clinical hypocalcaemia and reduced milk yield in the first 90 days postpartum. Thus, it is possible that DRT data may be used to identify cows at higher risk of periparturient diseases, however, the use of DRT data to select individuals for treatment without additional diagnostic examinations/procedures is likely to result in erroneous treatment of periparturient cows.

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4.4. Monitoring stress behaviour in grazing beef cows

R. Gabrieli[1] and E. Misha[2]*
[1]Ministry of Agriculture and Rural Development, Extension Service, Beit Dagan, Israel; [2]ENGS systems Ltd., P.O. Box 77, Rosh Pina 12000, Israel; ragav@shaham.moag.gov.il

Abstract

Commercial beef breeding is carried out in vast pastures. Hierarchy within the herd determines priority of access to limited resources, resulting in stress to the lower ranking cows. Identifying these cows may enable the breeder to improve grouping management and minimize stress. This will lead in turn to improved production and lower replacement costs. An innovative wireless pedometric system was modified to serve as a standalone station in a 300 ha pasture in northern Israel. Thirty randomly selected cows were tagged and their activity monitored. It was hypothesized that a comparative analysis of individual hourly activity might reflect the cow's social status within the herd. To test this hypothesis we conducted observations near the feed trough during feeding time. Cows which reached the trough but received up to two rejections before securing a place to eat were labelled 'High'. Cows that were rejected continuously or avoided the trough were ranked 'Low'. The ranking was validated by measuring the cortisol concentration in hair samples. Cortisol concentration were 0.16±0.02 and 0.246±0.07 for the High and Low cows respectively, P=0.0375. Data analysis showed that peak and low activity hours were identical for the two groups (06:00-07:00; 15:00-16:00, and 03:00-04:00, respectively). Hourly activity data were variable for all cows and were expressed as high CV values (coefficient of variance, 48±8%), meaning that all cows expressed continuously changing activity. Differences expressed in activity graphs with higher fluctuation, for example graph amplitude matched with hourly activity, were significantly higher for the 'Low' cows than for the 'High' ones (mean mean 259.9 and 222.8 respectively; P=0.029). Data were analysed using 'jmp' software. The continuous activity pattern reflects the measure of freedom of each cow to choose her own behaviour within a grazing herd. Assuming that establishing a daily routine, expressed in a graph with less fluctuation, is beneficial for each cow, detecting cows that are unable to do so and grouping them separately will minimize social stress and improve production.

Keywords: group behaviour, pedometric system, stress

Introduction

Beef cattle breeding is an extensive operation, carried out in vast pastures. Herd management and data collection are carried out manually due to the lack of suitable technology. Lack of online information inhibits the breeders' ability to address varied, transient physiological or behavioural events and perform adequate management modifications that will result in improved production during the same production cycle.

Previous attempts to apply electronic monitoring systems in open pastures have failed due to transmission limitations. Sampling activity at fixed times and locations, such as obligatory passage points, has resulted in irregular identification and data reception, due to the irregular daily behaviour patterns of grazing beef cows. This lack of regularity is reflected in activity graphs with a high degree of fluctuation which mask deviation patterns expressing physiological or behavioural

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phenomena. The use of electronic systems for continuous monitoring of cow activity has resulted in steadier activity graphs which allowed distinct deviation patterns to be identified, which could be correlated to physiological and behavioural events, such as peak activity during oestrus or weaning, decreased activity due to lameness, elevated activity expressing pre-partum behaviour, etc. Fluctuating graphs still occurred. The existence of these two distinct types of graph, coupled with observations, led us to hypothesize that the activity pattern may be connected to social status.

Feral cattle herds are organized in fusion-fission societies (Lazo, 1994). At the high level, cattle form stable social subgroups which travel over a well-defined area in the course of their daily activities (Burt, 1943). At the low level of social organization, subgroups are smaller and unstable, fluctuating in size and composition according to changing environmental conditions (Lazo, 1994). In domesticated cattle herds, culling and group management alters the natural social organization, mainly affecting the high-level, stable, usually matrilineal subgroups. Hierarchy is one of the primary factors that influence distribution of cows over a given range. It determines priority of access to limited resources, which leads to stress in the lower-ranking cows.

Group management is usually determined by the age and physiological status of the cows, and thus the social organization of intensively managed herds is often disrupted. For this study we chose a herd with minimal regrouping management. Culling is performed annually and subdivision takes place for a short period between two consecutive weaning events, but no transfer of cows occurs. Once yearly a group of second calving heifers (three years old) is introduced into the adult herd. We assumed that the social organization of the adult herd was well established and that interactions involving adaptation occurred around the period when the new heifers were introduced, six months prior to initiation of the study.

The study was conducted between 4 November 2013 and 25 January 2014. Grazing in the Mediterranean rangeland is poor during this period, and supplemented with additional feed. Feed troughs cause crowding, resulting in social stress in the lower ranking cows (Bennett *et al.*, 1985; Kondo *et al.*, 1989). Cows which avoid the trough could either be exceptionally good grazers, or they could be exposed to nutritional stress. Stress, whether social or nutritional, results in reduced productivity (Bennett *et al.* 1985; Bennett and Holmes, 1987; Broom and Leaver, 1978; Mench *et al.*, 1990; Wagnon *et al.*, 1966). By the time the reduced productivity is detectable by the breeder, it is too late to apply suitable management in order to improve production. Measurements of production, for example pregnancy test, calving time or weaning weight, are delayed in relation to the causative events (conception, abortion or milk production, respectively), resulting in a failure to differentiate between influencing innate traits and social or behavioural effects of stress. In the first case culling is inevitable; in the second case, production can be improved by applying adequate management which will prevent competition for essential resources.

An innovative wireless pedometric system was modified to serve as a standalone station in a 300 ha pasture in northern Israel. Data were recorded at hourly intervals, in each case logged for 12 hours with an hourly resolution, and expressed activity and posture (lying or standing). The software presented the results as graphs, showing activity, average lying duration and changes in position (lying vs standing). Typical deviations from average activity were analysed and correlated to different physiological and behavioural phenomena, for example: oestrous, pre- and post-partum behaviour and lameness. Individual physiological and behavioural events and group events were observed, recorded and correlated to the patterns shown on the activity graphs. Activity data were analysed by group and by individual animals. Observations were conducted in order to establish the hierarchy, and two groups of high-ranking and low-ranking cows were defined. A number of parameters were compared between the two groups. Similarities and differences were analysed in order to provide the breeder with a graphic tool which facilitates the detection of low-ranking, socially stressed cows.

The aim of the study was to create a management tool which can correlate activity patterns with social stress, thus making it possible for breeders to improve social management online and optimize productivity.

Materials and methods

The Pedometric system

The system comprises:
1. A central receiving unit: PC, Eco-herd software, RS485 communication box, UHF receiver + high gain antenna.
2. 12V battery-powered UHF transceivers + high gain antenna units based in the pasture, mounted on a 4-10 metre pole.
3. Each cow was fitted with a UHF transmitting tag (ENGS, Rosh Pina, Israel), which was strapped on the distal lateral aspect of the front metacarpus. The device had a rigid plastic housing (length 68.76 mm; width 26.53 mm; height 50.72 mm; weight 75 g). It measured acceleration (*g*) in the x, y and z-axes at a frequency of 1000 Hz. The device transmitted data wirelessly every 15 minutes to a computer with software provided by the manufacturer (ENGS, Rosh Pina, Israel) which converted on-line *g*-force readings into standing, lying and walking behaviour (i.e. number of steps).

Animals

Tags were fitted to 30 randomly selected cows. The common breed was Israeli Simmental, developed by repeated crossing with the local *Baladi* breed. The weight range was 530-620 kg, with the average being 560 kg. The average age was six years, ranging from three to fourteen. The total number of cows in the herd was 210 and the pasture area was 300 ha. Feed was supplied from 4 November until 26 January, when this session ended. Feed was distributed daily into a 250 metre long trough, allowing space of approximately 1.2 metres per cow. The feed ration was available each day between 10:00 to 18:00, when the herd finished eating.

Observations

Observations were conducted near the feeding trough during feeding hours and in the pasture during activity hours. Once weekly, observations were conducted during the rest period. During the observations in the pasture the observer made general observations and moved around the periphery of the herd recording group data and random interactions. Specific cows were followed and their activity and interactions were continuously recorded. Individual and group activities and physiological events (calving, oestrus, insemination, etc.) were recorded. Interaction recorded included: *approach, threaten, shove, invite, lick, withdraw, sniff* and any combination of the above. Each record specified the initiator and the responder and the intensity of the interaction. Interactions were defined as ‘positive’ or ‘negative’, according to their estimated influence on the position of the cow towards a higher or lower ranking cow, respectively. The activities of the cows were recorded as they approached the feeding trough and during the time spent near the trough. The number and type of interactions that each cow initiated in the vicinity of the trough, and the number and type of interactions she responded to, were all recorded. The order of feeding was established as a criterion in ranking social status, and in order to estimate its direct influence on body condition. Cows that managed to approach the trough with none, one or two rejections and ate and left voluntarily were ranked 'high'. Cows that were rejected repeatedly, or did not approach the trough at all, were ranked 'low'. Observations also included the number and definition of interactions in the vicinity of the trough. Cows in the vicinity of the trough which avoided approaching it and cows that were not seen in the vicinity of the trough were also recorded. The social ranking as 'high' or 'low' was established according to the proportion of positive to negative interactions per cow.

Results

Cows came together voluntarily to rest at specific sites, lying or standing in small groups of ten to twelve. Shade, wind and other favourable characteristics were abundant at resting sites. The space between members of each group was less than one metre, and they sometimes touched each other. The distance between groups averaged approximately eight to twelve metres. Few interactions were recorded between cows (within a group or between groups) during rest, throughout the whole period of the trial.

A seemingly uniform general activity pattern was observed repeatedly: activity was initiated by leader cows, and the level and pace of movement of the followers started uniformly as well. The observed overall pattern of activity and dispersion of the herd seemed to be repeated over time, but when observations were examined at the resolution of individual cows, a different pattern emerged each day. Each cow changed her activity, the region she occupied, the start and end time of grazing, the times of visits to the feed trough and to the water trough, etc. Few cows demonstrated conservative behaviour and timetables. These were the highest ranking cows.

Definition of parameters

The following parameters were defined and analysed, on the basis of the activity data transmitted online by the tags:

- Average hourly activity. Average activity for each hour over 24 hours of the day for each cow was recorded during the whole trial period.
- Rate of hourly activity change. The percentage of change between given average hourly activity for two consecutive hours, calculated as the absolute value of the difference in activity between two consecutive hours, divided by the activity of the first of the pair, was determined. For example: rate of change between 04:00 and 05:00, when the average activity measured at 04:00 was 120 activity units, and the average activity measured at 05:00 was 240 activity units, was calculated: $|(240-120)|/120 = 100\%$.
- Graph amplitude. The difference between maximum and minimum hourly activity during a given day, taking into account only the activity hours and excluding rest-periods.
- Lying percent. The percentage of time that the cow spent lying during a given hour. This parameter was averaged over 24 hours, and separately over activity hours (excluding rest hours).
- Average daily activity. The average activity over 24 hours for each cow.
- Average daily activity change. The average activity change for an individual cow from day to day, calculated as the absolute value of the difference between average activity on two consecutive days, divided by the average activity on the first day of each pair. For example: average activity on 13 November for cow no. 12 was 600 activity units, and on 14 November it was 300 activity units. The daily change between 13 and 14 November was $|(300-600)|/300=100\%$.

Data analysis

Average hourly activity was variable for all the cows (179±85 steps per hour). The high values for the coefficient of variance (CV), which averaged 48±8% for all the cows, indicate that all the cows exhibited continuously changing activity, regardless of their social status. Analysing average hourly activity by status shows no significant difference between High and Low cows (182±38 and 174±19; P=0.79 for High and Low cows, respectively). Average activity during activity hours only was higher and more variable (242±139 steps per hour, CV=60%). The rate of hourly activity change averaged 39±10% when calculated over 24 hours, and 19.3±6% when calculated over activity hours only. No significant difference in average hourly activity data was observed between High and Low cows.

Average daily activity was variable, with no significant difference between the two ranks (137.5±28.6 and 151.1±40.6; P=0.177) for High and Low cows, respectively. Average daily activity change was also variable for all the cows; the mean rate of change was 37.7±5.8% and 34.1±6.8% for High and Low cows, respectively (P=0.66).

Graph amplitude seemed at first to be significantly higher in the Low cows than in the High cows (327±45 and 254±36, respectively, P=0.02). The difference was expressed in higher fluctuations in the activity graphs. Close to the end of the trial period, four cows died in an outbreak of tick fever, and all data relating to them was excluded. Graph amplitude in the revised data showed only a numerical difference between ranks: 136±36.8 and 168.4±65, mean values for High and Low cows, respectively (P=0.08).

Matched-pairs analysis of graph amplitude and average daily activity showed no significant difference between High and Low cows in terms of the mean difference, and a significant difference in mean mean (222.8 and 259.9 for High and Low respectively, P=0.029), suggesting that a fluctuating activity graph coupled with high daily activity might imply a lower-ranking individual. Supporting this suggestion is another matched-pairs analysis of graph amplitude and the average hourly activity change between High and Low cows (mean difference 272.78 and 322.3, respectively, and mean mean 136.78 and 161.54, P=0.05), which suggests that an irregular activity pattern during each day is another characteristic of a stressed cow.

Refining the comparison of the average hourly analysis between High and Low cows to an hourly resolution revealed significant differences between High and Low cows in thirteen hours during the day. These differences are shown in Table 1.

Peak activity hours for all cows were 06:00-07:00, when cows were only grazing, and 15:00-16:00 when cows were grazing as well as feeding at the trough. During these four hours, all the cows were highly active regardless of their social status, the difference being the level of activity (number of steps per hour). The average ratio between this peak activity and the average activity for each cow was 1.70±0.15, with a CV of 8.8%, expressing uniformity in the amplitude of this peak in relation to average hourly activity. This uniform pattern of increased activity changed to a uniform pattern of decreased activity from 16:00, and divided into ranks from 19:00 onward, when H cows remained more static and L cows resumed higher activity until 23:00. This is demonstrated in Figure 1.

Lying percentage was not significantly different between the High and Low cows. Matched-pairs analysis of lying percentage and average daily activity was significantly different (mean difference -168.4 and -205.2; mean mean 84.5 and 102.9 for High and Low cows, respectively (P=0.0047)),

Table 1. Differences in hourly activity between High and Low ranking cows.

Hour	High ranking cows	Low ranking cows	*P*-value
07:00	286±42	336.79±79	0.05
08:00	250±34	300±69	0.03
10:00	116±39	153±40	0.02
11:00	121±26	158±49	0.03
14:00	233±52	297±85	0.03
15:00	280±44	333±76	0.04
16:00	277±46	345±83	0.02
17:00	214±42	264±78	0.05
19:00	109±42	150±46	0.02
20:00	121±50	188±81	0.02
21:00	135±48	174±49	0.03
22:00	151±42	200±52	0.02
23:00	156±38	188±45	0.04

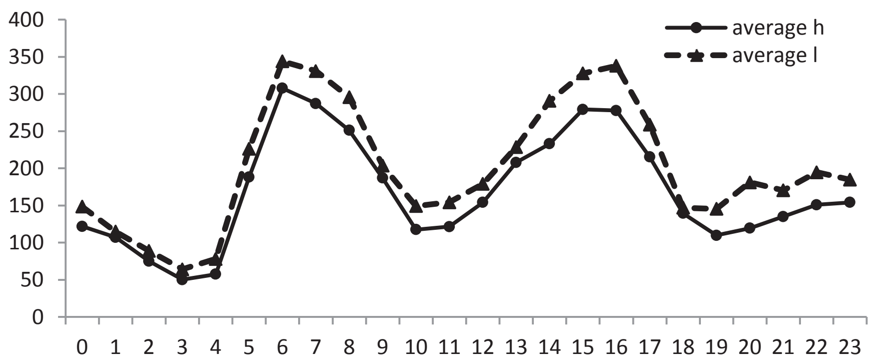

Figure 1. Average hourly activity of High and Low ranking cows.

suggesting that the graph for a low-ranking cow will be characterised by high daily activity and a low lying percent. The abovementioned significant findings are summarised in Table 2.

In order to further test the non-significant differences found in the abovementioned parameters, separate data analysis were conducted on cows from both ends of the social hierarchy – the three top-ranking cows and the three lowest-ranking cows. No differences (P>0.05) were found in any of the factors that were not significantly different in the full analysis. The different activity characteristics presented above are demonstrated visually by the relatively stable activity graph for an High cow, combined with a high percentage of lying (Figure 2), and by the highly fluctuating activity graphs for an Low cow, combined with a low percentage of lying (Figure 3).

Average daily gains of weaned calves, as a measure of milk production by the mothers, were analysed. The average daily gains of High and Low weaned calves were 1.21 (±0.2) and 1.09 (±0.16) kg, respectively (P=0.07). Considering the age differences, and the presence of second calving heifers, we may cautiously conclude that social status had an effect on milk production in this study.

Table 2. Main differences and important similarities between High and Low ranking cows.

	High ranking cows	Low ranking cows	*P*-value
Average daily activity	137.5±28.6	151.1±40.6	0.177
Average daily activity change	37.7±5.8%	34.1±6.8%	0.66
Graph amplitude	136±36.8	168.4±65	0.08
graph amplitude × average daily activity – mean mean	222.8	259.9	0.029
graph amplitude × average hourly activity change – mean difference	272.78	322.3	0.05
graph amplitude × average hourly activity change – mean mean	136.78	161.54	0.05
Average daily gains of weaned calves	1.21±0.2	1.09±0.16	0.07

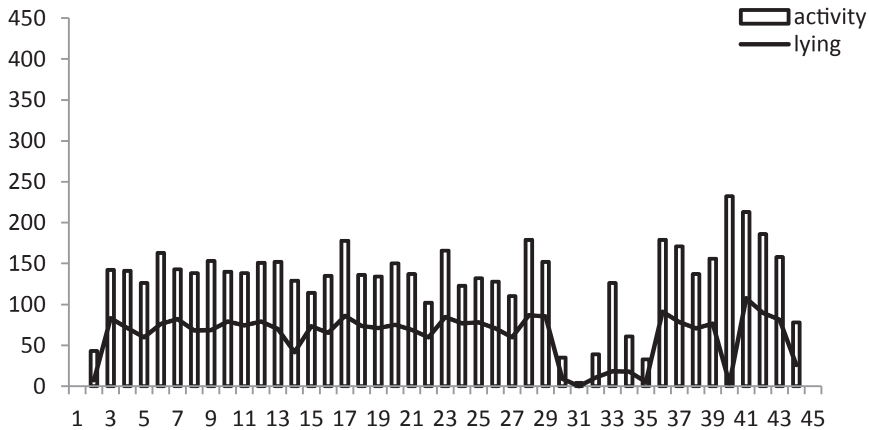

Figure 2. Activity graph of a high-ranking cow.

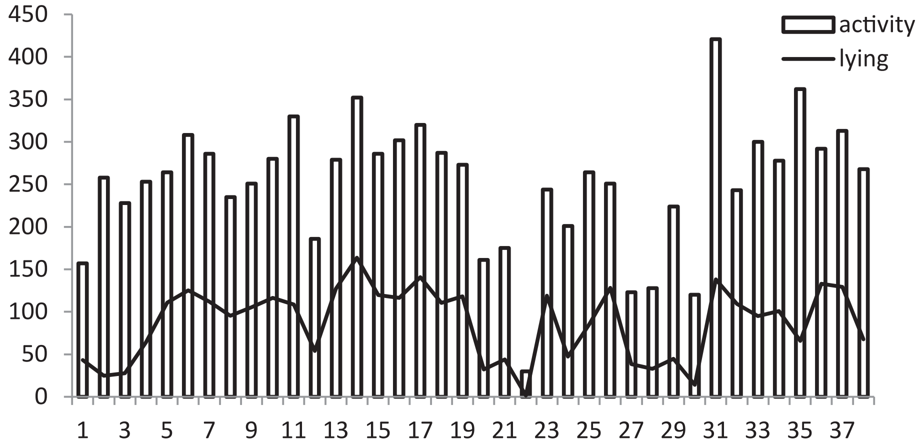

Figure 3. Activity graph of a low-ranking cow.

Discussion

The combination of observations and transmitted data showed variable, continuously changing behaviour patterns for all cows. Cows which managed to maintain a more stable, routine activity pattern were the highest-ranking cows. These findings imply that cows do not have regular, repetitive daily behaviour patterns, but rather a continuously changing activity pattern, expressed in high CV values for the relevant parameters such as daily and hourly activity. These findings could be correlated to diverse availability of resources, but more likely to individual social needs, referred to as 'auto-centric behaviour' by Mounaix *et al.* (2007). Different individual adaptations, including heat resistance, feed efficiency, grazing ability and other physical, physiological and behavioural traits, some innate and some acquired, play an important role in creating this diverse herd environment. This pattern of continuously changing activity was more prominent in the activity of Low cows, because they were affected by an unequal division of space and resources. High cows managed to establish a steadier activity pattern. This finding suggests that individual monitoring and individual management are necessary. The different activity patterns between High and Low cows are demonstrated visually by the relatively stable activity graph of High cows, combined with a high percentage of lying (Figure 2), and by the highly fluctuating activity graph of Low cows, combined with a low percentage of lying (Figure 3).

During our observations, feeding hours and resting hours were the only time of day when crowding occurred. Syme (1981) suggested that hierarchies based on competition for food do not always accord with those based only on social interactions. Resting times in the current study included very few interactions of any kind. Kondo *et al.* (1989) reported that agonistic interactions were negatively correlated to space allowance, but when space allowance per cow exceeded 360 square metres, the distance between neighbouring cows remained within 10-12 m. In the present study the space allowance per cow was approximately 5,000 m^2 and during grazing times distances between individual cows very often exceeded 15 m. This may be due to the fact that natural vegetation in the Mediterranean pasture is variable.

When the space allowance was reduced voluntarily during resting hours, as cows gathered together to rest, the number of agonistic interactions was very limited – fewer than 1 per hour per cow – thus suggesting a free choice of the space maintained between cows in a stable society which imposes no stress on either the dominant or the subordinate animals. Boran cattle herds in Kenya and Tanzania were observed resting with similar proximity (personal communications). However, this breed of cattle has a strong herding instinct, and animals also remain in close proximity during grazing activity. The close physical contact during the period of time when no competition for resources occurred may be an expression of the feral instinct of prey animals, as suggested by Lazo (1994). It may also be an expression of the time needed to maintain the social organization in surroundings and at a time of day that offer no competitive challenges.

Hourly analysis showed significantly higher uniformity (lower CV values) in hourly activity during high activity hours than during low activity hours. This contrast between the general variable, changing individual activity pattern and discrete times when uniformity was expressed suggests that a higher emphasis should be placed on refining the definition of crucial times when the herd can be addressed as a group, and other times when individual-specific management is needed in order to avoid competition and stress in the lower ranking cows.

Comparison between high and low ranking cows

Social status was established according to the observations. The data analysis considered the definition of High and Low cows as an independent variable. The different parameters that had been defined were calculated from the activity data that were transmitted online. The purpose of the analysis was to identify parameters which differ significantly between High and Low cows in order to include them in a profile of activity graphs which characterize cows suffering from social stress. These characteristics will make it possible to create a management tool for identifying socially stressed animals and regrouping them. The hypothesis was that Low cows would be more susceptible to social stress. Social stress is more common in lower ranking cows and may have considerable economic consequences, due to long term endocrinological and immunological changes which may lead to production losses such as lowered reproductive rates, increased mastitis, lower weight gains and pathological conditions, as suggested by Mench *et al.* (1990). The main differences between High and Low cows are summarized in Tables 1 and 2.

The peak activity hours for all cows were 06:00-07:00, when cows were only grazing, and 15:00-16:00 when cows were grazing as well as feeding at the trough. Since High cows enjoyed priority of access to limited resources, including superior grazing areas, the differences in activity during peak activity hours may reflect the added energy expenditure required by the Low cows to satisfy their nutritional needs. An interesting fact is the concurrent grazing activity of High cows and Low cows. Since hierarchy is passive and preferences are not disputed, one might expect that Low cows would rest while the High cows are grazing and resume grazing when the High cows reduce activity, in order to avoid competition. This choice of simultaneous activity, although inflicting stress on the Low cows, reflects a need that must be facilitated by the breeder by supplying adequate grazing and supplementary feed for simultaneous consumption by the entire herd.

A third surge of activity, lower than the two main peaks and occurring from 19:00 to 23:00, was more pronounced in the Low cows, resulting in significant differences between High and Low cows, as shown in Table 1 and Figure 1. This may express an effort by the Low cows to feed on the last remains of the supplementary feed.

Examining activity during the four peak hours mentioned above in relation to the average individual activity resulted in an average ratio of 1.70±0.15. This ratio expresses uniformity in the extent of peak activity for all the cows, regardless of their social status, with a CV of 8.8%. All the cows increase activity by 70% on average during peak activity hours, suggesting that the focus should be on improving management and resource availability at these times, when the herd expresses a unified need to act together. These hours should be considered a 'bottleneck' and management modifications in terms of resource allocation should be addressed accordingly.

Positive interactions, typical of the fused high-ranking sub-herds discussed by Lazo (1994), were not observed in this study; instead, random positive interactions between cows were observed, with changing combinations. Howery *et al.* (1996) suggested that sub-herds were a result of gregariousness rather than tightly knit, social interactions. This suggestion agrees with our findings, assuming that social organization of the current herd into high-ranking sub-herds by means of human management can be excluded. Thus most cows do not create distinctive sub-herds, high or low ranking, but rather express an individual behaviour.

Negative interactions were correlated to social status by definition. These were recurrent and involved the same individual recipients. The response of Low cows to negative interaction varied. Some were observed insisting on approaching the trough repeatedly despite being shoved consistently by different cows, some waited their chance for a free space and engaged in eating until the next shove, some waited long periods of time in the vicinity of the trough, and some were not seen near the trough at all.

Dominance factors in cattle are varied and their relative influence is a subject of debate. Age is generally corroborated (Bouissou, 1975; Mench *et al.*, 1990, reviewed in Ingrand, 2000 and Wierenga, 1990) but its effect may be altered by regrouping. Weight and size are much more disputed (Bennett and Holmes, 1987; Bouissou, 1975). Other factors, such as horns, sex, temperament and race have also been discussed (Bennett and Holmes, 1987; Bouissou, 1975; Bouissou *et al.*, 2001; Mench *et al.*, 1990). None of these factors was found to have an influence on the definition of High and Low cows in the current study, suggesting once more that cows did not form well-defined societies, but rather expressed individual independent behaviour. None of the cows in each group in the current study shared any physical or physiological factor.

No significant differences between High and Low cows were found in the average hourly activity, average daily activity, average daily activity change or average hourly activity change. This, coupled with the matched pairs analyses presented in Table 2, implies that none of these factors on their own can predict a socially stressed cow; they can only be identified by a combination of high, changing and fluctuating activity. The lack of difference between High and Low cows in terms of the discrete parameters is a measure of the high variability in activity patterns for all the cows, regardless of their social rank. The matched pairs analyses stresses the two conditions needed to define an Low cow: (1) high activity, and (2) irregular activity. Both are demonstrated visually in Figures 2 and 3.

As mentioned above, dominant animals may prevent subordinate animals from occupying certain sites, thus retaining priority to access available resources (Bennett and Holmes, 1987; Bennett *et al.* 1985). If the relative differences in resource utilization are great, dominant animals and their offspring gain more weight and reproduce more successfully (Bennett and Holmes, 1987; Bennett *et al.* 1985; Broom and Leaver, 1978; Wagnon *et al.*, 1966). In the current study we could not identify any influence of social status on the average calving intervals because of age differences and the presence of second calving heifers which lacked such data.

An indication that social status does have an effect on productivity is expressed by the numeric difference in the average daily gains of weaned calves, as shown in Table 2.

Conclusions

The cows in the current study demonstrated variable activity patterns which changed continuously, stressing the need to monitor cows' activity individually and continuously. The acquisition of continuous online information results in improved control over the herd, enabling relevant decision making that may have an immediate effect on productivity. Activity data (number of steps per hour) and posture (lying or standing), when transmitted continuously, provide a management tool which enables the farmer to detect stressed cows and apply adequate stress prevention management practices (regrouping, resource allocation).

High ranking cows manage to establish a steadier routine behaviour, expressed in more stable activity graphs. Low ranking cows express high and fluctuating activity with lower lying times, reflecting limitations in resource availability which are imposed upon them by high ranking cows.

Discrete activity parameters such as level of activity, measured hourly, or daily or lying times are not sufficient to define social rank and characterize socially stressed cows. A combination of high and fluctuating activity levels and lower lying times is necessary in order to characterize low ranking cows. The study herd was socially stable. Other less stable herds may show significant differences in discrete activity parameters, thus improving this management tool.

The herd expressed a distinct need for all the cows, regardless of their social rank, to perform some of the activities simultaneously. This need was expressed by identical peak activity hours. The main activity during these peak hours involved feeding, whether grazing or feeding at the trough. This finding stresses the need to ensure that resources, mainly food, are available for the entire herd during a short and defined period of time during the day. Online monitoring makes it possible to detect this 'bottleneck' and probably others that did not exist during our study period.

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4.5. The potential of using sensor data to predict the moment of calving for dairy cows

C.J. Rutten[1], W. Steeneveld[2], C. Kamphuis[2], K. Huijps[3] and H. Hogeveen[1,2]*
[1]Department of Farm Animal Health, Faculty of Veterinary Medicine, Utrecht University, Yalelaan 7, 3584 CL Utrecht, the Netherlands; [2]Business Economics Group, Wageningen University, Hollandseweg 1, 6706 KN, Wageningen, the Netherlands; [3]CRV, Postbus 454, 6800 AL Arnhem, the Netherlands; c.j.rutten@uu.nl

Abstract

On dairy farms, management of calving is important for the health of dairy cows and the survival rate of calves born. Although an expected calving date is known, farmers need to check their cows regularly to estimate the moment when a cow will start calving. A sensor system which predicts the moment of calving could help farmers to check cows effectively for the occurrence of dystocia. In this study, a total of 450 cows on two farms were equipped with Agis SensOor sensors (Agis Automatisering B.V., Harmelen, the Netherlands), which measure rumination activity, activity and temperature hourly. Data were collected over a one-year period. During that period, the exact moment of 417 calvings was recorded using camera images of the calving pen taken every 5 minutes. In total 110 calvings could be linked with sensor data. The moment when calving started was defined as the hour in which the camera images showed the cow having contractions or labour initially started. Two logit models were developed: a reduced model with the expected calving date as the independent variable and a full model which additionally included independent variables based on sensor data. The areas under the Receiver Operating Characteristic curves were 0.682 and 0.878 for the reduced and full model with, at a false positive rate of 10%, sensitivities of 22 and 69%, respectively. Results indicated that the inclusion of sensor data improved prediction of the start of calving and thus that the sensor data used have some potential for predicting the moment of calving.

Keywords: sensor technology, calving management, dairy farming

Introduction

Up to one third of the calves born on dairy farms are born following *dystocia* and are at increased risk of disease and mortality (Barrier *et al.*, 2013). *Dystocia* can therefore be seen as a problem for dairy cow health and welfare. Furthermore, high calf mortality can be regarded as a major image problem for the whole dairy sector. Risk factors for *dystocia* are dependent on biological factors such as breed, parity and calf weight and management, e.g. housing and pre-calving movement (Mee *et al.*, 2014). Farmers can influence these factors through their management practices, for instance by changing their breeding strategy. Another element of operational management on dairy farms is supervision during the calving process. This supervision enables timely intervention during the calving process, which could reduce the negative effects of *dystocia* on calves and dairy cows (Barrier *et al.*, 2013; Mee *et al.*, 2014).

Traditionally, farmers base their supervision of pre-calving cows on the expected calving date, which varies between 267 and 295 days after successful insemination. Farmers look for visual and

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physical signs of the onset of calving. It has been recognised that heifers behave differently before calving than multiparous cows, but no typical behavioural indicators have been found for *dystocia* (Miedema *et al.*, 2011).

It has been shown that feeding and rumination behaviour in dairy cows decrease gradually in the last two weeks before calving and drop suddenly at calving (Bar and Solomon, 2010). Sensor technology which measures rumination time has been developed and seems capable of detecting changes in rumination behaviour prior to calving (Bar and Solomon, 2010; Bucher and Sundrum, 2014; Schirmann *et al.*, 2013). The time spent ruminating decreased by 60 minutes in the 24 hours prior to calving, time spent on feeding also decreased and dry matter intake tended to decrease a little (Schirmann *et al.*, 2013). Another study reported similar observations: in the last six hours before calving rumination time decreased significantly, as did the time spent feeding and dry matter intake (Bucher and Sundrum, 2014). As the time spent ruminating can be estimated with sensor technology, it might be possible to predict the onset of calving by using sensor data.

This study explored the possibilities for using sensor data relating to activity, rumination and feeding time to predict the moment when the calving process starts.

Material and methods

Expected calving date

Insemination data were available for each cow and were used to calculate the expected calving dates (insemination date + 280 days). Expected calving dates were required to fall within the period from three weeks before to three weeks after the actual calving date. If there was no expected calving date within this six-week period, it was assumed that no insemination was recorded. The expected calving date was used to calculate the variable 'days to expected calving date' (*Exp*). This variable was negative on the days prior to and positive in the days after the expected calving date, and on the day of calving all hours of the day between 00:00 hours and the moment calving started had the same value for days to the expected calving date.

Data collection

Sensors were fitted to 450 cows On two Dutch dairy farms. The Agis SensOor (Agis Automatisering B.V., Harmelen, the Netherlands) was used in this study. The sensor is a 3D accelerometer attached to the ear tag and measures rumination, activity and temperature on an hourly basis (Bikker *et al.*, 2014).

Farmers were asked to record data and the time when they noticed that a cow had calved. These recorded calving moments provided a rough estimate of the actual calving moment. The actual calving moment was assigned by evaluating images captured by video cameras which took snapshots of the calving pen every 5 minutes. Students were instructed to use the camera images to determine the start of the calving process for each cow, and the farmer's records were used to reduce the number of images they were required to screen. In total 583 cows calved, with calving moments determined for 417 of these. Calving moments from 110 of these were linked with sensor data and an expected calving date and, therefore, included for further analysis.

Gold standard definition

It is essential to define the moment of calving in order to develop a system which predicts the calving moment. For a farmer, the moment a cow has calved is not very informative, as potential *dystocia* should be detected and resolved shortly after the start of calving. The length of the calving process varies and more problematic calvings will take longer. Therefore, the start of the calving process is a better time to generate a calving alert because the farmer can then check for the presence of *dystocia* in good time. The start of the calving process was therefore taken as the gold standard. The start was defined as the first camera snapshot on which it could be seen that the cow was having contractions or had started labour. Although this moment was not clearly visible in all cases, it does represent the moment at which a farmer should be informed.

Data analysis

Data were analysed using R 3.0.2 (RDC Team, 2008) with the add-on packages plyr 1.8 (Wickham, 2011), Zoo 1.7-10 (Zeileis and Grothendieck, 2005) and ROCR 1.0-5 (Sing *et al.*, 2005). The moment when calving started was combined with sensor data in such a way that the start of calving was connected to the hourly block of sensor data in which calving started. Sensor data were selected for 240 hours before the start of calving up to the hour when calving started.

Sensor data

The SensOor system assigned the minutes within each hour of the day to one of the five following sensor variables (Var_i): ruminating (i=1), eating (i=2), active, highly active (i=3) or not active (i=4). As these five sensor variables add up to a total of one hour they are not independent variables. Therefore, the sensor variable 'active' was omitted from the analysis. In addition to these five sensor variables, ear temperature (i=5) was also measured. For all sensor variables a rolling mean was calculated over 72 hours ($rollVar_i$) (Equation 1).

$$rollVar_i = \frac{\sum_{t=1}^{-72} Var_i}{72} \tag{1}$$

Model variables (X_i) at moment t were calculated by estimating the relative deviation of each observation from the rolling mean for 72 hours before (lagged value at moment $t-72$) the current observation (Equation 2). This lagged difference meant that there was a 72-hour burn-in period for the data, as the first 72 hours have no lagged value which can be used to calculate the relative deviation. The remaining dataset consisted of 168 hours before the moment of calving.

$$X_i^t = \frac{Var_i^t - rollVar_i^{t\text{-}72}}{rollVar_i^{t\text{-}72}} \tag{2}$$

Two logit models with the binary dependent variable 'start of calving' (1 = start of calving and 0 = calving not started) were developed. The first model included the days to the expected calving date as the independent variable (reduced model) and the second model (Equation 3) included the days to the expected calving date and the model variables derived from sensor data as independent variables (full model).

$$p_t = \frac{1}{1+e^{-\beta_{intercept}-\beta_{Exp}*Exp-\beta_1*X_1-\beta_2*X_2-\beta_3*X_3-\beta_4*X_4-\beta_5*X_5}} \tag{3}$$

Model evaluation

The output generated by the models was a chance that calving had started. To evaluate the predictive performance of the models, Receiver Operating Characteristic (ROC) curves were created for both models. Based on the ROC curve, a cut-off value for the chance that calving had started, as used to define alerts, was chosen, resembling a false positive rate of 10%. This cut-off value was used to define alerts which were classified as true positive, false positive, true negative or false negative, with a time window of 1 hour. The total number of false positive alerts was calculated per 24 hour period (block of 24 hours before the start of calving). The sensitivity and area under the ROC curve (AUC value) were also calculated

Results

Table 1 summarises the model estimates for a logit model with only days to the expected calving date as the independent variable and for a logit model with both days to the expected calving date and the model variables based on sensor data as independent variables. McFadden's R^2 value increased from 2.52% for the reduced model to 20.41% for the full model. In both models all parameter estimates were significant.

Figure 1 shows the ROC curve for a logit model which predicts the moment of calving based on the expected calving date. At a false positive rate of 10% the sensitivity was 22%, indicating that the days to expected calving date had some predictive value. The corresponding AUC value was 0.682. Figure 2 shows the ROC curve for the full logit. At a false positive rate of 10%, the sensitivity was 69%, indicating that more calving moments were predicted correctly when sensor data were added. The corresponding AUC value was 0.878.

Table 2 summarizes the classification of all alerts generated by the full logit model. The cut-off probability value of 0.09 was based on the point in the ROC curve shown in Figure 2 where the false positive rate was 10%. It shows that the start of calving was predicted correctly for 27 calvings, and 83 calvings did not receive an alert at the start of calving (false negative classification). Furthermore, 218 false positive alerts were observed. Figure 3 plots the time when these false

Table 1. Estimated model coefficients for reduced (independent variable: days to expected calving date) and full (independent variables: days to expected calving date and variables derived from sensor data) logit model with moment of calving as dependent variable.

	Reduced model	Full model
Intercept	-4.90622**	-5.53840**
Days to expected calving date	0.08429**	0.08093**
Feeding		-0.44837**
Ruminating		-2.55681**
Not active		-0.41140**
Highly active		0.87609**
Temperature		-4.38658**

** *P*-value <0.01.

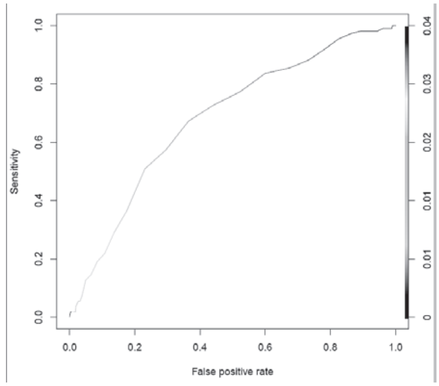

Figure 1. ROC curve of full logit model predicting the start of calving based on the days to expected calving date. The curve displays the sensitivity and false positive rate at different cut-off values (2nd y-axis) for the generated chances that calving had started.

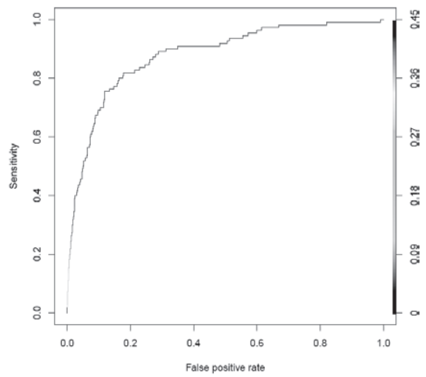

Figure 2. ROC curve of the full logit model predicting the start of calving based on the expected calving date and variables derived from sensor data. The curve displays the sensitivity and false positive rate at different cut-off values (2nd y-axis) for the generated chances that calving had started.

Table 2. Classification of alerts based on the gold standard within a 1 hour time window. Predicted values from the full logit model were used to produce alerts (cut-off value = 0.09).

Classification	Number of cases
True positive	27
True negative	18,208
False positive	218
False negative	83

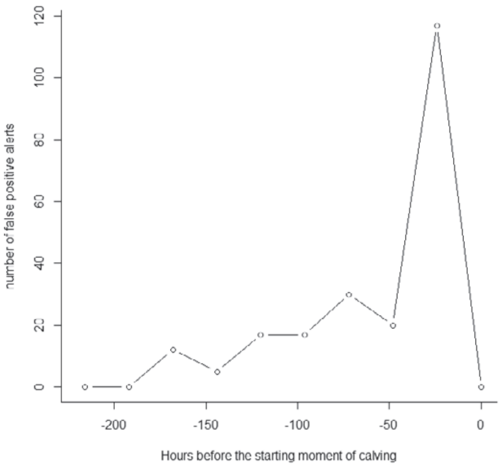

Figure 3. Number of false positive alerts per 24 hour period prior to the start of calving (moment 0).

positive alerts were produced relative to the start of calving. The majority of these false positive alerts were generated in the 24 hours before calving actually started.

Discussion

This study indicates that sensor data can be used to give a more accurate prediction of the start of calving than the expected calving date alone. However, the number of false positive and false negative alerts was high.

Most false positive alerts were observed within 24 hours before the start of calving. A more relaxed time window for detection would improve detection performance. Classifying alerts one or two hours before the start of calving as true positive can be argued to be reasonable, because these alerts can be seen as an indicator that calving is about to start. Alerts produced three or more hours before the start of calving could be considered to be too early. If a farmer checked a cow after such an early alert, calving would not have started and the farmer would need to recheck the cow. It should be noted that in this study the model was not validated on an independent dataset.

The start of calving was determined through visual evaluation of camera images. These camera images can be interpreted differently by multiple observers. To test the inter-observer variability, a subset of camera images was given to two students, who judged the same images independently. The reported starting moments were compared and varied between 5 to 30 minutes. Although these differences existed, their consequences were minor. As sensor data were summarized per hour, some starting moments were associated with a block one hour earlier or later.

A timely alert for start of calving would enable a farmer to check the cow for possible *dystocia*. Future research should focus on predicting *dystocia* from sensor data. Although earlier studies might suggest that behavioural parameters are not likely to provide much information, other parameters (e.g. body weight) might have potential.

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4.6. Discussion: PLF in genetics & health of beef, calves and heifers

I. Halachmi[1], A. Schlageter Tello[2], A. Peña Fernández[3], T. van Hertem[3], V. Sibony[1], S. Weyl-Feinstein[1], A. Verbrugge[3], M. Bonneau[4] and R. Neilson[4]*
[1]Agricultural Research Organization, P.O. Box 6, Bet-Dagan 50250, Israel;[2]Livestock Research Wageningen University, P.O. Box 338, 6700 AH Wageningen, the Netherlands; [3]M3-Biores: Measure, Model & Manage Bioresponses, KU Leuven, P.O. Box 2456, 3001 Leuven, Belgium; [4]European Federation of Animal Science (EAAP), Via G. Tomassetti 3, 1/A, 00161 Rome, Italy; halachmi@volcani.agri.gov.il

Preface

This chapter documents the questions and the answers that were expressed during the 2014 EU-PLF/EAAP joint-sessions. They were documented verbatim, but each questioner and responder were given the opportunity to rewrite/edit their questions and/or answers for more clarity. This discussion is related to Chapters 4.1 to 4.5.

Discussion

Question: Bert Ipema (Wageningen UR Livestock Research, the Netherlands) – (Sarah, Chapter 4.2) The growth rate was lower after mixing and didn't recover?

Answer: Sarah Weyl-Feinstein (ARO, Israel) – No, one month after the mixing it still did not recover.

Question: Bert Ipema (Wageningen UR Livestock Research, the Netherlands) – So 30 days was not enough?

Answer: Sarah Weyl-Feinstein (ARO, Israel) – No, it was not enough. We even had one calf that lost 100 kg.

Question: Bert Ipema (Wageningen UR Livestock Research, the Netherlands) – You tested your model just on one farm; do you expect to test it on more farms?

Comment: Niels Rutten (Utrecht University, the Netherlands) – If you develop a model based only on one farm, your parameters are specific to that farm only and there can be differences between farms. In my experiment (Chapter 4.5) I have used two farms.

Question: Hélène Soyeurt (Gembloux AgroBio Tech, Belgium) – Niels, did you see differences between the farms (Chapter 4.5)?

Answer: Niels Rutten (Utrecht University, the Netherlands) – I didn't check it yet. We are collecting data and afterwards we will do it. It is very relevant thing to look at.

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Question: Hélène Soyeurt (Gembloux AgroBio Tech, Belgium) – Did you (Chapter 4.5) test the sensor on one example of pasture or have you tested it in more farms with other climate? Because I will expect that the behaviour of the cow will change.

Answer: Bert Ipema (Wageningen UR Livestock Research, the Netherlands) – The current results are from one sensor type used in one situation: grazing of cows in the Netherlands. We know that there are different types of activity sensors that could be used. Different sensors will provide different results but we hope to find an activity sensor that gives better results. This year we will get data from other partners in the EU-PLF project, that used other sensors. The goal is to develop a general model that generates alerts on herd level when problems in grazing (feeding) management occur. The alerts that are provided are based on sudden deviations from the normal situation. Hopefully commercial companies will implement this in the robotic milking software programmes.

Question: Bernadette Earley (Teagasc, Ireland) – The presentations that we just heard informed us about the various sensors that are in use. I have one question – have you considered using these activity sensors to relate to other behavioural measurements that may be of interest?

Answer: Marcia Endres (University of Minnesota, USA) – I have always wondered about activity as another measurement method that could help us detect cows that may be at risk. In our study, we didn't find any relationship between activity and health, so I was a little bit disappointed. However, rumination was a more sensitive measurement; this is very promising, but we need to conduct more studies to confirm these findings.

Answer: Sarah Weyl-Feinstein (ARO, Israel) – In my presentation (Chapter 4.2), I talked about using two sensors for the same parameters, which gave different outcomes. So I guess every parameter should be tested according to what you want to find, otherwise we will have different outcomes. Also as opposed to your study (Marcia Endres' study, Chapter 4.3) we found rumination is less sensitive because there was very quick recovery back to the initial situation for rumination while activity was not restored even a month after the group mixing.

Answer: Rachel Gabrieli (Ministry of agriculture and rural development, Israel) – I monitored the activity because this is what I had. So in order to make it more effective I combined different parameters that were all related to activity. I think there are two different possibilities, either add sensors or add parameters to the same monitoring system. I also think if you're going to the final resolution, you need to define the place where you will be monitoring activity. When you have all the data online I think you can detect those sensitive places. The moment where you can really use activity as a measure or any other sensory equipment.

Answer: Bert Ipema (Wageningen UR Livestock Research, the Netherlands) – I can also add something to activity measurements. Activity sensors are being further developed. In the near future, the activity sensors will have additional features; the new sensor we are testing right now gives information about activity as well as eating time; it is also possible to measure lying and standing time with the same sensor. Combining the measurement of as many as possible parameters with the same sensor is the way to go for the future.

Part 5. Precision livestock farming for automatic detection of animal health in poultry and pigs

5.1. Facilitation of assessment of technical measures and its potential for implementation of the Broiler Directive (2007/43/EC)

A. Butterworth[1], G. Richards[1] and E. Vranken[2*]*
[1]Clinical Veterinary Science, University of Bristol, Langford, N Somerset, BS40 5DU, United Kingdom; [2]FANCOM B.V., P.O. Box 7131, 5980 AC Panningen, the Netherlands; andy.butterworth@bris.ac.uk; evranken@fancom.com

Abstract

The Broiler Directive (2007/43/EC) is unique amongst current EU Directives which address Animal Welfare in that it uses outcome data, collected at abattoirs and on farms, to monitor on-farm broiler welfare and vary the maximum permitted stocking density on farm. In this paper we describe the process by which manually assessed animal outcome measures for broiler chickens have started to be used alongside automated on-farm measurements of climate, feed intake and animal growth and camera and sound based automated precision livestock farming (PLF) methods (eYeNamic) in our pilot studies. We describe how the data collected from this process (both human assessor based and automated farm measures) have enabled the start of a process of 'joint validation' which it is anticipated will lead to advances in automated measurement of environmental and animal parameters, some of which may be potentially fed into the statutory requirement for on-going assessment under the Broiler Directive 2007/43/EC. The pilot study has identified the key components for assessment of the 'baseline standard' for animal-based measures against automated on-farm measures, and this information is summarised in the paper. For example, foot-pad dermatitis, hock burn, walking ability (Gait Score), avoidance distance touch tests and response to the stockman are identified as some of the measures of medium to high priority in terms of high potential for automated measurement, and also relating well to the requirements both of the Broiler Directive, but also as management information which is of commercial use to broiler production companies. On the other hand, breast lesions, cellulitis, emaciation, joint lesions, scratches and wing fractures were identified as difficult or impossible to assess on farm, but suitable for measurement in the slaughterhouse.

Keywords: broiler, chicken, outcome assessment, precision livestock farming, camera

Introduction

Poultry meat is the second most important type of meat in the European Union today. European annual production is approximately 6 billion birds, with an average poultry consumption of about 23 kg per capita per year. The European poultry industry employs 300,000 people across Europe and has an annual turnover of 30 billion euros (AVEC, 2014). From 1 July 2010 new welfare rules for meat chickens came into effect across the EU through Directive 2007/43/EC (EC, 2007a). For the first time in the construction of animal focussed legislation, this Directive provides for variable levels of stocking density dependent on the performance of the farm and on animal based outcomes:

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2. Member States shall ensure that the maximum stocking density in a holding or a house of a holding does not at any time exceed 33 kg/m^2.
4. Member States shall ensure that, when a derogation is granted under paragraph 3, the maximum stocking density in a holding or a house of a holding does not at any time exceed 39 kg/m^2.
5. When the criteria set out in Annex V are fulfilled, Member States may allow that the maximum stocking density referred to in paragraph 4 be increased by a maximum of 3 kg/m^2 (i.e. to 39 + 3 = 42 kg/m^2)

The competent authority is directed to provide trigger levels based on post-mortem inspection to identify possible indications of poor welfare. Annex II of the Directive permits the competent authorities to increase the stocking density on farms which comply with these specific 'outcome' measure results, and target 'trigger' levels for these outcomes are set, monitored and enforced by the competent authority.

The Directive also affects the poultry production industry and the enforcement bodies through the requirement for keeper training (in physiology, feeding needs, animal behaviour, the concept of stress, practical aspects of poultry handling, catching, loading and transport, emergency care, emergency killing and culling and biosecurity measures), record keeping, poultry meat labelling, statutory inspections and provision of codes of management practice. The Directive also provides criteria for lighting patterns, ventilation, air quality parameters, humidity and temperature, litter quality, house noise levels, cleaning schedules, inspection intervals for animals, farm plans, alarm systems and feed withdrawal times. These requirements do not apply to parent flocks, hatcheries, extensive indoor production (a legally defined category rarely applied commercially), free-range or organic birds and producers with <500 birds. The Directive also includes a 'Grandfather Rights' scheme (where keepers can apply for Grandfather Rights for a limited period of time only).

In line with the requirements of the Directive, a number of animal-based outcome parameters are used to identify possible on-farm welfare problems. As an example of how a competent authority has set the 'trigger levels', the UK has chosen to make measures of cumulative daily mortality rate and seven post-mortem conditions, which are: (1) ascites/oedema; (2) cellulitis & dermatitis; (3) dead on arrival; (4) emaciation; (5) joint lesions/arthritis; (6) septicaemia/respiratory; and (7) total rejections. A trigger level is also set for Foot-Pad Dermatitis (FPD). Condition cards, pictures and written descriptions are used to provide consistent scoring of these conditions at the slaughterhouse, and training has been given to slaughterhouse staff to help ensure harmonised approaches to scoring and reporting of the data collected. The system in the UK, as an example of an EU approach to the requirements of the Directive, involves two processes. For Process 1: an alert to the competent authority (AHVLA – Animal Health Veterinary Laboratories Agency) will be triggered if the rate of any of the post-mortem conditions is exceptionally high (defined as greater than 6 standard deviations above the mean, see Table 1). For Process 2: an alert to the competent authority AHVLA will be triggered if the cumulative daily mortality rate is unusually high (defined as greater than 3 standard deviations above the mean = 7.37%) and, additionally, the level of three or more of the post-mortem conditions is high (defined as above the mean, see Table 1).

Enforcement

Where levels of the trigger level conditions exceed a certain threshold (as indicated in Table 1), the keeper of the animals (the producer or the producer company) will be alerted. Where poor welfare is suspected, the Official Veterinarian can advise the keeper of the animals. Action resulting from

Table 1. Trigger levels to be used for Process 1 and Process 2. For Process 1, Animal Health will be alerted if the level of a post-mortem condition is exceptionally high (exceeds mean + 6SD). For Process 2, Animal Health will be alerted if the cumulative daily mortality rate is unusually high (exceeds mean + 3SD = 7.37%) and, additionally, the rate of three or more post-mortem conditions is high (exceeds the mean).

Post-mortem condition	Process 1 trigger level (%)	Process 2 trigger level (%)
Ascites/oedema	2.02	0.21
Cellulitis & dermatitis	3.00	0.20
Dead on arrival	1.51	0.12
Emaciation	0.67	0.04
Joint lesions	0.43	0.02
Respiratory problems	9.28	0.49
Total rejections	11.76	1.11
FPD score[1]	167	60
Cumulative daily mortality	11.85	N/A

[1] The Foot-Pad Dermatitis (FPD) score is not a percentage but is a score of the severity and extent of lesions (between 0 and 200) based on scoring 100 feet.

these trigger levels is enforced by the local agency of the competent authority, and action following a trigger level may include a visit to the production site by the competent authority and creation of an 'action plan' (a plan of steps to be taken to reduce or eliminate the problem which has been identified in the trigger report). In some cases, the competent authority may choose to make welfare inspections of the farm (and sometimes to the slaughterhouse).

Potential costs and potential benefits of outcome based measures in the Broiler Directive

As a result of the requirements stemming from implementation of the Directive, there are additional costs associated with enforcement and inspection, costs to the producer, and it is possible that there will be increased costs to the consumer of chicken produced under the conditions of the Directive. As well as potential costs, there are potential benefits. The Directive, through the use of agreed trigger levels, supplies assessment tools to target underperforming producers (by inclusion of the means to identify unsatisfactory levels of stockmanship and provision of feedback between enforcement bodies and the producer). Through use of the trigger level tools, competent authorities in the EU may be better able to target their inspection and enforcement resources, and the use of outcome measures has the potential to result in overall improvements in bird welfare. Through this, and through the direct effects of the implementation of Directive 2007/43/EC, there may be a measurable improvement in the welfare of chickens kept for meat. The public may feel reassured that welfare standards are being applied, and there may be increased confidence in the welfare gain from improvements in broiler welfare (EC, 2007b). There may be improvements in the quality of management of meat chickens through the implementation of the post-mortem pathology trigger level analysis, through training (keepers will have enhanced knowledge of poultry husbandry and associated welfare) and through increased attention to lighting, ventilation, record keeping and the management practices promoted in the Directive. Additionally, through application of the same standards for all producers (nationally and within EU), there may be greater consumer reassurance as to the overall welfare standards of meat chicken.

The costs of assessing welfare

The sampling and data collection requirements of the Directive offer the potential to promote improved welfare conditions and to provide information of management value to farmers – but there are costs in terms of time and resource allocation for both assessment and also enforcement and rectification. For these reasons of practicality and the large scale of the total number of animals to be inspected, there is significant interest in automation of measures to permit cost-effective and harmonised assessment of the trigger level requirements across EU member states. Precision Livestock Farming (PLF) uses continuously automated measurements made directly on the animal or in its environment (examples: body movements measured with cameras on-farm, images taken of carcasses at slaughter, sounds measured with microphones on-farm) and has the potential to be translated into key indicators for animal welfare, animal health, productivity and environmental impact, thus allowing the farmer to better manage his farm (Kashiha *et al.*, 2013). EU-PLF is a European funded research project that is developing continuously automated measurements for direct application to animals in the farm environment. The PLF data (bird mobility movements measured with cameras, bird-generated sounds measured with microphones, dust, temperature, humidity, light levels) are collected on experimental farms. During the first stages of this project, the data collected by the camera and sound systems are translated into algorithms which can be compared against key indicators for animal welfare, animal health, productivity and environmental impact. A key step in the development of algorithms based on automated measures is the creation and testing of 'gold standards' whereby automated measures are compared with existing key indicator (KI) outcome measures obtained on the same farms as those where the automated systems have been installed.

Key welfare indicators are defined here as parameters that provide information about a domain that is relevant to farm management. For each defined KI in the domains animal welfare and health, production and environmental load, an agreed methodology for assessing and reporting the incidence/severity or extent of that KI is described. An example of a KI would be 'walking ability' (Botreau *et al.*, 2007a,b; Butterworth, 2009).

A 'gold standard' (GS) is defined here as the aspect of the animal measure which is to be addressed, and which is the 'focus' of the measure. For example, the GS measure for the walking ability KI is 'gait score' (a measure of walking ability). In relation to each defined KI in the different domains of animal welfare and health, production and environmental load, a reference method for determining the value of that indicator at farm level was defined according to available knowledge and experience. A gold standard may be measured at farm level in different ways. For instance, it may include establishing a blood parameter for health monitoring or visual scoring by experts (e.g. Welfare Quality® assessments) (Veissier *et al.* 2008, 2011; Welfare Quality, 2009). The GS is only used during the project as a reference to test and validate the performance of the PLF techniques in measuring these KIs at farm level.

A set of KIs for the different domains in broiler production was described based on expert consultation with experts drawn from the EU-PLF project teams. A literature review and results from EU projects, such as Welfare Quality®, European Animal Welfare Platform (Blokhuis *et al.*, 2003) and others was used to inform the potential list of both key welfare indicators and the GS measures associated with them. The objective was that, when used together, the set of KIs and GSs for a specific domain would be able to capture the main aspects of the performance of a farm in that domain at a specific point in time.

Linking Key Indicators, Gold Standards, possible technology based measures and their potential in fulfilling the Broiler Directive

A list of KIs and GSs is listed in Table 2. Technical solutions which might have potential for automatic measurement of the KIs are also shown. The technical measures are those which are currently anticipated to be within applicable reach, i.e. methods which are at a stage of development that will enable their realistic use within the duration of the EU PLF project (by the end of 2016). The last column of Table 2 indicates whether the automated measure has the potential to address measures required by the Broiler Directive. A 'yes' denotes full capacity to address the technical requirements of the measures as listed in Tables 1 and 2 and hence real value in meeting the requirements of the Broiler Directive 2007/43/EC. A 'partial' denotes partial capacity, which means that the measure may in principle be addressed through application of the automated measure in line with the requirements of the Broiler Directive, but that currently the method has not been fully validated or proven for on-farm commercial use. A 'no' denotes that there is not currently an automated measure that can assess the given area of the requirement of the Broiler Directive.

Table 2. Key welfare indicators, gold standards and technology in relation to the measures required by the Broiler Directive (2007/43/EC).

A. Broiler Directive (2007/43/EC) Measure (yes, partial, no)[1]	B. Key welfare indicator[2]	C. Gold standard[3]	D. Use of the data/action by the farmer	E. Can available automated technology provide this measure? (how) (yes, partial, no)[4]
Ascites/oedema (yes)	Ascites, hepatitis, septicaemia	Energy balance, ketosis (fatty liver) and acidosis	Early detection of disease (isolation + inactivity)	Yes (camera) Bird activity at farm: changes in characteristic patterns of activity (feeding, movement, etc.)
Cellulitis and dermatitis (yes)	Scoring scales available for cellulitis and dermatitits (e.g. Welfare Quality, 2009)		Early detection of disease and of management issues (high bird activity and scratching) (isolation + inactivity)	Yes (camera) Taken at slaughterhouse, skin lesions already commonly detected at slaughter using camera based 'quality' systems
Dead on arrival (DOA) (yes)	Number of birds found dead after transport to slaughter.		Fitness to travel – warning of risk factors for high DOA may enable prevention in further batches on the same day, for example as a warning of effects of high temperatures or poor weather conditions	Partial Camera systems may be able to be adapted to detect birds not mobile on arrival at slaughterhouse
Emaciation, joint lesions, respiratory disease (yes)	Number of birds found to be affected by these conditions at post mortem inspection.			Partial Camera systems may be able to be adapted to detect visible pathologies at slaughter.

Table 2. Continued.

A. Broiler Directive (2007/43/EC) Measure (yes, partial, no)[1]	B. Key welfare indicator[2]	C. Gold standard[3]	D. Use of the data/action by the farmer	E. Can available automated technology provide this measure? (how) (yes, partial, no)[4]
Foot-pad dermatitis (yes)	Scoring scales for Foot pad, hock burn lesions	Foot pad scoring Hock mark scoring	Improve litter quality, reduce drinker leakage, optimise nutrition	Yes At slaughter: well-developed systems exist to measure FPD at the slaughterhouse Partial At farm: camera systems on farm may be able to measure mobility of birds, which is (sometimes) linked to Foot Pad lesions
Cumulative daily mortality (yes)	Mortality	Number of dead birds	Management barometer for effectiveness of many factors including biosecurity, house environment control, vaccination effectiveness, culling policy.	Partial Camera systems on farm may be able to measure mobility of birds, which is (sometimes) linked to Foot Pad lesions.
Space allowance (yes)	Space allowance	Calculated stocking density	Increase (or decrease) space available to the birds	Yes (camera) Activity and spatial distribution
Bird cleanliness (partial) Potentially of use linked to Directive requirement, litter quality)	Bird cleanliness	Bird cleanliness score	Improve litter condition and maintain and optimise drinkers and humidity to provide dry, clean environment for the birds	Partial Camera observation of bird 'colour'/bird cleanliness
Thermal behaviours of the birds (partial) Potentially of use linked to Directive requirement, House temperature)	Thermal behaviours	Panting, huddling	Regulate house temperature, humidity, air flow, thermal input through metabolic heat (feed input)	Partial Camera observation of activity levels and of individual bird behaviour
Water use (partial) Potentially of use linked to Directive requirement, Adequate supply of water)	Water usage	Drinking behaviour	Maintaining water system, maintaining heating system	Partial Water meters and camera observations of birds activity around drinkers (eyenamic)
Walking ability (no) Not required by Directive	Walking behaviour	Gait score (measure of walking ability)	Optimised nutrition, disease control (prevention and effective treatment) biosecurity (to protect from disease), selection of genetic lines of birds with reduced lameness	Partial (camera) Activity levels

Table 2. Continued.

A. Broiler Directive (2007/43/EC) Measure (yes, partial, no)[1]	B. Key welfare indicator[2]	C. Gold standard[3]	D. Use of the data/action by the farmer	E. Can available automated technology provide this measure? (how) (yes, partial, no)[4]
Hock burn (no) Not required by the Directive	Hock burn	Hock marks scoring scales	Improve litter quality, reduce drinker leakage, optimise nutrition	Yes At slaughter: well-developed systems exist to measure hock marks at the slaughterhouse Partial At farm: camera systems on farm may be able to measure mobility of birds, which is (uncommonly) linked to hock burn
Resting behaviour (no) Not required by Directive	Resting behaviour	Duration of resting, walking, preening, social behaviours	If disturbed resting behaviour – attention to lighting patterns, bedding, avoidance of disturbance (noise, light) and adjustment of feeding times (time feed provided) to allow periods of rest	Partial (camera) Activity monitoring
Human animal interaction (no) Not required by Directive	Human animal interaction	Avoidance distance/touch test	Optimise the experience of the birds so that they are neither 'too scared' of people, nor 'not at all fearful' – as birds that do not move in response to people are difficult to manage	Partial (camera) Analysis of bird response to stockman walking through the flock (this is a daily activity during bird inspection)
General activity levels / patterns (no) Not required by Directive	General activity	Clinical scoring	Early detection of disease (isolation + inactivity)	Yes Activity meters, measuring movements in 3 dimensions
Growth/performance (no) Not required by Directive	Growth performance	European Production Efficiency Factor	Optimal living, health, nutrition, management, stockmanship and genetic capacity	Partial (step-on weighers, cameras) Weight gain (step-on weighers); distribution of feeding, drinking, activity and even spread of bird 'size' across flock (cameras)
Body condition (no) Not required by Directive	Body condition score, feeding, drinking	Emaciation in birds at slaughter	Increase or decrease feeding scheme, attention to feeding equipment and the nutritional composition of the food (including protein/carbohydrate balance, vitamin, mineral and micronutrients)	Partial (step-on weighers, cameras) Weight gain (step-on weighers); distribution of feeding, drinking, activity and even spread of bird 'size' across flock (cameras)

[1] Required by the Broiler Directive (yes, partial, no).
[2] Management use of the measure by the producer.
[3] Gold Standard indicates whether automated systems with potential to record the measure currently exist, are in development or currently in use.
[4] Indicates whether the automated measure has the potential to address measures required by the Broiler Directive. Yes = can address the technical requirements; partial = yes, but not yet proven or validated; no = currently no automated measure exists.

Discussion

PLF represents the potential for use of continuous, automated measurements made directly on the animal or in its environment. PLF data may be translated into key indicators for animal welfare, animal health, productivity and environmental impact, thus allowing the farmer to better manage his farm process.

The competent authority is already required to collect some measures in order to comply with the requirements of the Broiler Directive (2007/43/EC) – and on the farm, it is apparent from Table 2 that automated (PLF) measures are potentially highly applicable for:

- On-farm measurement of: space allowance.
- At-slaughter measurement of ascites, oedema, cellulitis, dermatitis, dead on arrival, emaciation, joint lesions, respiratory disease, and foot-pad dermatitis.

It is apparent from Table 2 that PLF measures may be 'partially' applicable in other areas that are required under the Broiler Directive:

- On-farm measurement of litter quality, bird thermal behaviours, bird cleanliness, and water use.

It is apparent that PLF measures may be highly applicable in other areas that are *not* (currently) required as part of the Broiler Directive:

- On-farm measurement of walking ability (gait score), resting behaviour, general activity levels, human animal interaction, growth/performance, and body condition.

This mixture of capabilities and potential indicates that (1) there is great potential for combining automated (PLF) measures and conventional measures to provide the data currently required by the existing legislation (Broiler Directive), and that (2) PLF techniques have the potential to augment or replace other measures not currently required by law, but which have clear value in monitoring and managing welfare on broiler farms.

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5.2. Monitoring the hatching time of individual chicks and its effect on chick quality

Q. Tong[1], T. Demmers[1], C.E.B. Romanini[2],V. Exadaktylos[2], H. Bergoug[3], N. Roulston[4], D. Berckmans[2], M. Guinebretière[3], N. Eterradossi[3], R. Verhelst[4] and I.M. McGonnell[1]*
[1]The Royal Veterinary College, Hawkshead Lane, North Mymms, Hatfield, AL9 7TA Hertfordshire, United Kingdom; [2]Division M3-BIORES: Measure, Model & Manage Bioresponses, KU Leuven, P.O. Box 2456, 3001 Leuven, Belgium; [3]UEB-Anses, Ploufragan-Plouzané Laboratory, Avian and Rabbit: Epidemiology and Welfare Unit/Virology-Immunology-Parasitology Unit, BP 53, 22440 Ploufragan, France; [4]Research and Development, Petersime N.V., Centrumstraat 125, 9870 Zulte (Olsene), Belgium; qtong@rvc.ac.uk

Abstract

Monitoring the hatch process demands continuous assessment of the number of hatched chicks, which is usually a disruptive event as it requires the incubator door to be opened. Therefore, a real-time monitor for the hatching time of individual chicks is of interest to both researchers and industry. An alternative non-invasive method which involves measuring the eggshell temperature using small, accurate temperature sensors is presented. Continuous recordings of eggshell temperature (Tegg) of the focal eggs were analysed and the temperature profiles for plotted Tegg showed a temperature drop of around 2-6 °C when the chick hatched. It was therefore possible to identify the hatching time for individual eggs in real time during incubation based on this registered temperature drop. Furthermore, linear regression analysis showed a positive correlation between hatching time ($r=0.32$; $P=0.001$) and chick weight at take-off which indicated that early hatched chicks started to lose weight during the holding period.

Keywords: incubation, eggshell temperature, temperature sensor, hatching time, chick score, chick weight

Introduction

In the commercial hatchery, large numbers of eggs are incubated in one machine. Variable hatching times in industrial incubators for chickens can cause considerable economic losses. Firstly, while the incubator is operating it consumes energy and therefore money, so the longer it is active, the higher the costs. Secondly, the incubator has to remain active until all the eggs have hatched and the newly hatched chicks do not get access to food and water, which results in a delayed growth pattern (Exadaktylos *et al.*, 2011; Noy and Sklan, 1999). After hatch the chick must wait until the take-off (when chicks are removed from machine) which occurs once the entire batch has hatched. This results in variable holding periods, which means that early hatchlings are deprived of food and water (for up to 48 hours) and endure longer exposure to poor air quality (feather and shell debris, high temperature and high CO_2 level) while waiting for the late hatchers. Early hatchlings cannot be removed individually since opening the machine doors disrupts the proper temperature, humidity and CO_2 levels needed for the remaining eggs. A mixed batch of early hatchers and late hatchers creates an uneven start for the flock in the growing cycle, since the early birds exhaust their yolk sac (energy reserve) disproportionately. Therefore, feed deprivation should be regarded as starting at the individual time of hatching and not from the end of incubation (Careghi *et*

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al., 2005; Van de Ven *et al.*, 2011). However, there is no specific data to show the effect of exact hatching time on chick quality in commercial incubators. This study presents a new method of monitoring eggshell temperature in order to precisely detect the hatching time of individual chicks and investigate the effect of hatching time on chick score and chick weight at take-off.

Material and methods

Eight batches of fertile eggs from Ross 308 broiler breeders (Henry Stewart & Co. Ltd., Lincolnshire, United Kingdom) were incubated and hatched in laboratory scale incubators (Petersime N.V., Zulte (Olsene), Belgium) using a standard 21-day incubation programme. Twenty out of 600 eggs in each batch were individually labelled as focal eggs in each incubation cycle. A temperature sensor (TSic 716, Innovative Sensor Technology IST AG, Wattwil, Switzerland) with an accuracy of ±0.07 °C between 25 and 45 °C was attached to the equator of the eggshell to record the eggshell temperature (Tegg) of each focal egg. The Tegg was recorded every minute throughout the entire incubation. The incubation process was stopped after 512 h. At take-off, the successfully hatched focal chicks were weighed and scored using the standard method from Petersime.

Tegg data were organised in columns and imported into Matlab (Mathworks, Natick, MA, USA) as column vectors associated with their respective time. The Tegg vs the incubation time were plotted to show the temperature profile trend throughout incubation and to identify the time of temperature drop during hatch. The relationship between the identified hatching time and chick weight or chick score was analysed using IBM SPSS Statistics 20 (Armonk, NY, USA).

Results

A total of 113 focal eggs from 8 batches were hatched. The analysis of Tegg profiles for hatched focal eggs indicated that a temperature drop of about 2-6 °C occurred during hatch (Figure 1). The hatching time of 109 focal chicks was successfully determined using the registered Tegg drop and recorded as the incubation time (hours). The hatch time of the 109 focal chicks ranged from 467.03 to 504.42 hours and was normally distributed (Figure 2). Linear regression analysis showed that hatching time did not affect the score of newly hatched chicks. However, there was a positive linear relationship between chick weight and hatching time (Figure 3): chick weight = 0.19 × hatching time-47.50 ($r=0.32$; $P=0.001$), suggesting that chicks lose weight at a rate of 0.19 g for every hour post hatch.

Discussion

Heat production (HP) increases during incubation due to the increased growth and conversion of nutrition. Changes in HP by the embryo have an influence on the eggshell temperature. Using an accurate temperature sensor on the eggshell makes it possible to identify the exact moment of hatch in real time and in large sample sizes. The identified Tegg drops occurred just after the hatch when the chick emerged from the shell and the heat source, represented by embryonic heat generation, was no longer present. We identified the exact individual hatching time of focal eggs using eggshell temperature (Romanini *et al.*, 2013) and thus it is possible to investigate the effects of hatching time on the quality of newly hatched broiler chicks at take-off. It is difficult to evaluate chick uniformity at hatch, but chick weight at hatch has been traditionally employed as an important indicator of chick quality. Chick body weights at hatch are similar, but we found

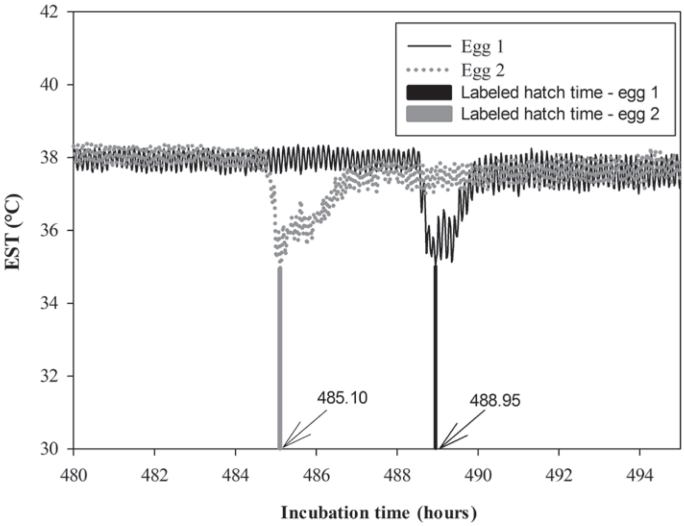

Figure 1. Example of the eggshell temperature drop which occurred during hatch for two focal eggs.

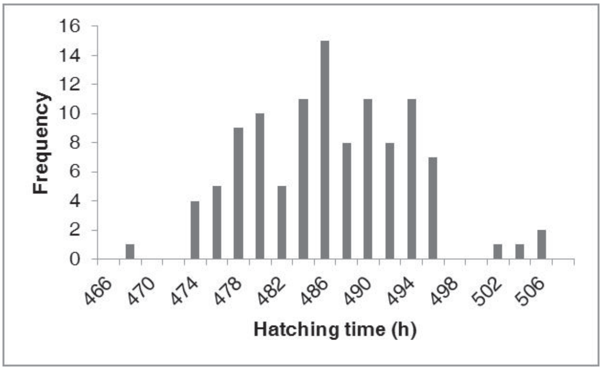

Figure 2. The distribution of hatching time as determined using eggshell temperature monitoring for 109 focal chicks. Hatch time is expressed as incubation time of the eggs in hours. Incubation ends at 512 hours.

that hatching time had an effect on chick weight at the end of incubation. In agreement with the findings of Van de Ven (2013), chick weight at take-off increased with hatching time, indicating that chicks started to lose weight after hatch, possibly due to fasting. Therefore, identifying methods to reduce the negative effect of widely spread hatching times may be beneficial in maintaining chick uniformity and improving welfare and post-hatch performance.

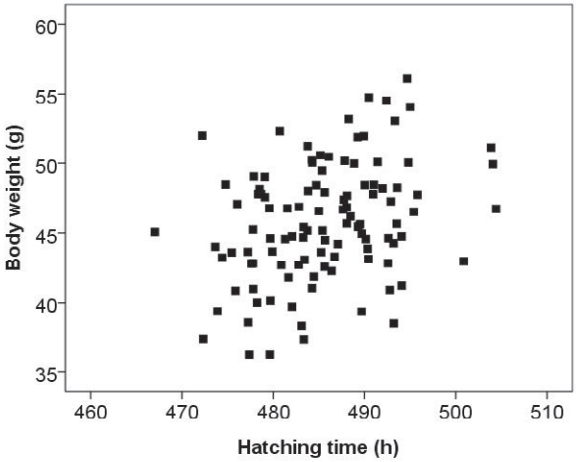

Figure 3. The relationship between chick body weight and hatching time in newly hatched broiler chicks (n=109) at take-off.

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5.3. The use of vocalisation sounds to assess responses of broiler chicken to environmental variables

I. Fontana[1], E. Tullo[1] and A. Butterworth[2*]*
[1]Department of Health, Animal Science and Food Safety, Università degli Studi di Milano, Via Celoria 10, 20133 Milan, Italy; [2]Department of Clinical Veterinary Science, University of Bristol, Langford, North Somerset BS40 5DU, United Kingdom; ilaria.fontana@unimi.it; andy.butterworth@bristol.ac.uk

Abstract

The vocalisation sounds of broiler chicken have been studied previously; however, in this study we describe the monitoring of broiler chicken vocalisation under normal farm conditions, with sound recorded and assessed at regular intervals throughout the life of the bird from day 1 to day 37 to assess whether recognisable, and even predictable, vocalisation patterns, based on frequency and bandwidth analysis, are evident in birds at different ages and stages of growth within commercial broiler production timescales. Two experimental trials were carried out in a 'conventional' indoor reared broiler farm, and the audio recording procedures lasted for 38 days. The recordings were made at regular intervals with the equipment in the same position inside the broiler house during each period of data collection. The recordings were made automatically, without the presence of human operators, using a professional hand-held solid state recorder (Marantz PMD 661 MK II) and provided sound recordings which represented situations without disturbance of the birds beyond that created by the farmer. Digital files of one hour duration were cut into short files of 10 minutes duration, and these sound recordings were analysed and labelled using analysis software: Adobe Audition CS6. Analysis of the sounds recorded, using audio software, identified that the sounds and the related frequencies changed in relation to increasing age and the weight of the broilers. Statistical analysis (Proc CORR, SAS) showed a significant correlation (P<0.001) between the frequency of vocalisation and the age and behaviour of the birds. This method, based on identification of specific frequencies of the sounds emitted compared with age and weight could potentially be used in a system to evaluate the health and welfare status of birds at farm level.

Keywords: acoustic parameters, welfare, labelling, spectrogram

Introduction

There is an increasing demand for poultry meat and poultry production is growing rapidly every year (Weeks and Butterworth, 2004). Systems for rearing chickens for meat have changed significantly during the last 40 years: the aim is to obtain animals that grow faster with high feed efficiency, high processing yield (Rauw *et al.*, 1998), reduced slaughter age and higher final weight (Bokkers, 2004).

As reported by Weeks and Butterworth (2004) and Bokkers (2004), broilers are among the fastest-growing farmed species. Under commercial/intensive conditions, broilers are kept indoors in flocks of 10,000-30,000 birds, with stocking densities of 18-23 birds/m^2. At the moment of hatch, a chick weighs about 50 g and grows to a slaughter weight of nearly 2,700 g in around 42 days. Modern strains of broilers can have weight gains of over 100 g per day. In general, broiler chickens

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are reared in closed systems; there is therefore a need to provide the birds with all the energy and nutrient requirements for maintenance, growth and health. Broiler houses use low-intensity artificial lights and a lighting schedule. Under intensive farming conditions, water and feed are provided by automated feeding and drinking systems (Appleby *et al.*, 1992). Chicken performance is influenced by ambient temperature, relative humidity, air quality and air ventilation speed, thus adequate ventilation is required. Growth, performance, health and welfare depend on proper management of breeding practices (Kenny, 2012).

Animal health is the foundation of good welfare, and much progress has been made in developing new indices of animal welfare in the last few years. However, it is now widely accepted that it is not possible to use one single measure to assess welfare but rather it is appropriate to use a range or spread of measures.

As reported by Bokkers (2004), behaviour could be a useful indicator of welfare; in fact it could provide indirect evidence of how an animal feels, in a non-invasive way and, in many cases, in a non-intrusive way (Dawkins, 2004).

One way of assessing an animal's health and welfare status is the use of audio and video recording analysis to identify behaviours producing vocal and other sounds. Animals use vocalisations to express different inner states which are provoked either internally or by external events, and also to reveal some needs. Furthermore, it is reasonably easy and feasible to record animal vocalisations (Manteuffel *et al.*, 2004). For these reasons, analysis of vocalisation may be considered a potential indicator of animal health and welfare.

Hearing is an important sense for birds; they are sensitive to a frequency range of about 60 to 11,950 Hz (Appleby *et al.*, 1992; Broitman, 2007; Tefera, 2012). Immediately after successful hatching, chicks are mature and mobile, and they instinctively follow the first moving thing they see, learning its main characteristic (Appleby *et al.,* 1992). In the wild, chicks which have just hatched are able to identify their mother and their siblings; one day old chicks can recognise and discriminate their mother's vocalisations from sounds emitted by other conspecifics (Ferrante and Lolli, 2009). Social behaviour is the behaviour displayed by animals in relation to other animals (Appleby *et al.*, 1992). Social interaction in chicks is important for group development and chicks indeed show social behaviour precociously. Vocalisation is strongly dependent on social contact in chicks (Marx *et al.*, 2001), moreover, chicks vocalise with each other even at the very start of life in the commercial hatchery, slowing down or accelerating the physical development of other chicks in order to synchronise the hatching moment (Ferrante and Lolli, 2009).

The first two days of a chick's life are the most important period for the development and acquisition of a correct ethogram. In the wild, during the imprinting phase/period chicks learn fundamental behaviours from their mother, such as foraging, drinking, how to properly utilise the home range area, and the pattern of intensive vocal communication (Appleby *et al.*, 1992; Marx *et al.*, 2001). Under intensive farm conditions, when the mother is absent, chicks can perform and learn fundamental behaviours on their own or by reproducing their hatch-mates' activities due to the strong social interaction in bird groups. Pecking at random gradually leads the birds to be able to distinguish food and water; sometimes they do not learn from conspecifics, but copy their behavioural activities. Feeding and drinking are social activities and, even under intensive farm conditions, chickens tend to perform some behaviours simultaneously. As reported by Tolman and Wilson (1965), birds isolated from the group eat less than chicks with companions. Synchrony during eating and drinking may be fundamental for welfare (Appleby *et al.*, 1992).

Precision livestock farming aimed at monitoring welfare and behaviours

Automatic animal monitoring could potentially be used to support farmers in achieving farm sustainability (Costa *et al.*, 2013). Among the principal objectives of Precision Livestock Farming (PLF), there is potential for the development of a fully automatic on-line monitoring tool (Viazzi *et al.*, 2011) to monitor animal behaviours and their biological responses. These analyses, including image and sound analyses, can be carried out using non-invasive PLF methods; they can be innovative, may be low-cost, and they are potentially of great interest in animal husbandry applications (Halachmi *et al.*, 2002; Ismayilova *et al.*, 2013; Tullo *et al.*, 2013).

The PLF approach can be applied to different aspects of management, with a focus on the animals and/or on the environment, and at different scales, from the individual to the entire flock/herd (Wathes, 2010).

In general, the reliability of PLF is determined primarily by the animal and then by the physiological variables that can/must be continuously measured, such as weight, activity, behaviour, food intake, noise produced, body temperature, heart or respiratory rate. Continuous measurement may mean that, depending on the variable in question, the frequency of measurements must be high or at least regular. Other requirements include the ability to provide reliable prediction and, along with on-line measurement, integration of the algorithms that are necessary for automatic animal monitoring in order to implement the correct control strategies.

A recent approach to the application of sound analysis techniques has been to measure and analyse the amplitude and frequency of animal sounds (De Moura *et al.*, 2008) in order to discriminate and classify specific vocalisation in poultry houses (Manteuffel *et al.*, 2004).

The object of this study is to identify and characterise vocalisations emitted by chicks during their first five days of life under normal farm conditions, looking for possible connections between specific individuals and social behaviours. The final goal is to detect possible vocal changes in terms of frequency and type of sound emitted with increasing age.

Material and methods

Two experimental trials were carried out at an indoor reared broiler farm; the first took placed in June and July 2013 (trial 1) and the second in August and September 2013 (trial 2). The farm where the experimental trials took place was an indoor broiler farm rearing birds to the RTFA (ACP) standard. The house dimensions were 61×21 m and the total floor area available to the birds was 1,130 m^2. Inside the house 2,340 nipple drinkers and 385 feed pans were available to the birds. 27,940 one day old chicks were placed inside the house at day one in both trials.

Sound recordings were collected using a professional hand-held solid state recorder (Marantz PMD 661 MK II; Marantz, Kanagawa, Japan) which was connected to two different directional microphones placed at a variable height between 0.4 and 0.8 m (depending on the height of the animals in order to keep the same distance – approx. 0.3 m – between the animals and microphones throughout the data collection process).

The supercardioid/lobe microphone (Mic. 1) was a Sennheiser K6/ME66' (frequency response: 40-20,000 Hz ± 2.5 dB; Sennheiser, Wedemark, Germany) and it was held above the feeder on a short tripod microphone stand (Quiklok A341; US Music Corp, Buffalo Grove, IL, USA). The cardioid microphone (Mic. 2) was a Sennheiser K6/ME64' (frequency response: 40-20,000 Hz ± 2.5 dB) and it was placed on a tall tripod (Quiklok A492 Heavy-Duty Boom Mic Stand) directly above the drinkers. Both the microphones were slightly inclined towards the floor in order to preferentially capture the sounds coming from the birds walking directly in front of the microphone axis. The recordings provided a sound image of background noise, and gave a better idea of what was happening overall inside the broiler house.

The video recordings were made by placing a digital video camera on a low-level tripod, and focussed on the area where the birds being recorded by Mic. 1 were active. After the period of continuous recording, three randomly selected chicks were moved into an enclosed box-shaped 'shielded recording area' with 30 cm high sides for 5 minutes, in order to collect clear (as clear as was possible in the farm environment) sounds by shielding the microphone from background environmental noise. At the same time, video recordings were made by positioning the video camera on the top of the box, focusing on the chicks to identify their behaviours both inside and outside the box. After 5 minutes of recording, the barrier was removed and the chicks could return to the flock.

The Marantz PMD 661 MK II recording machine had a large range of potential recording settings. The settings found to give the most sensitivity to bird sounds in the poultry house environment were: Rec. Format: PCM-16; Stereo Sample Rate: 44.1k; Level Control: Manual; Low Cut: Off; High Cut: Off.

Animal sounds were continuously recorded for 1 hour using 2 different microphones during each experimental session from day 1 to day 38. Recordings were made at regular intervals every Monday, Wednesday and Friday, with the equipment in the same position throughout the trial procedures.

The entire data collection consisted of 16 days of sound recordings for trial 1 and 15 days of sound recordings for trial 2. It was decided that the vocalisations recorded with Mic. 1 would be analysed and manually labelled as the sounds were of higher quality than those recorded with Mic. 2.

In this study only the sounds extracted from day 1 to 5 of recording were used for sound analysis in order to focus attention on the vocalisations emitted by the animals during the first days of their life.

Sound and image analysis

Sound recordings were manually analysed and labelled using sound analysis software: Adobe® Audition™ CS6 (Adobe, San Jose, CA, USA). Sound labelling involved the extraction and classification of both individual animal sounds and general sounds coming from the whole flock based on the amplitude and frequency of the sound signal in audio files recorded at farm level (Tullo *et al.*, 2013).

Labelling is a manual procedure based on acoustic analysis combined with visual spectral analysis, which is used to extract intervals of sounds from the entire recording file. The labelling procedure was carried out offline by extrapolating those sounds that the operator classified as significant vocalisation sounds through auditive analysis and visual observation of the spectrogram of the sounds (Ferrari *et al.*, 2008). Using Adobe Audition CS6 (2003), each sound was identified and analysed on the basis of time (x-axis) and frequency (y-axis). Each hour-long recorded digital file was cut into shorter files of 10 minutes duration in order to make the sound analysis and labelling process easier. Data analysis was divided into two different phases. Firstly, the file was listened to in its entirety in order to recognise the regions of the recording with the clearest sounds, then during the 'listen through' the regions of the recording with the clearest sounds were marked in order to classify different types of sound (Tullo *et al.*, 2013). The Fast Fourier Transform (FFT) was used to perform the frequency analyses using a Hamming window with a FFT dimension of 256 (Figure 1). The mean duration, mean interval and number of repetitions of each kind of vocalisation were collected.

During analysis of the sounds recorded inside the box on both days, 12 different types of vocalisations were found and labelled as A, B, C, D, E, F, G, H, I, J, K, L. The eight sounds labelled A to H were recorded during the first day of recording (Day 1), and the four sounds I to L were recorded during the fifth day of the chicks' life (Day 5). For statistical analysis of those sounds, it was decided that the five clearest five sounds from each category (A to L) would be considered: 8×5 = 40 sounds for day 1 and 4×5 = 20 sounds for day 5.

During analysis of the sounds coming from the entire flock (general sounds-barn) the clearest sounds which were useful for the statistical analysis numbered 68 for both day 1 and day 5 of recording.

For each sound the peak frequency (PF= representing the frequency of maximum power) was manually extracted. The frequency range was band pass filtered between 1000 and 13,000 Hz. The lower frequency limit was set at 1000 Hz to remove the low-frequency background noise and the upper limit was set at 13,000 Hz to cut off the high-frequency noise and also because broilers are sensitive to a frequency range of about 60 to 11,950 Hz (Appleby *et al.*, 1992; Broitman, 2007; Tefera, 2012).

Video and sound recordings were synchronised during the labelling procedure in order to link the behaviours to the sounds emitted by the animals.

Figure 1. Screenshot of the Adobe Audition software showing the spectrograms and the frequency analysis window relative to a specific vocalisation.

Statistical analysis

Statistical analysis was performed using the statistical software SAS 9.3 for Windows (SAS Institute, Cary, NC, USA). The differences in PF for the sounds recorded inside the box and in the barn (during day 1 and 5) were tested using the paired t-test in order to evaluate the changes in vocalisation PF for different days and situations (isolated/in group). Paired sample t-tests were conducted to evaluate the difference in PF for vocalisations emitted by the chicks in six specific situations:

- comparison between sounds recorded on day 1 and 5 inside the box (box 1_box5);
- omparison between sounds recorded on day 1 and 5 in the barn (barn1_barn5).
- comparison between sounds recorded in the box and in the barn on day 1 (box1_barn1);
- comparison between sounds recorded in the box and in the barn on day 5 (box5_barn5);
- comparison between sounds recorded in the box on day 1 and in the barn on day 5 (box1_barn5);
- comparison between sounds recorded in the box on day 5 and in the barn on day 1 (box5_barn1).

The correlations between vocalisations recorded in the box and in the barn were evaluated to verify whether the chicks emitted sounds (A to L) on a specific day (1 or 5) or during a stress situation (isolated or in group). According to the results of the correlations and the spectral analysis, the 12 types of vocalisation were compared using the PDIFF option in the general linear model procedure (GLM) of SAS to verify their similarity and dissimilarity. The differences between the PF, duration and interval of vocalisations emitted by the birds in association with the response of the chicks outside the box were tested using the proc TTEST.

In this study, the response of chicks outside the box according to the PF of the vocalisation of chicks isolated from the flock was analysed using PROC LOGISTIC, and the odds ratio was calculated. Logistic regression is an appropriate analysis because the chicks' response in this study consists of a dichotomous, categorical variable, e.g. presence or absence around the box. It should also be noted that logistic regression makes no assumption about the distribution (normal or otherwise) or the equality of variances within each group of independent variables. The results from the logistic regression are presented as odds ratios (OR) for the predictors. The *P*-values were calculated based on Wald χ^2 and 95% Wald confidence limits were used.

PROC LOGISTIC was used to model the response of chicks outside the box in relation to the PF, duration and interval of vocalisation. The Contrast statement in PROC LOGISTIC was used to determine which frequency mainly affects the response of the chicks outside the box.

Results

During the labelling procedure for the audio files recorded in the box, 12 different kinds of vocalisation sounds were detected by measuring duration, intervals, repetitions and PF (Figure 2 and 3, Table 1).

The PF range for vocalisations emitted by one day old chicks (day 1 of recording) is higher than the PF for vocalisations emitted by five day old chicks (day 5 of recording). The PF of the sounds emitted by the birds decreased by about 500 Hz in five days (Table 2), showing a general significant difference ($P<0.001$) between sounds emitted by the animals on day 1 and 5 (Table 3), while no significant differences were found between PF recorded on the same day.

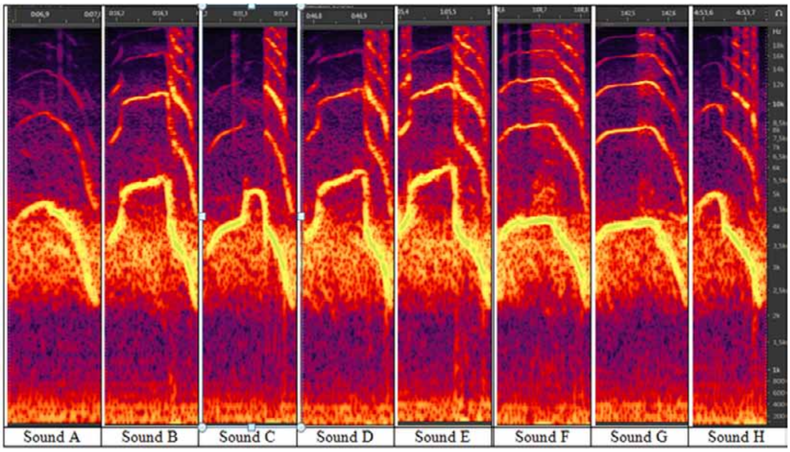

Figure 2. Screenshot of the Adobe Audition software showing the spectrograms of the sounds recorded on day 1.

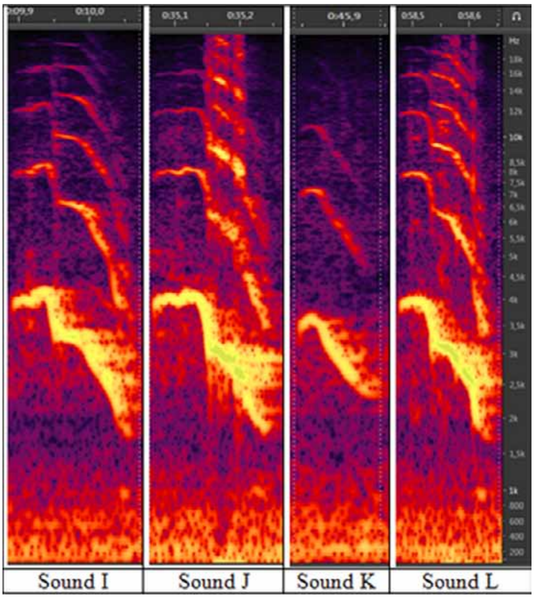

Figure 3. Screenshot of the Adobe Audition software showing the spectrograms of the sounds recorded on day 2.

The correlations between vocalisations (data not shown) recorded both in the box and in the barn were evaluated to verify whether the chicks emitted sounds (A to L) on a specific day (day 1 or day 5) or during a stress situation (isolated-in the box or in group-in the barn). A significant correlation was found between sounds recorded inside the box and in the barn during day 1

Table 1. Mean duration, number of repetitions and peak frequency (PF) ranges of the 12 different types of vocalisation sound collected on day 1 and 5.

Sound type	Day of recording	Mean duration (s)	N of repetition	Range of PF (Hz)
A	1	00:00.205	14	3,445-3,962
B	1	00:00.214	31	3,101-3,618
C	1	00:00.214	9	3,445-3,962
D	1	00:00.210	31	3,445-3,618
E	1	00:00.222	26	3,445-3,790
F	1	00:00.223	7	4,134-4,307
G	1	00:00.222	11	3,962-4,134
H	1	00:00.176	8	3,273-3,790
I	5	00:00.199	78	2,929-3,273
J	5	00:00.209	7	2,929-3,273
K	5	00:00.123	7	2,756-3,273
L	5	00:00.180	6	2,929-3,273

Table 2. Mean, standard deviation, minimum and maximum value of the peak frequency extracted in the vocalisations recorded in the 4 situations.

Sounds	N	Mean (Hz)	Std dev (Hz)	Minimum (Hz)	Maximum (Hz)
box_day1	40.00	3,717	336	3,187	4,393
box_day5	20.00	3,075	188	2,670	3,531
barn_day1	68.00	3,613	415	2,670	5,426
barn_day5	68.00	3,162	395	2,498	4,393

Table 3. Statistical difference in peak frequency for sounds emitted by the animals on day 1 and 5.[1]

	Paired differences					t-value	d.f.	*P*-value
	Mean	s.d.	s.e.	95% CI				
				lower	upper			
box_day 1 – box_day 5	525.4	332.9	74.4	369.6	681.2	7.0	19	<0.001
barn_day 1 – barn_day 5	450.9	584.8	70.9	309.4	592.5	6.3	67	<0.001
box_day 1 – barn_day 1	81.8	562.6	88.9	-98.1	261.8	0.9	39	0.363
box_day 5 – barn_day 5	60.2	322.4	72.1	-90.5	211.2	0.8	19	0.413
box_day 1 – barn_day 5	620.2	536.0	84.7	448.7	791.6	7.3	39	<0.001
box_day 5 – barn_day 1	534.0	538.7	120.5	281.9	786.1	4.4	19	<0.01

[1] s.d. = standard deviation; s.e. = standard error; CI = confidence interval of the difference; d.f. = degrees of freedom.

(box 1_barn 1; r>0.75; *P*<0.001) and also between sounds recorded in the box and in the barn during day 5 of recordings (box 5_barn 5; r>0.70; *P*<0.001).

There was a low correlation between sounds recorded inside the box during day 1 and 5 (box 1_box 5; r <0.50; *P*<0.001) and also between sounds recorded in the barn during day 1 and 5 (barn 1_barn 5; r<0.50; *P*<0.001). As expected, the low correlations between sounds recorded in box 1_box 5 and sounds recorded in barn 1_barn 5 imply a reduced correlation between sounds recorded in box 1_barn 5 and those recorded in box 5_barn 1 (*P*<0.001) as well.

When analysing the correlation table and the spectrogram for each sound, it was observed that, based on the frequency level, some sounds were more similar than others. For this reason, the 12 types of vocalisation sound were compared using the PDIFF to verify their similarity and dissimilarity.

There were no statistically significant differences between sounds B and D, B and E, A and H, J and I and I and L (data not shown), confirming the findings from the spectral analysis and correlations.

The odds ratio (Table 4) showed that there was a significant association between the high frequency of vocalisations by chicks inside the box and a positive response (presence) by chicks outside it (OR=1.012; Wald CI 95%=1.006-1.019).

According to the results reported in Table 5, the probability of a positive response by the chicks outside the box is only 0.037 when the PF is 3,000 Hz but it rises to 0.82 when the PF reaches 3,400 Hz (*P*<0.001). When the PF is 3,600 Hz the probability of a positive response by the chicks outside the box is higher than 0.98 (*P*<0.001).

Discussion

The object of this study was to identify and characterise vocalisations emitted by chicks, looking for possible connections between specific individuals and social behaviours. The results obtained from the video analysis showed how, during recording of the sounds inside the box (day 1), a large number of chicks around the box responded to the vocalisations emitted by the animals inside. The same video recording procedure was adopted during day 5: in this case, the chicks were moved into the box, but the situation was different from day 1 in that there were no chicks around the box to respond to the vocalisations emitted by the birds inside. At the beginning of the isolation period, when the first one-day-old chick was moved into an enclosed box, the vocalisations immediately increased, demonstrating that social isolation in chicks leads to an increase in vocalisations.

Table 4. Odds ratio between the high frequency of vocalisations by chicks inside the box and the response of chicks outside the box.[1]

Variable	b	s.e.	Wald χ^2	OR	Wald 95% CI
Intercept	-39.415	10.519	14.041		
PF	0.012	0.003	14.103	1.012	1.006-1.019

[1] PF = peak frequency; s.e. = standard error; OR = odds ratio; CI = confidence interval.

Table 5. Results of logistic regression for changes in peak frequency (PF).[1]

PF (Hz)	Estimate	s.e.	95% CI		Wald-χ^2	*P*-value
			lower	upper		
freq_Hz=3000	0.037	0.036	0.005	0.221	10.17	<0.001
freq_Hz=3200	0.298	0.120	0.12	0.567	2.22	ns
freq_Hz=3400	0.825	0.095	0.563	0.945	5.51	<0.05
freq_Hz=3600	0.981	0.021	0.841	0.998	11.49	<0.001
freq_Hz=3800	0.998	0.003	0.948	0.999	13.01	<0.001
freq_Hz=4000	1.000	0.000	0.983	1.000	13.54	<0.001
freq_Hz=4200	1.000	0.000	0.994	1.000	13.77	<0.001

[1] s.e. = standard error; CI = confidence interval; ns = not significant.

The vocalisations decreased slightly as soon as the other two chicks were moved into the box; as also reported by Marx *et al.* (2001), the occurrence of distress calls is higher when the group of isolated chicks is smaller than three animals. The presence of chicks around the box during day 1 leads us to think that the sounds emitted by one day old chicks which are isolated from the group may be classified as calling sounds towards their conspecifics, whereas the sounds emitted by five-day-old chicks can be classified as distress calls due to the social isolation.

This classification of calling and distress vocalisation is also confirmed by the low correlation obtained between the sounds for the two days (day 1 and 5) recorded both in the box and in the barn. The 0.70 and 0.75 correlation coefficients (for day 1 and 5, respectively) indicate, in general, that the sounds emitted have a PF which is typical of the age of the birds, but isolation from the flock strongly affects the type of vocalisations produced by chicks inside the box.

Moreover the histogram shown in Figure 4 represents the difference in the response (absence/presence) of the chicks outside the box in relation to the PF level of vocalisations emitted by isolated chicks. This difference confirms that the higher the PF emitted by the animals, the greater the presence of chicks around the box. The reason why chicks reacted positively to the vocalisations

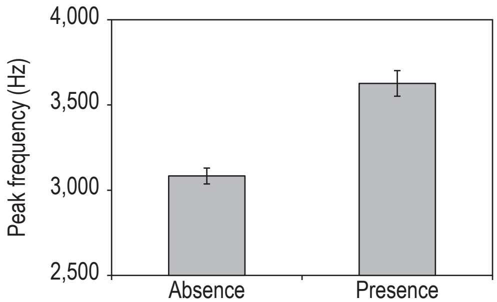

Figure 4. Effect of peak frequency emitted by the isolated chicks on the response (absence/presence) of the chicks outside the box. *P*<0.01 as compared with placebo treatment. Error bars represent standard error.

of the animals inside the box during day 1 and not during day 5 is probably due to two different key factors: the frequency of the sounds and the specific meaning of the vocalisations emitted. They responded positively to calling sounds emitted by the chicks inside the box during day 1 but not to distress sounds emitted inside the box during day 5.

Conclusions

The results indicate that the peak frequency of the sounds emitted by the animals is inversely proportional to the age and weight of the broilers; specifically the more they grew, the lower the frequency of the sounds emitted by the animals.

The presence of chicks around the box leads us to conclude that the sounds emitted by one-day-old chicks isolated from the group may be classified as 'calling sounds' directed towards their conspecifics, whereas sounds emitted by five-day-old chicks can be classified as 'distress calls' due to the social (and physical) isolation.

Furthermore, this study leads us to conclude that calling sounds are vocalisations emitted by the animals during the imprinting phase when chicks (in the first two days of their life) are learning fundamental behaviours with regard to social behaviour and vocal communication.

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5.4. Pig cough monitoring in the EU-PLF project: first results

M. Hemeryck and D. Berckmans*
SoundTalks, Kapeldreef 60, 3001 Heverlee (Leuven), Belgium; martijn.hemeryck@soundtalks.com

Abstract

In recent years, an interest in Precision Livestock Farming (PLF) has emerged. The Pig Cough Monitor (PCM) is an instance of PLF technology, enabling continuous automated measurement of porcine respiratory health. This paper presents the first results from the PCM in the context of the EU-PLF project. The EU-PLF project aims to provide a better understanding of the economic application of PLF technology. Its aim is to collect data from 60 pig fattening cycles, geographically distributed over 10 farms in Europe. The data include quantitative measurements from PLF sensors, including the PCM, as well as qualitative expert analyses and farmer-provided batch metadata. The results for three selected cases are presented, each from a different farm, showing PCM data over the course of a fattening cycle. The cases were selected on the basis of events which influenced the normal respiratory status of the pigs. The PCM data are discussed in terms of cough index: the number of cough groups per day. The first case compares two simultaneous batches in different compartments on the same farm. Both batches exhibited an increase in cough index initially which could be attributed to the environmental change experienced by the piglets when they were moved to the fattening unit; one of the batches also shows a clear increase near the end. The second case presents the results for a batch with a given baseline level of cough index over the main portion of the batch and a relatively big increase near the end. The third case considers the cough index for a batch with a temporary failure of the ventilation. Three weeks after the failure the effect on the cough index was still apparent. The three cases show the effectiveness of the PCM in a practical setup. Further research is still required, combining inputs from the different project partners.

Keywords: precision livestock farming, acoustic monitoring, fattening pigs, EU-PLF, pig cough monitor

Introduction

Traditional livestock farming has come under stress in recent years for a number of reasons. Firstly, global demand for meat has been on the rise as the world's population keeps growing (FAO, 2013). Additionally, income per capita is also increasing substantially, particularly in the developing countries (e.g. the BRIC countries), enabling a whole new population to consume meat. Another trend, which has specifically emerged from the developed countries, is increased concern about how meat is produced. Modern consumers demand that livestock should be produced in an ethical and environmentally friendly way. A major example of this is the significant reduction in the use of antibiotics, as seen for instance in The Netherlands (Stichting Werkgroep Antibioticabeleid, 2009) and Denmark (Danish Veterinary and Food Administration, 2009). Lastly, the market for meat has also experienced a shift towards a lower number of bigger retailers which operate internationally. As a consequence, livestock farmers have to face lower margins per animal, which in turn forces them to increase efficiency and exploit economies of scale, leading to a lower number of farms with more animals per farm.

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To increase the efficiency of livestock farms, Hanton *et al.* (1981) put forward the idea of combining information about biological processes (biological organisms) with the principles and practices of modern engineering and technology. Essentially, livestock farming is described as a process control technology, having the living organism at its centre.

Subsequently, Berckmans (2006) expanded the notion of livestock farming as a process control problem with the aforementioned issues in mind and coined the term Precision Livestock Farming (PLF). A number of principles are proposed. Firstly, PLF does not aim to replace the farmer, but rather aid the farmer in the decision making process. Secondly, the animal must be considered the most crucial element of the biological production process. Three conditions are deemed important for effective monitoring and control: the animal variables need to be monitored continuously, prediction (expectation) of the animal variables needs to be reliable with respect to environmental changes, and the prediction needs to be integrated with on-line measurements to crease an analysis algorithm.

In recent years, numerous instances of PLF-techniques have emerged: Moura *et al.* (2008) report, for example, the use of automatic acoustic monitoring to assess thermal comfort in young chicks; Aydin *et al.* (2014) present a technique for monitoring feed intake by broilers, also based on sound techniques and many more examples are available.

Techniques specifically aimed at acoustic monitoring of coughing in pigs have also appeared and undergone a long research trajectory. Moshou *et al.* (2001a,b) presented a proof-of-concept for pig cough detection using artificially induced coughing in pigs confined in a metal box. The algorithm proposed could discriminate between recorded cough and metallic sounds. Van Hirtum *et al.* (2002) investigated cough detection for both pathological and non-pathological cough sounds. They also presented a physiological model explaining the basic phases of coughing. Guarino *et al.* (2008) presented an algorithm for cough sounds recorded in a specific commercial setting for a short period of time. Exadaktylos *et al.* (2008) demonstrated an algorithm for real-time cough detection from a set of labelled sounds recorded in controlled conditions. Further details of the early development of the pig cough monitor are presented by Vandermeulen *et al.* (2013).

In 2011, SoundTalks NV and Fancom BV together released the pig cough monitor (PCM) as a commercialisation of the earlier research on pig cough detection. The evolution from academic research to a commercial product is inherently subject to a number of challenges. In the course of development of the cough monitor, the key issue that needed to be resolved was the issue of robustness: building acoustics differ, cough sounds differ between seasons, climate control systems and feed systems vary between farms, the animal age and corresponding weight affect the nature of the animal sounds produced, the disease types are different and lastly, farm management practices also differ greatly between farms.

This paper describes the first results obtained with the PCM in the context of the EU-PLF project. The outline of this paper is discussed in greater depth. The materials and methods section details the context of the EU-PLF project, data collection by the PCM and a generic description of the cough detection algorithm. The results and discussion section presents the initial results from PCM analyses for three selected cases. The conclusions section closes by summarising the results and providing some final thoughts on further research.

Materials and methods

EU-PLF

The data presented in this paper were measured in the Collaborative Project EU-PLF KBBE.2012.1.1-02-311825 under the Seventh Framework Programme. In this project, 40 compartments with fattening pigs (four per farm) were monitored for a combined total of 60 fattening cycles. The 10 pig farms selected were located in the Netherlands, Hungary, Spain, France, Italy and Northern Ireland (UK). By selecting farms across Europe, the objective was to cover the widest possible range in climatological conditions, management styles, housing layouts/materials, pig breeds, etc. The data collected in this project comprise both quantitative and qualitative data. Examples of quantitative data are the PCM data as well as data from other PLF sensors such as camera technology that is installed in the compartments selected. The qualitative data are made up of logbook data, i.e. animal welfare assessments by trained experts as well as input by the farmers involved. These combined inputs should provide a better understanding, both from a scientific interest perspective and in terms of how PLF technology can be employed to support the farmer in an economically viable way. The EU-PLF project ends in November 2016 and measurements will continue over the next two years.

This paper will limit the discussion to PCM data and inputs from the logbooks. A combination of the results from different sensors will be presented at a later date when more data become available. Cough results from three different farms are presented below, showing the initial results that were recorded with the PCM in this project. The selection of compartments and batches used in this paper was based on logbook data: events with an influence on the respiratory status of the pigs were selected.

PCM data collection

The sound acquisition system used in the PCM consists of a condenser microphone (Behringer C4; Behringer, Zhongshan, China) and a sound card (ESI Maya 44; ESI Audiotechnik GmbH, Leonberg, Germany). The microphones are phantom-powered and are connected using balanced audio in order to allow the use of long cables with very limited susceptibility to noise. The sound data are recorded with a precision of 16 bits and a sampling frequency of 22,050 Hz. The sound card is mounted in an embedded board (x64 architecture), running a GNU/Linux operating system. The embedded board is fan-less and installed in a sealed enclosure to protect the system from the harsh environment. The microphone itself is protected by a thin and flexible plastic cover in order to withstand the harsh conditions in the compartment whilst at the same time not interfering with the sound acquisition itself in the frequency range of interest. The embedded board is equipped with diagnostics software which regularly checks system operation, including monitoring the sound recording quality, system temperature and system processing load. The system status can be checked remotely via a wired or wireless internet connection. Several factors put high stress on the equipment and the requirement for a robust design as well as automatic diagnostic utilities is built into the equipment; these factors include unstable power supplies, high temperatures and humidity, acid compounds in the air, internet connection problems, accelerated corrosion due to ammonia concentrations, rats biting the cables, etc. An overview of the practical difficulties associated with deploying PLF technologies on the farm and the solutions invented in order to overcome them is presented in (Banhazi *et al.*, 2014).

The microphone is typically mounted in the centre of the pig compartment, at a height of at least 2 m. Recordings are continuous, i.e. 24 hours/day, 7 days/week. All raw sound recordings are stored on external hard drives, in order to allow further post-processing if needed. Figure 1 shows the microphone and the protective case for the hardware. Figure 2 shows the microphone in a typical setup in this project, next to a camera.

Cough detection

Following sound acquisition, an essential element is the cough detection algorithm which separates cough sounds from other sounds. An overview of such algorithms and the research trajectory

Figure 1. Pig cough monitor in its protective enclosure, with microphone (shown unprotected here) and microphone cable.

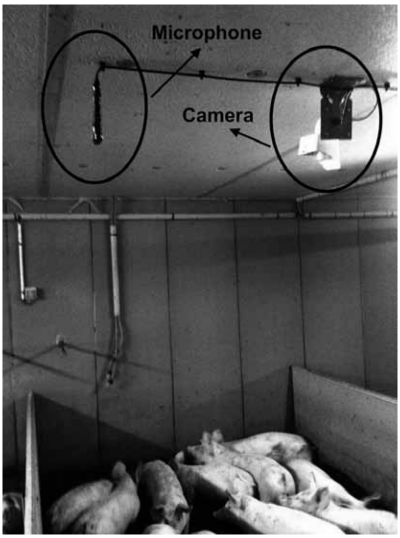

Figure 2. Microphone and camera in a typical setup on a commercial pig fattening farm in the EU-PLF project.

which led to the PCM is presented in the introductory text. All approaches typically share the following steps: firstly, a procedure to isolate meaningful audio events for which distinguishing time-frequency features are derived, and secondly, a classification step where cough sounds are separated from non-cough sounds based on those audio features. Given that the PCM is used in commercial settings, the audio features employed aim to be robust to withstand all possible acoustic environments and practical conditions.

Results and discussion

Three cases are further discussed. Each case uses data from a different farm involved in the EU-PLF project. The names of the farms are anonymised, i.e. farm A, B and C. For each farm, the PCM-data are presented over the duration of a single batch. In the first case, two batches from the same farm were compared with each other and are presented here as batch X and Y. The cases were selected on the basis of logbook entries detailing events with an influence on the respiratory status of the pigs. For each of the cases selected, results are presented in terms of cough index. The cough index graph is then further analysed and related to the corresponding case metadata.

The cough index is an indication of the level of coughing during the fattening cycle, based on the output from the PCM. It expresses the number of cough groups per day, with coughs no more than five seconds apart regarded as belonging to the same group. Cough groups, as opposed to individual cough events, are counted in order to reduce the influence of episodes of coughs from individual pigs.

A time frame of one day is used to abstract daily recurring patterns which might influence the cough pattern, such as fixed feeding times. Note that the cough index shown here does not take the number of monitored animals into account. Although a normalisation of the graphs with respect to the number of animals would yield an absolute cough index, the acquisition of this information is in practice not always that evident and therefore the results are not yet normalised here. Furthermore, the relative increase in cough index alone is an excellent indicator of events (other than the normal situation) which affect the respiratory health status of pigs.

Case 1: comparison of 2 simultaneously occurring batches on farm A

The first case is taken from farm A. Two different batches of pigs of the same breed are considered (batch X, batch Y). They share the same time-frame, from mid-February to the beginning of June 2014. The batches differ in terms of the compartments where they were measured, with each batch containing the same number of pigs. Figures 3 and 4 show the cough index graphs for batches X and Y respectively. A number of observations can be made with regard to these batches.

Both batches display an increase in cough index at the beginning of the batch. This increase in cough at the beginning of the fattening cycle can be attributed to the change of environment experienced by the piglets when they are moved to the fattening stage. Apart from the stress associated with this move, the temperature in the fattening unit is much lower on this farm. To accommodate for this change in temperature, some production systems use heaters to warm the compartments before the piglets are moved into them. From the available metadata we know that the compartments on this farm are not pre-heated at the beginning of the batch. For batch X, a second clear peak occurs around the end of April and is related to a clear relative increase in cough. Batch Y serves as a control batch: no significant increase in cough was observed here throughout the duration of fattening.

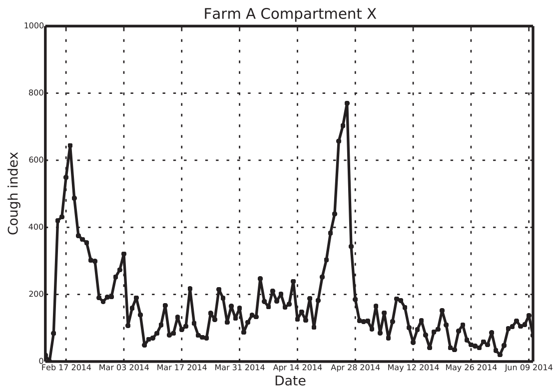

Figure 3. Cough index compartment X farm A: increased cough index.

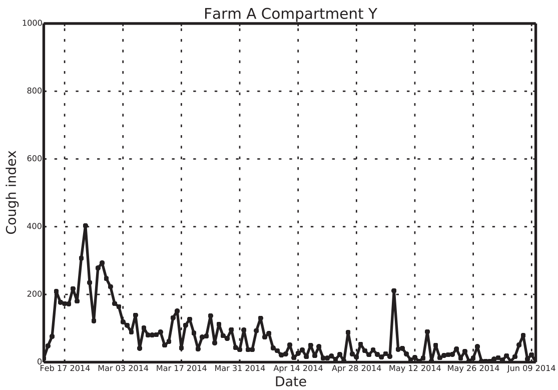

Figure 4. Cough index compartment Y farm A: no increase in cough index.

Case 2: batch farm B

Case 2 describes a batch on farm B, where a single batch was studied from the beginning of March to mid-May 2013. Its cough index graph shows a clear peak near the end of the batch.

Figure 5 shows the cough index for this batch. On the day when the animals were introduced to the housing, the number of detected coughs reached a cough index of 3,000. This level serves as a baseline level during the main period of this batch. The cough index again shows a significant relative increase towards the end of the batch.

This abnormality in cough index was not described in the logbooks, which means that the farmer (or worker) did not notice the increase. The cough monitor is thus able to indicate anomalies in respiratory behaviour which are not directly apparent to a human observer under practical conditions with limited assessment time. The cough monitor is hence able to analyse the cough pattern using continuous objective measurements, whereas a human observer is limited to subjective snapshots.

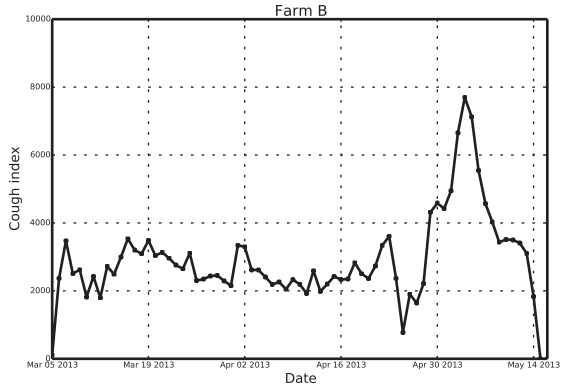

Figure 5. Cough index farm B: increased cough index near the end of the batch.

Case 3: batch farm C

Case 3 describes a batch on farm C. A single batch of animals is analysed from the beginning of February to mid-May 2014. The cough index here shows a clear peak in the middle of the batch.

Figure 6 shows the cough index for the batch. The cough index starts around a value of 500 cough groups per day. On 23 February, a power failure – resulting in malfunctioning ventilation – was reported in the logbook. The ventilation problem lasted for several hours before it could successfully be addressed. As a consequence of this technical failure, the air quality was drastically reduced, which translated into a rapid increase in the cough index until the end of March. Note that it was three weeks before the cough index finally decreased again. The period of time where an increased cough index was apparent was also influenced by the outside temperatures, which were unusually warm in March and a lot colder in April.

The initial results presented for the three cases clearly demonstrate the potential of cough monitoring as a farm management tool: relative increases in the cough index level can be related to actual events occurring on the farms. This study was mostly based on cough index analyses

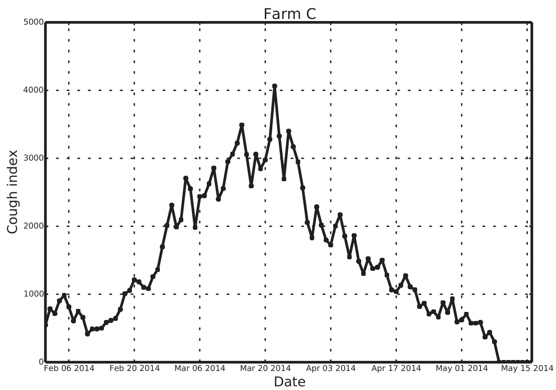

Figure 6. Cough index farm C: increased cough index in the middle of the batch.

and qualitative batch metadata. It is clear that a more thorough analysis based on combining the quantitative inputs made available through the EU-PLF project would help to obtain a better understanding of the cough index graphs presented. This is a clear objective to be achieved once more data becomes available during the remainder of the project.

Conclusions

The PCM allows the Precision Livestock Farming principles to be applied in a real, commercial setting. Specifically, this research presents the first results from pig cough detection trials on three selected European farms, which are part of the EU-PLF project. These early results show the effectiveness of the PCM in a practical setting. The PCM has a real added value, as it was able to indicate a number of issues correctly. Its use in conjunction with the logbook information noted by the farmer shows the clear potential for an early warning system under practical conditions. Further scientific and economic analyses are required, combining additional batch metadata from different EU-PLF project partners.

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5.5. Assessing the drinking behaviour of individual pigs using RFID registrations

J. Maselyne[1,2], I. Adriaens[1], T. Huybrechts[1], B. de Ketelaere[1], S. Millet[3], J. Vangeyte[2], A. van Nuffel[2] and W. Saeys[1]*
[1]KU Leuven Department of Biosystems, MeBioS, Kasteelpark Arenberg 30, 3001 Leuven, Belgium; [2]Technology and Food Science Unit –Agricultural Engineering, Institute for Agricultural and Fisheries Research (ILVO), Burg. van Gansberghelaan 115 bus 1, 9820 Merelbeke, Belgium; [3]Animal Sciences Unit, Institute for Agricultural and Fisheries Research (ILVO), Scheldeweg 68, 9090 Melle, Belgium; jarissa.maselyne@ilvo.vlaanderen.be

Abstract

Automatic detection of health, welfare and productivity problems in individual animals enables rapid intervention by the farmer, reducing the risk of economic losses, excessive use of antibiotics and animal suffering. Since animals change their behaviour in response to problems or stress, it is hypothesised that the drinking behaviour of pigs can be a valid indicator of health or welfare problems. A system was designed to register drinking behaviour automatically. A High Frequency Radio Frequency Identification (HF RFID) system was placed around four nipple drinkers and 55 pigs were equipped with RFID ear tags. Validation of the HF RFID system was carried out by comparing drinking bouts derived from the RFID data with visual observations. Registrations which were too long and too short were deleted. On average, 97% of the drinking bouts observed were also registered by the RFID system. This corresponds to 99.2% of the total duration of drinking observed. However, the RFID system overestimated the number and duration of the drinking bouts by 10 and 19%, respectively. This can be corrected for by using flow meter data. Measurements of drinking behaviour of individual pigs will be used for further development of a system for early problem detection.

Keywords: pigs, drinking, radio frequency identification, precision livestock farming

Introduction

Automatic monitoring of pig behaviour can reveal upcoming or present health, welfare and productivity problems (Weary *et al.*, 2009). Faster and more accurate farmer interventions can not only reduce economic losses and use of antibiotics but can also increase pig welfare and health due to a better awareness of the presence of problems. Using precision livestock farming techniques, automatic monitoring can be carried out continuously, in real-time, without disturbing the pigs and even for individual pigs (Wathes *et al.*, 2008; Maselyne *et al.*, 2014). This monitoring also has advantages compared to the live visual monitoring of the animals that the farmer currently performs, which provides only a snapshot of the (possibly disturbed) animals (Pluym *et al.*, 2013). Besides, visual monitoring is time-consuming and identification of individual pigs is difficult. Automatic monitoring has the potential to be more objective and repeatable than visual monitoring.

As part of the behavioural response of a pig to illness or reduced welfare, drinking behaviour is suggested as a valid indicator for problems (Kruse *et al.*, 2011; Madsen and Kristensen, 2005).

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Drinking is closely related to feeding behaviour and thus to performance, while both feeding and drinking are directly influenced by the occurrence of stress or disease. However, drinking behaviour also depends on body weight, age, temperature, group size, time of day, drinking device, etc. (Mroz *et al.*, 1995; Turner *et al.*, 2000). Besides these influences, drinking behaviour also depends on the individual, which is a reason for automatic monitoring of each individual pig instead of the group of pigs. Individual monitoring could provide more accurate and earlier detection of problems before the situation deteriorates (for example, the disease spreads).

In the field of automatic identification of individual animals, Radio Frequency Identification (RFID) is a popular technology. RFID is a robust identification technology which is already established in industry and is becoming increasingly important in agriculture and animal production (Ruiz-Garcia and Lunadei, 2011). RFID tags with unique identification codes can be attached to the animal, and can be identified by means of a fixed or portable antenna and reader unit (Maselyne *et al.*, 2013b, 2014). By inserting an RFID tag into a pig's ear tag and attaching an RFID antenna to a drinker device, it is possible to identify pigs when they are drinking. The duration of presence can also be measured by means of repeated identifications at a certain frequency. This information can then be used for monitoring and problem detection.

Before the data can be useful to the farmer, it is necessary to extract relevant information. Therefore, RFID registrations have to be transformed into variables for drinking behaviour, such as number of drinking bouts and duration of drinking bouts. This information is useful to the farmer and can be used for a health monitoring system when time series of individual pigs are followed up over time.

This paper describes (1) the novel RFID system developed for monitoring the drinking behaviour of individual pigs, (2) a validation of this system for the intended purpose.

Materials and methods

Infrastructure

The experiments were performed in one pen in the experimental barn of ILVO (Institute for Agricultural and Fisheries Research). The floor was partially slatted concrete, partially full concrete. The barn was automatically ventilated and feed was supplied automatically to two feeders with two feeding places each. The pigs were fed *ad libitum* with a commercial dry pelleted feed with a net energy content of 9.3 MJ and a protein content of 15.5% with 0.92% lysine in total. *Ad libitum* water was supplied through four bite nipple drinkers (Suevia Haiges GmbH, Kirchheim am Neckar, Germany).

An RFID system was already present for measuring the feeding pattern of the pigs (Maselyne *et al.*, 2014). The components designed for measuring the feeding pattern were also used to measure the drinking pattern. A round High Frequency (HF) RFID antenna (DTE Automation GmbH, Enger, Germany) was installed around each nipple drinker, parallel to the wall, as shown by Figure 1. The antennae were mounted on a wooden block to move them away from the wall in order to achieve a better read range (antenna is closer to the drinking pig). Standard pen division panels were arranged in a triangle shape and placed at each side of the nipple to prevent pigs that were not drinking from coming too close to the antenna. The four antennae were connected to one reader (ID ISC.LR2500-A, Feig Electronic GmbH, Weilburg, Germany) using a multiplexer. Each antenna was addressed in turn with a cycle time of 2±1 s. The reader was connected to a computer

Figure 1. RFID system installed around the nipple drinker to enable monitoring of the drinking behaviour of each individual pig.

for data-logging. At the time of moving to the experimental barn (10 weeks of age), each of the 55 pigs (mixed group, Hybrid sow × Piétrain boar) was fitted with two HF RFID tags (IN Tag 300 I-Code SLI, HID Global Corporation, California, USA), one in each ear.

Validation

For validation of the RFID system, the pig registrations were compared (1) to live visual observations of the drinking behaviour of the pigs and (2) to the output from flow-meters installed in the water line before each nipple drinker. Live observations were performed on all 55 pigs (marked with a number) using The Observer 5.0 (Noldus Information Technology, Wageningen, the Netherlands) on a portable computer. The start and end time of drinking was noted, along with the number of the pig and the nipple from which it was drinking. All other behaviours close to the nipple drinkers (in the estimated range of the RFID antenna, see Maselyne *et al.*, 2013b) were also documented. Each nipple was observed for 6 hours in total (in pairs of two nipples each time – part 1 and part 2), spread across two days (1 and 3 October 2013 – day 1 and day 2). The pigs were on average 20-21 weeks old at the time of observation and weighed 68.2±8.8 kg (average ± standard deviation).

Turbine flow-meters (FT210-Turboflow, Gems Sensors & Controls Inc., Plainvilles, CT, USA) were installed before each nipple drinker. The frequency of the square wave output signal from the flow-meters was logged at 1 Hz and was a measure of the flow running through the nipple. Logging was carried out on 1 October 2013 and on the same computer as the RFID signals.

RFID registrations are not continuous, but have time gaps between them. Some criteria are required in order to construct drinking bouts from the registrations. A bout criterion was defined as the maximum time gap between registrations at the same nipple which could be considered part of the same drinking bout. The duration of drinking bouts was also limited between a minimum and a maximum duration. The optimal criteria were identified by comparing the observed duration and number of drinking bouts for each pig with the RFID based drinking bouts. The RFID system and bout criteria were then validated by comparing RFID based drinking bouts, observed drinking bouts and flow-meter based drinking bouts. Exact synchronization between the computer in the animal house (for RFID and flow-meter logging) and the portable computer (for observation loggings) was not achieved. Comparison was therefore carried out on the basis of overlap instead of exact agreement.

Results

Bout criteria

From the bout criteria tested, namely 7, 9, 11 and 13 s, a bout criterion of 11 s was chosen. This resulted in the smallest difference between total number and total duration of observed and RFID based drinking bouts. However, there was not much difference between the bout criteria tested. The minimum duration criterion chosen was 2 s and the maximum duration criterion chosen was 180 s (the longest observed drinking bout was 120 s). Based on the minimum duration criterion, 32 short RFID bouts or single registrations were removed, totalling 16 s. Using the maximum duration criterion, six RFID based bouts were removed, totalling 49 min (27.3% of the total observed duration of drinking). These very long RFID bouts were mainly pigs lying or standing near to the nipple and antenna without drinking. The antenna and nipple were used as playing material or the pigs would lie down in front of the triangles and still be registered by the RFID antenna. In addition, four actual drinking bouts totalling 139 s were also deleted. In these cases, it was not possible to distinguish between the time for which the pig was drinking and the time for which it was close to the nipple without drinking.

In total, 401 drinking bouts and a total drinking duration of 177.6 min were observed. For 27 bouts, identification of the pigs by means of the observed markings and by the RFID tag did not match. These were probably observation errors (markings that resemble each other, most errors at nipples furthest away from the observer). The observed identifications were adjusted accordingly. The number of drinking bouts and duration of drinking were overestimated by the RFID system, by 10 and 19%, respectively, using the criteria described above.

Overlap comparison

The results of the comparison between RFID based drinking bouts, observed drinking bouts and flow-meter based drinking bouts can be seen in Tables 1 and 2. By comparing observed bouts and RFID based bouts, using observed bouts as the standard, 97.3% of the number of bouts overlap (corresponding to a duration of 98.0%). The surplus (non-overlapping) bouts include both observed bouts (11, 3.5 min) and RFID based bouts (65, 21.1 min). Most (75%) of the surplus RFID based bouts are very short (<20 s). Comparison between observed and flow based bouts, using observed bouts as the standard, reveals that 93.5% of bouts overlap, corresponding to 97.9% of the duration. Both surplus observed bouts (13, 1.9 min) and surplus flow based bouts (23, 2.5 min) occur. Finally, comparison between flow and RFID based bouts, using the flow based bouts as the standard, shows that 98.7% of bouts overlap, with a duration of 99.1%. Most surplus bouts are RFID based bouts (40 of the 44, 14.1 min of the 14.8 min) in this case.

Table 1. Comparison between observed (obs), RFID based and flow based number of drinking bouts.

Comparison	Date[1]	# overlap	# obs surplus	# RFID surplus	# flow surplus	% overlap
Obs-RFID	day 1 part 1	95	1	27	/[2]	
	day 1 part 2	104	1	11	/	
	day 2 part 1	103	4	13	/	
	day 2 part 2	88	5	14	/	
	Total	390	11	65	/	97.26%
Obs-flow	day 1 part 1	91	5	/	11	
	day 1 part 2	97	8	/	12	
	Total	188	13	/	23	93.53%
RFID-flow	day 1 part 1	141	/	28	3	
	day 1 part 2	166	/	12	1	
	Total	307	/	40	4	98.71%

[1] Day 1 is 1 October 2013, day 2 is 3 October 2013; part 1 is for the first two nipples (measured in the morning), part 2 is for the last two nipples (measured in the afternoon).

[2] For the comparison between observations and RFID the flow meter visits were not used, similar for the other comparisons.

Table 2. Comparison between observed (obs), RFID based and flow based duration of drinking.

Comparison	Date[1]	Duration overlap	Duration obs surplus	Duration RFID surplus	Duration flow surplus	% overlap
Obs-RFID	day 1 part 1	44.10	0.26	2.22	/[2]	
	day 1 part 2	47.12	0.25	1.20	/	
	day 2 part 1	46.07	0.61	2.62	/	
	day 2 part 2	36.81	2.41	5.02	/	
	Total	174.09	3.53	21.05	/	98.01%
Obs-flow	day 1 part 1	43.75	0.61	/	1.37	
	day 1 part 2	46.07	1.29	/	1.17	
	Total	89.83	1.90	/	2.53	97.93%
RFID-flow	day 1 part 1	34.72	/	12.48	0.48	
	day 1 part 2	36.97	/	1.57	0.17	
	Total	71.68	/	14.05	0.65	99.10%

[1] Day 1 is 1 October 2013, day 2 is 3 October 2013; part 1 is for the first two nipples (measured in the morning), part 2 is for the last two nipples (measured in the afternoon).

[2] For the comparison between observations and RFID the flow meter visits were not used, similar for the other comparisons.

Most of the surplus RFID based bouts versus flow meter bouts are the same as the surplus versus observed bouts. This means that the RFID based bouts can be improved by incorporating the flow-meter data. Surplus RFID based bouts are mainly due to the pigs lying, sitting or standing near the nipples without drinking (for example lying in front of the triangles, playing with the antenna or nipples). Some bouts were not detected by the RFID system. A plausible explanation is that the orientation of the RFID transponders in the pig's ear was not favourable for detection during that visit (Maselyne *et al.*, 2013b). Flow-meter and observations do not match entirely due to the lack of synchronization, observation errors or when a pig is sucking instead of drinking (flow is not high enough to be considered a drinking bout by the flow-meter, but the difference between sucking and drinking could not be observed).

Regressions

To determine the usefulness of the RFID measurements, regressions between the RFID based variables and actual water consumption (determined via the flow-meters) were carried out for the data for 1 October. A regression between the duration of flow based bouts and water consumption was also performed. One nipple was not considered because its measured flow rate was not correct. Two pigs were removed from the analysis due to outliers (long RFID bouts without drinking). Table 3 presents an overview of the coefficients of determination (R^2) for these regressions. For RFID based drinking bouts, the total duration has the best correspondence with the volume of water consumed. As could be expected, number of bouts and mean duration of a bout are not such good indicators of water consumption.

If flow meter data are not available, the total duration of RFID based bouts could thus be a good indicator of the water volume consumed. Total duration of RFID based drinking bouts is potentially a good parameter for further use in a health monitoring system. This will be further explored in future research.

Discussion

The RFID system proposed proved to be an effective means of monitoring the drinking behaviour of individual pigs. The overlap between RFID bouts and observed bouts was high, but duration and number of bouts were overestimated by the RFID measurements. This is mainly due to playing and lying around the nipples without drinking and standing close to the nipple before and after drinking. A two-sensor system with flow meters and an RFID antenna for each nipple could further improve the system. However, flow meters must be robust in order to withstand the variable water quality and must be suitable for the low flow rates and short drinking bouts (so a very fast start-up is essential). Furthermore, the combination of two sensors per nipple logically implies higher system costs. The total duration of RFID based bouts is highly correlated with water consumption and could thus be used when flow meter data are not available. Both the sensor system with RFID alone and the two-sensor system (RFID and flow) will be investigated in future studies.

Table 3. Linear regression between water consumption and variables based on RFID or flow based bouts.

Variables tested for linear regression with volume of water consumed	R^2
Total duration of RFID based bouts	0.87
Number of RFID based bouts	0.49
Mean duration of RFID based bouts	0.29
Total duration of flow based bouts	0.98

In order to turn individual RFID registrations into drinking bouts, a bout criterion and a minimum as well as a maximum duration were determined. The maximum duration criterion proved to be very important for reducing the number of non-drinking RFID registrations. In this study it was impossible to investigate the effect of age, production system, group size, etc. on the optimal bout criteria. Further validation of the system could take this into account.

For health monitoring, time series of drinking patterns should be constructed for each individual pig. The relationship between variations in drinking pattern and problems with health, welfare or productivity of the pigs can then be investigated. A synergistic control framework could be well suited to this, by analogy with the work of Mertens *et al.* (2011) and Maselyne *et al.* (2013a).

Conclusions

The registrations of the presented High Frequency (HF) RFID system can be used to measure drinking behaviour of individual pigs. Bout criteria are necessary to cluster registrations into drinking visits. Performance of the system was sufficient in terms of overlap of RFID based visits compared to observed and flow-meter based visits. The RFID system overestimated the number and duration of visits, but a high correlation was found between RFID based drinking duration and water consumption. The RFID system can be used to follow-up drinking patterns of pigs for future research or on-farm purposes such as health monitoring.

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5.6. Continuous surveillance of pigs in a pen using learning-based segmentation in computer vision

M. Nilsson[1], A.H. Herlin[2], O. Guzhva[2], K. Åström[1], H. Ardö[1] and C. Bergsten[2]*
[1]Lund University, Centre for Mathematical Sciences, P.O. Box 118, 22100 Lund, Sweden; [2]Swedish University of Agricultural Sciences, Department of Biosystems and Technology, P.O. Box 103, 23053 Alnarp, Sweden; anders.herlin@slu.se

Abstract

This work investigates the feasibility of extracting the ratio of pigs located in the pig pen dunging area from video recordings. Pigs generally move to the wet dunging area if the ambient temperature is too high in order to avoid heat stress, as wetting the body surface is an important method of dissipating heat by evaporation. Thus, the ratio of pigs in the dunging area and resting area could be used as an indicator for controlling the climate in the pig environment. The computer vision methodology utilises a learning-based segmentation approach with several features. This approach is used in order to overcome some of the limitations found in a setup using grey-scale information only in this difficult imaging environment, which includes shadows and challenging lighting conditions. Additionally, the method is able to produce probabilities per pixel rather than a hard decision. In order to test practical conditions, a pig pen containing ten young animals was filmed from a top view perspective by an Axis M3006 camera with a resolution of 640×480 in three ten-minute sessions under different lighting conditions. The results indicate that a learning-based method improves on greyscale methods in terms of reliable identification of the ratio. This ratio could be an important feature for use in control climate on the basis of observed pig behaviour. It could also be used to identify boxes where individual pigs may deviate from normal behaviour or location in the box, which may indicate inferior health or acute illness.

Keywords: behaviour analysis, image segmentation, ratio in areas

Introduction

Climate control in pig houses is essential for the welfare of pigs. As pigs lack sweat glands, their thermal regulation in warm temperatures relies on their behaviour of wallowing in mud in order to enhance cooling evaporation from the body surface (Ekesbo, 2011). The microclimate in the animal occupied zone (AOZ) is important for animal welfare and production. Local temperatures in the pig house and pen will fluctuate depending on ventilation, the heat produced by the animals and external temperatures (Hoff *et al.*, 1992; Van Wagenberg *et al.*, 2005).

Normally, pigs have separate areas for dunging and feeding/resting. In Sweden, pens for pigs are required to separate these areas, by contrast to the fully slatted floor pens which dominate in Europe (Mul *et al.*, 2010). Defecation and urination will normally not occur in the lying area (Horsted *et al.*, 2012; Wechsler, 1996) as animals prefer a warm lying area and a cooler area for dunging at normal and cold temperatures (Hacker *et al.*, 1994). However, at warmer temperatures, pigs spend more time in cooler places in the pen, which is usually the dunging area (Botermans and Andersson, 1995). They will also use the lying area for excretion of dung and urine (Ekesbo, 2011), which results in increased fouling of the pen (Aarnink *et al.*, 2006) and impaired animal hygiene.

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The response of the pigs to microclimate changes at different locations in the pen, especially during warm weather, could be used to monitor and control the climate in the pig pen according to the principles of Precision Livestock Farming (PLF) (Berckmans, 2004). This work investigates possible methods of extracting the ratio of pigs in different areas of a pen using video image analysis.

Material and methods

Equipment and video data

Pigs in a pen located at the pig experimental farm site at Odarslöv in south Sweden were recorded. Nine pigs in a pen were filmed in a top down view by installing an Axis M-3006 camera (Lund, Sweden) producing a 640×480 colour mjpeg video (Figure 1A). A manually marked Region Of Interest (ROI) capturing the pen was used (Figure 1B).

Approach and method

A segmentation approach is the natural method of obtaining the information needed to estimate the ratio of pigs in the dunging area (white) and the whole pen area (grey) as a key indicator. Initially we attempted to explore Otsu's method for segmentation, since this has previously been successful in some pig pen scenarios (Kashiha *et al.*, 2014; Otsu, 1979; Ott *et al.*, 2014).

However, we found it had shortcomings for the scenario we intended to use it in (Figure 2C). Reasons for this might be that previous scenarios involved fairly dark background and bright target (i.e. pig) pixels, and that the setup addressed here had brighter non-pig pixels (e.g. straw) as well as more shadows. Additionally, it could be beneficial to determine the probability at each pixel, rather than a hard decision. This led us to seek a learning-based approach for segmentation. Key elements of the learning-based approach will be highlighted in the next section; the interested reader can find further technical details of this segmentation approach in the work by Nilsson *et al.* (2014).

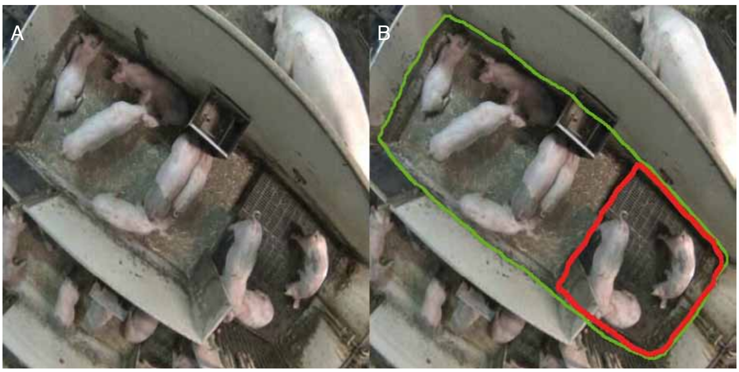

Figure 1. (A) Top-down view of pigs in a pen. (B) Manually marked region of interest for whole pen (grey) and for the dunging area (white).

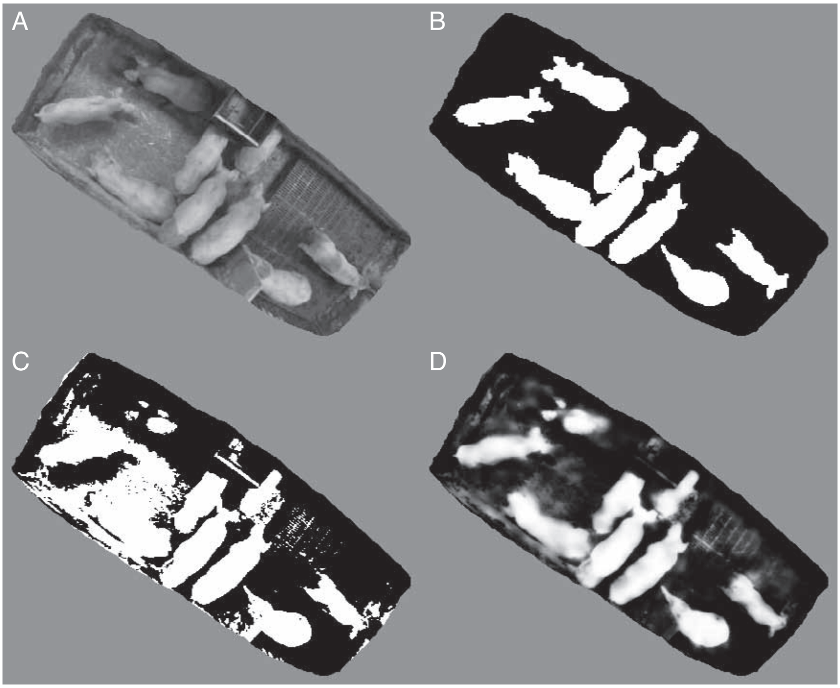

Figure 2. (A) Region Of Interest (ROI) of image. (B) Manual segmentation. (C) Otsu segmentation. (D) Learning-based segmentation with probability result.

Learning-based segmentation and indicator

The learning-based approach utilises ten channels of features (Dollár *et al.*, 2010, 2014) plus two additional channels (Nilsson *et al.*, 2014) (Figure 3). The first ten are values for describing LUV colour space (three channels), normalised gradient magnitude (one channel) and oriented gradients (six channels). The additional two channels are a soft Otsu channel and a max-min filter. The soft Otsu channel will enable the learning framework to use the Otsu result if it finds it suitable. The max-min filter is a complement to the gradient magnitude, and helps to provide information about small (spatial) textures with edges (i.e. straw and other similar backgrounds).

A learning-based framework is applied to these features. A circular area is set with A pixels and all features in this area is used to produce segmentation information. The learning framework utilises elastic net regularised logistic regression as its main learning component (Nilsson, 2014). The method employs a structured prediction approach and maps every area to a new output area of probabilities, and this is repeated for every pixel (Figure 4).

The final result from the learning-based approach is probabilities (Figure 2D), for each pixel in the ROI, see the pen area in Figure 1B. Note that the dunging area is a subset of the total pen. If $p_{i,j}(t)$ is the output probability image, where t is a frame/time index and i, j is a pixel, then two sums can be formed:

$$S_{pen}(t) = \sum_{i,j \in \text{pen ROI}} p_{i,j}(t)$$

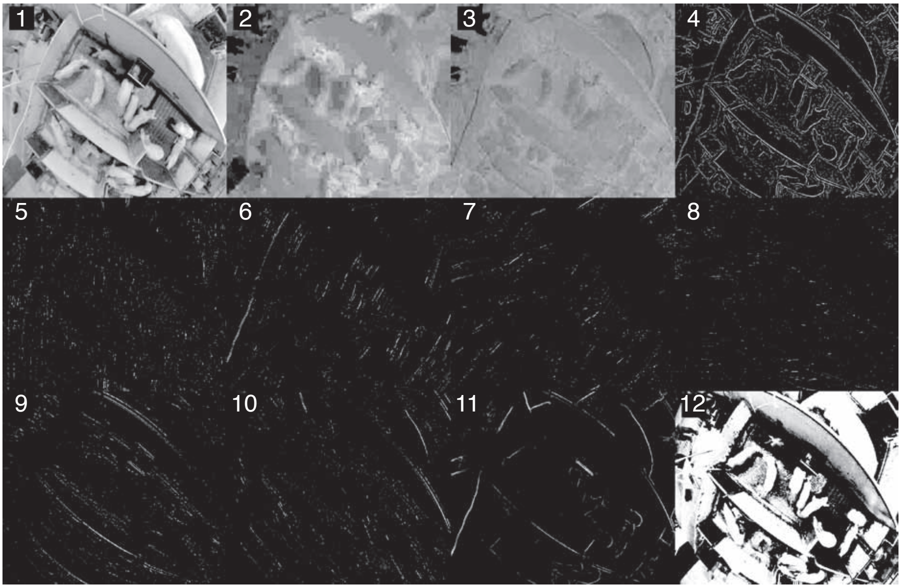

Figure 3. Channel features used. From left to right and top to bottom: LUV colour space (channel 1-3), gradient magnitude (channel 4), six oriented gradients (channel 5-10), max-min filter result (channel 11) and soft Otsu (channel 12).

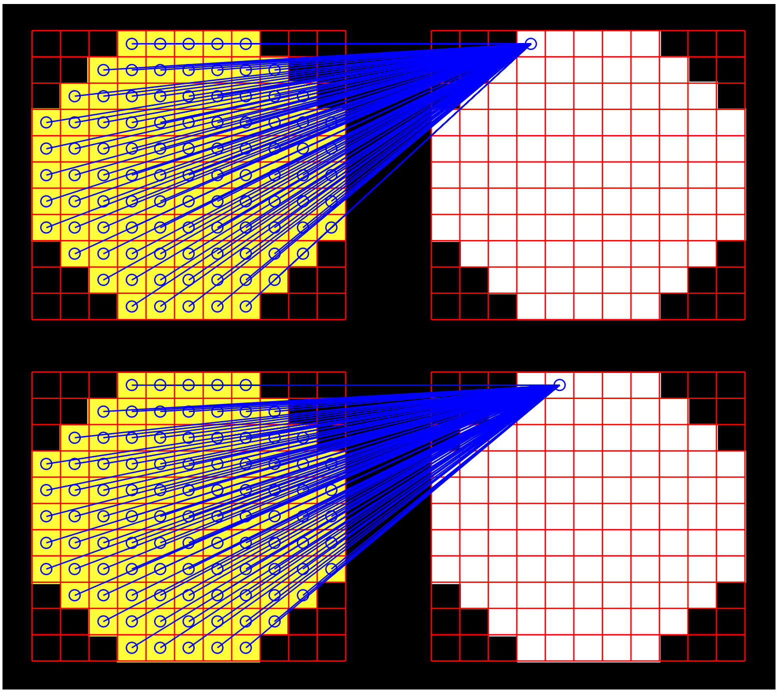

Figure 4. Left position indicates a vector containing all the channels. Right indicates a single output value which will be a probability. Note how one input patch gives rise to outputs equal to the size of the area A.

$$S_{dunging}(t) = \sum_{i,j \in \text{dunging ROI}} p_{i,j}(t).$$

The ratio indicator of interest, here denoted $r(t)$, can now be found:

$$r(t) = \frac{S_{dunging}(t)}{S_{pen}(t) + \varepsilon}$$

where ε is a small numerical value to avoid a possible division by zero.

Results and discussion

Utilising only video and two manually placed ROIs, a ratio can be found using learning-based segmentation. This method enables continuous, automatic identification of the pigs' locations in different parts of the pen (Figure 5).

The learning-based method could reliably find the ratio of pigs in the ROI. An excerpt of about 10 seconds from the recordings (Figure 5.) shows a section when pigs were leaving the dunging area ROI and the response in the ratio. The method also overcame problems encountered with previous greyscale methods where disturbances in the environment, such as straw and shadows, caused problems in producing a probable segmentation. Direct and continuous tracking of the ratio of pigs in different parts of the pen could be an important feature for use in monitoring and control of the climate based on observed pig behaviour, as it has been earlier suggested by Shao and Xin (2008) and for the use as an early warning system for poultry (Kashiha *et al.*, 2013). A further development could be to identify pens where individual pigs may deviate from normal behaviour, or to identify their location in the box, which may indicate inferior health or acute illness. In earlier studies (Kashiha *et al.*, 2013; Oczak *et al.*, 2013; Shao and Xin, 2008) segmentation benefitted from the flooring being uniform and lack of bedding material. Therefore, in studies and applications in these types of animal environments, with varying backgrounds, the approach used in this paper should be beneficial. Thus the proposed method is promising and could be robust, working in many kinds of environments.

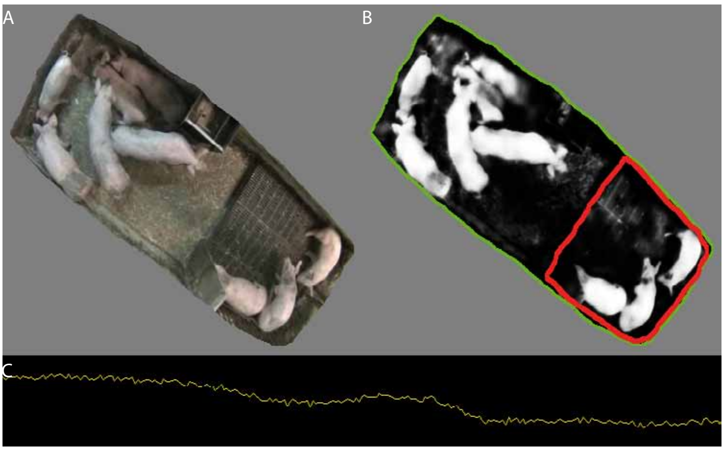

Figure 5. (A) Input image. (B) Segmentation results and the two ROIs. (C) The ratio *r(t)* for ten seconds. Note that in (C) one can see that two pigs have left the red ROI during the latter part of the shown period.

Conclusions

This study has shown that it is possible, using learning-based segmentation, to extract a ratio of pigs in the dunging area. This is a promising development since this ratio is a measure which indicates pig behaviour and could be used as a feature for controlling ventilation. The next steps to be taken in order to fully comprehend the advantages of the technology would be to conduct studies at more sites, take recordings from several pens in a barn, take recordings for longer periods, and link a whole system to an operating ventilation system. Furthermore, the segmentation and ratio extraction framework proposed could also be applied to other species.

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5.7. Discussion: PLF for automatic detection of animal health – poultry and pigs

I. Halachmi[1], A. Schlageter Tello[2], A. Peña Fernández[3], T. van Hertem[3], V. Sibony[1], S. Weyl-Feinstein[1], A. Verbrugge[3], M. Bonneau[4] and R. Neilson[4]*
[1]Agricultural Research Organization, P.O. Box 6, Bet-Dagan 50250, Israel;[2]Livestock Research Wageningen University, P.O. Box 338, 6700 AH Wageningen, the Netherlands; [3]M3-Biores: Measure, Model & Manage Bioresponses, KU Leuven, P.O. Box 2456, 3001 Leuven, Belgium; [4]European Federation of Animal Science (EAAP), Via G. Tomassetti 3, 1/A, 00161 Rome, Italy; halachmi@volcani.agri.gov.il

Preface

This chapter documents the questions and the answers that were expressed during the EU-PLF/EAAP joint-sessions. They were documented verbatim, but each questioner and responder were given the opportunity to rewrite/edit their questions and/or answers for more clarity. This discussion is related to Chapters 5.1. to 5.6.

Discussion

Question: Daniel Berckmans (KU Leuven, Belgium) – What are the main factors involved in the inversely proportional relationship between frequency of the vocalisation sounds and the age of the birds (Chapter 5.3)?

Answer: Emanuela Tullo (University of Milan, Italy) – The main factor for the lowering in the frequency range of the vocalisation sounds as the birds grow is the physiological modification of the Larynx, as in humans. A simple regression approach to the relation frequency-age shows a linear relationship between these two variables. Also it has been found there is a linear relationship with weight as well. All these are going to be further investigated.

Question: Erik Vranken (Fancom, the Netherlands) – How is the difference between sounds determined (Chapter 5.3)? Only using their frequency value or taking into account the human interpretation as well?

Answer: Emanuela Tullo (University of Milan, Italy) – For the work carried out in these research; all the sounds were treated as different from each other. The sounds of similar frequency shape were grouped together and a sample of the different groups of sounds was presented to some farmers. For them it was difficult to give a meaning to all of them, because the farmers are used to the combination of all the sounds in the whole house, not for each of them in an isolated way. Of course, a further investigation could stimulate challenges to the birds and see how they respond to them in terms of vocalisation sounds to establish a real meaning for each sound.

Question: Dries Berckmans (SoundTalks, Belgium) – In the set-up you showed during the presentation (Chapter 5.6), is there a clear separation between the downing area and the clean area of the pen? Do the different batches use the areas in the same way?

Ilan Halachmi (ed.) **Precision livestock farming applications**
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Answer: Anders Herlin (Swedish University of Agricultural Sciences, Sweden) – Although you clean everything each time a new batch is going to arrive, pigs usually choose the same areas for the same activities as the previous batches. This is mainly due to the fact feeding takes place in one part of the pen and pigs will normally not excrete in the lying and feeding area. The pigs generally choose a warmer area for lying and a cooler area for excreting. However, in periods of higher temperatures in the summer, the pigs will prefer the wetter and cooler downing area in order to be able to control body temperature.

Question: Elizabeth Magowan (AFBI, UK) – Has anybody tried to get the cost of implementing some of these systems for pigs?

Answer: Jarissa Maselyne (ILVO/KU Leuven Belgium) – A batch of RFID can be re-used for experimental purposes, which make them really affordable, but for their implementation in a real farm their price should lower to 0.50 € each or so. The main expense depends on how many antennas you need to use, according to the number of feeders and nipples you want to monitor, but you can link several antennas to only one reader so this would be a fixed cost. Reducing the cost of RFID systems is something which the RFID industry is working on nowadays, but will depend mainly on the demand.

Question: Hans Spoolder (Wageningen UR Livestock Research, the Netherlands) – Some things cease to be expensive as soon as their benefits are proven to overcome the initial investment. Did anyone calculate the benefits in euros for some of these PLF technologies?

Answer: Martijn Hemeryck (Soundtalks, Belgium) – In the case of our company (SoundTalks), we can monitor several animals with only one microphone. In my presentation, I've showed real-life results for three different batches. The first case compares two simultaneously occurring batches on the same farm in different compartments. Both batches have an increase in cough index in the beginning that can be attributed to the environmental change the piglets undergo when being moved to the fattening unit; one of the batches also shows a clear increase near the end. The second case shows the results of a batch with a given baseline level of cough index over the main portion of the batch and a relative big increase near the end. The third case gives the cough index for a batch with a temporary failure of the ventilation. Three weeks after the failure the effect on the cough index was still apparent. The three cases show the effectiveness of the PCM (Pig Cough Monitor) in a practical setup. Of course further analysis of these kinds of uses of PLF technology should be studied to be able to translate the benefits you obtain into euros.

Question: Simon Lague (Fancom, the Netherlands) – EU-PLF project is trying to show the benefits of PLF technology in terms of production efficiency. In your presentations, you are implying that there are also benefits in terms of welfare using PLF technology. Could this open the way for a new approach on how to set a place for PLF technology in the market showing not only benefits for the farmer but also for the retailers?

Answer: Andy Butterworth (University of Bristol, UK) – The retailers are of course interested in farmers being able to follow the key indicators to achieve good welfare conditions for the animals because it is translated into, normally, better product quality. Probably they, the retailers, would not be directly interested in taking part in the necessary investment in the farm itself but some benefits for the farmers can be set, such as price premium qualifications if they are farm assured or certified, or if their animals are well monitored using PLF technology for example. Anyway, this may be something difficult to get in a short term, but in the long term there are great opportunities.

Question: Daniel Berckmans (KU Leuven, Belgium) – In research, most of the money nowadays goes to labelling. This is the way to get the meaning to the signal we want to trace automatically. The idea of involving the farmers in this is great, but how can the farmer do that exactly?

Answer: Andy Butterworth (University of Bristol, UK) and Emanuela Tullo (University of Milan, Italy) – We understand the labelling as a tool for giving a meaning to the scientific information we are gathering. In our study we were able to characterise 12 different sounds using labelling. Once this is done our aim is to automate the detection of these sounds for the future. Labelling is a critical stage but does not have to go on forever, thanks to the use of PLF technology. In relation to the farmers, they can provide a lot of information by giving the right 'behavioural' meaning to the different sounds and activities we are studying, so we must involve them in it. The EU-PLF project provides the possibility to engage the farmers by showing them all the information that it has gathered and decide what they perceive as important and useful.

Question: Daniel Berckmans (KU Leuven, Belgium) – Do you not still need classical labelling for developing the detection algorithm?

Answer: Emanuela Tullo (University of Milan, Italy) – Nowadays, you need the labelling as your gold standard, but maybe some kind of artificial intelligence can be developed to simulate the results gotten by the labelling.

Question: Vasileios Exadaktylos (KU Leuven, Belgium) – There are discrepancies between the implementations of the EU directives among the different countries. What is the reason for this?

Answer: Andy Butterworth (University of Bristol, UK) – The EU directives set a range of measures that help each country to be able to set the thresholds, but each country has the freedom to decide to which extent they use the results from these directives.

Part 6. Precision livestock farming for automatic detection of animal health in cows

6.1. Monitoring the body temperature of cows and calves with a video-based infrared thermography camera

G. Hoffmann and M. Schmidt*
Department of Engineering for Livestock Management, Leibniz Institute for Agricultural Engineering Potsdam-Bornim, Max-Eyth-Allee 100, 14469 Potsdam, Germany; ghoffmann@atb-potsdam.de

Abstract

In this study a video-based infrared camera (IRC) was investigated as a tool to monitor the body temperature of cows and calves. Body surface temperatures were measured by contactless methods using videos from an IRC fixed in the automatic milking system (cows) or calf feeder (calves). The body surface temperatures in two larger areas referred to as the head (before the forehead) and body area (behind the forehead) were subsequently analysed. The rectal temperature served as the reference temperature and was measured with a digital thermometer at the corresponding time point. Altogether, 10 milking cows (Holstein-Friesians, 3 to 9 years of age) and 9 calves (Holstein-Friesians, 8 to 35 weeks old) were examined. The range between the minimum and maximum temperature in the two abovementioned areas was large (between 1.6 and 2.7 Kelvin), and many outliers were found. However, the maximum temperatures measured by IRC in the head and body area increased with an increase in rectal temperature in cows and calves. Ongoing investigations are taking place in order to define algorithms and reference values. Advances in the IRC mean that more than one picture per animal can be analysed in a short period of time in contrast to single picture cameras. Therefore, this system shows potential as an indicator tool for continuous temperature measurements in cattle.

Keywords: contactless, health control, hyperthermia, non-invasive

Introduction

One of the most important disease indicators in livestock production is the rectal temperature. The procedure itself is, however, time consuming and requires direct contact with animals. In contrast, infrared thermography represents a non-invasive, contactless method of measuring the body temperature in livestock.

Although measuring the rectal temperature is a common method used by veterinarians and farmers, it also has limitations. Investigations showed that the technique employed when using the digital thermometer and thermometer type can also have an effect on rectal temperature measurements (Burfeind *et al.*, 2010; Naylor *et al.*, 2012).

Other technologies have already been developed to continuously record the body temperature in cattle, e.g. rumen temperature boluses (Rose-Dye *et al.*, 2011) and subcutaneous implanted transmitters (Georg *et al.*, 2009). These methods seemed to be promising, but are all invasive and more applicable to research farms.

Recent studies have already shown that infrared thermography may be a useful tool for analysing animal stress and welfare (Stewart *et al.*, 2005), and that it seems to be promising as an early

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detection method for mastitis if coupled with environmental temperature monitoring (Berry *et al.*, 2003). Investigations with calves have already shown that infrared thermal measurements can be used to develop an early prediction index for infection, and that orbital temperatures displayed the earliest and most consistent increases in temperature (Schaefer *et al.*, 2004). Infrared thermography can also be used for detection of foot-and-mouth disease virus by measuring the foot temperatures of cattle (Rainwater-Lovett *et al.*, 2009). The authors of this study found moderate positive correlations between maximum foot temperatures and both rectal and eye temperature as well as between rectal and eye temperatures, but they also reported that a potential limitation of this technology is the cost of the infrared cameras used in their study (Rainwater-Lovett *et al.*, 2009). In a further study it was reported that, using IR measurement, fever could be detected at the eye in ponies with a sensitivity of 74.6% (Johnson *et al.*, 2011). When influencing factors such as climate, circadian rhythms or surface dirt are considered in the analysis of the measurement results, the results indicate that IR thermography certainly offers an option for early recognition of temperature increases and therefore of diseases (Knížková *et al.*, 2007).

All previous studies used infrared thermography cameras which only used single images for temperature detection. The present study is, to our knowledge, the first investigation which uses a thermographic video camera to measure cattle temperatures, which enables us to obtain more images for evaluation. Therefore the aim of this study was to establish whether an infrared thermography camera can be used to detect body temperature in cows and calves. This would be a fast and non-invasive method, which can be installed in a barn (e.g. in the milking or feeding system) in order to measure the body temperature of every animal daily, automatically and continuously.

Animals, materials and methods

The study was carried out at a dairy barn in Brandenburg (Germany). Altogether, ten milking cows (Holstein-Friesians between 3 and 9 years of age) and nine calves (Holstein-Friesians, 8 to 35 weeks old) were used. Skin temperature was recorded with a portable IR camera OPTRIS® PI 160 (Optris, Berlin, Germany) in the form of infrared thermography videos. The infrared camera (IRC) featured a temperature range from -20 to 900 °C with a resolution of 0.1 °C, a spectral range from 7.5 to 13 μm and a sensitivity of 0.08 K. The detector provided an optical resolution of 160×120 pixels. The emissivity was adjusted to 0.985. The videos were recorded at 9 frames per second, and the duration of the video was about 8 to 16 minutes per cow and approximately 5 minutes per calf. The camera was fixed at a specific location near to the animals so that measurements could be taken with an almost constant distance and angle of measurement between the IRC lens and the body surface. For the measurements on cows, the camera was placed sideways in front of an automatic milking system to film the head and front part of the cows during the milking process. In the calf barn, the camera was placed sideways to the automatic calf feeder to film the head and back of the calves while they were drinking. The advantage of this experimental setup was that it provided a defined distance (approximately 100 cm to the head of the animals) between the camera lens and the body surface. A plate with a reference temperature (pre-set to 40.0 °C) was installed and served as a comparison value for the IRC.

For temperature analysis, every video was viewed again later (using the software PI Connect 2.0.2009.0, Optris, Berlin, Germany). Two main areas of the animals (body and head) were defined for analysis of these videos. For the cows, one area included the entire visible part of the body, and the second area was limited to the head area in front of the ears (Figure 1). For the calves, the first area included the part of the body caudal to the forehead, including the ears.

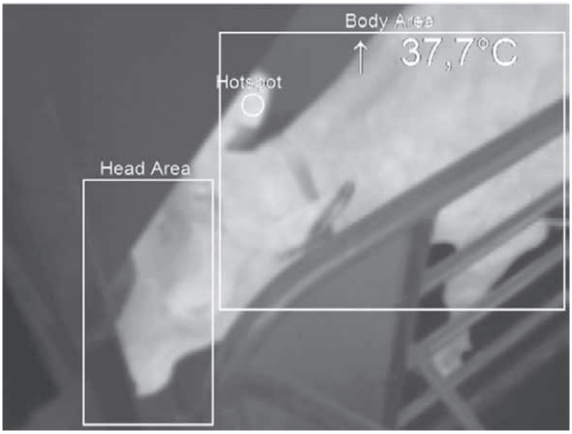

Figure 1. Infrared image of a cow in the automatic milking system showing the measuring areas defined.

The second area included the part of the head in front of the ears. While playing these videos, the software saved the maximum temperature (hot spots) of both main areas from each video picture. The 10 highest values for each animal and each main area were chosen for use in the subsequent statistical analysis.

A digital thermometer (ApoNorm®, Hillscheid, Germany) was used to measure the rectal temperature (REC) of every cow and calf at the beginning of every thermography recording. The REC served as a reference temperature. The measurement range of the thermometer was from 32.0 to 43.9 °C with an accuracy of ±0.1 °C and a resolution of 0.1 °C. The rectal temperature was always measured at the same insertion depth (8 cm) to minimise bias due to the measuring process (Burfeind *et al.*, 2010).

The statistical analysis was performed using SAS 9.2 (SAS Institute Inc. Cary, NC, USA). The data were investigated descriptively by body surface temperature (IRC) and corresponding rectal temperature (REC) using box-and-whisker plots. Values that were more than 1.5 interquartile ranges above the 75%-quartile or 1.5 interquartile ranges below the 25%-quartile were considered as outliers in the box-and-whisker plots.

Differences between body regions were investigated using mixed linear models. Fixed effects were the method of temperature measurement (IRC, REC) and body region as well as interaction between both, where applicable, while the animal effect was considered to be random. Degrees of freedom for the F-Tests were calculated by the Kenward-Roger method. In pair-wise comparisons of fixed effect levels, adjusted *P*-values for multiple testing were computed from a simulation of the true 95% confidence interval. The significance level for all tests was set at 5%.

The method described by Bland and Altman (1999) was used to compare IRC and REC temperatures.

Results

Earlier analyses as part of this study had already shown that the IRC temperatures of the cows and calves have a very large range overall. The IRC temperatures of the cows were between 36.0 and 38.7°C (range: 2.7 K) in the body area and between 35.5 and 37.5 °C (range: 2.0 K) in the head area, and in the calves between 36.4 and 38.2 °C (range: 1.8 K) as well as between 36.8 and 38.4°C (range: 1.6 K), respectively. Therefore, it is important to focus on the individual relationship between the reference temperature and the IRC temperature for every animal.

Measurements of the body surface temperatures of the cows showed that the IRC temperature in both the body and head areas increased when REC rose to temperatures up to 38.7 °C (Figure 2). When the REC neared the upper limit (>38.7 °C), the IRC temperatures decreased. However, the maximum temperature of the entire body area (mean ± standard deviation: 37.3±0.8 °C) was always significantly higher (*P*<0.001) than the maximum temperature of the head area (36.5±0.7 °C). Viewing the video clips of the cows showed that the hot spots in most cases were located at the back of the ear (body area) and the region of the eye (head area).

In contrast to the cows, the mean temperature in the head area of the calves (mean ± standard deviation: 37.5±0.4 °C) was higher (significant for REC≤38.7 °C, not significant for REC≥38.9 °C) than the mean of the body area temperatures (37.2±0.5 °C). A tendency for the IRC temperatures to increase with increasing REC was also observed in the calves in both the body area and the head area (Figure 3). The videos of the calves showed that the hot spots in the head area in most of these cases were located at the medial or lateral angle of the eye. The hot spots in the body area were mostly located at the back of the ear.

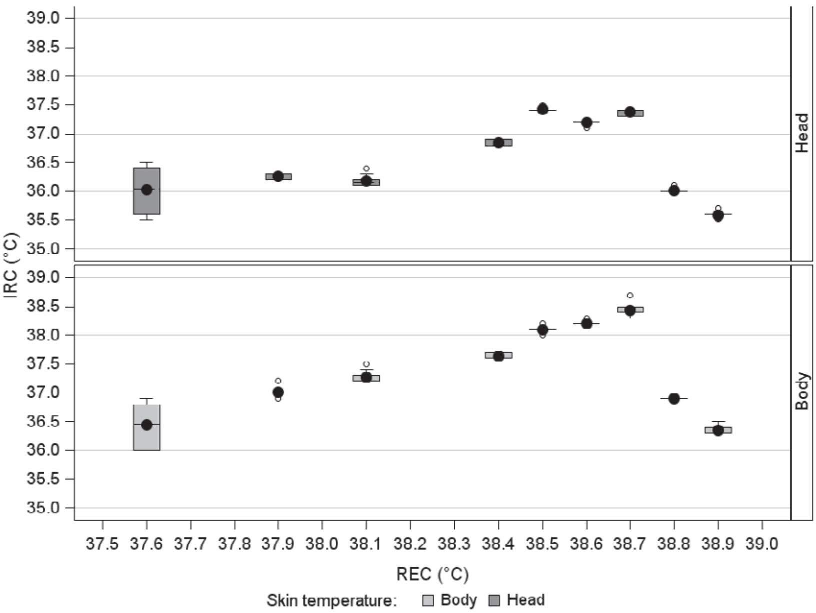

Figure 2. Relationship between rectal temperature (REC) and body surface temperature (IRC), measured in the head and body area of cows (n=10).

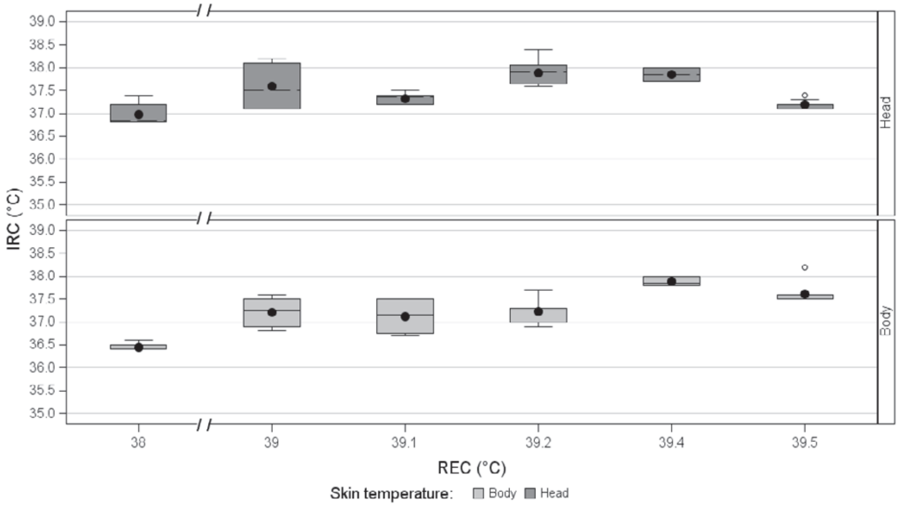

Figure 3. Relationship between rectal temperature (REC) and body surface temperature (IRC), measured in the head and body area of calves (n=9).

The Bland-Altman plot for REC-IRC differences and arithmetic means demonstrated that most values were within the 95% limit of agreement, in both the body area and the head area. However, the individual temperature differences for the cows showed a larger range for the 95% confidence interval than the individual temperature differences for the calves. The temperature differences for the body area of the calves were closer to the arithmetic mean than the temperature differences for the head area (Figure 4).

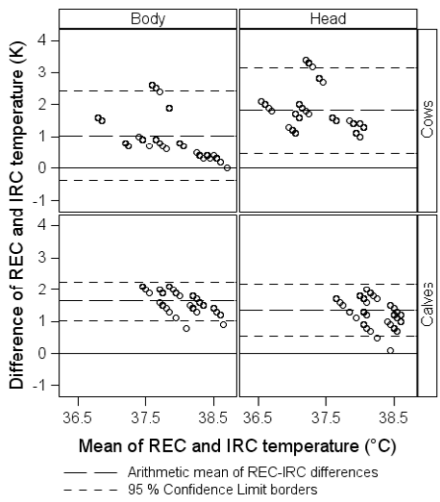

Figure 4. Bland-Altman plot of the values from the infrared camera (IRC) compared to the rectal temperature (REC) (10 cows, 9 calves).

Discussion

Measuring the rectal temperature with a digital thermometer is still deemed to be the best method of recording the temperature of animals. However, this method requires direct contact with the animals and is time-consuming. Moreover, the technique itself, the penetration depth and the thermometer type can affect the measured values as previously described (Burfeind *et al.*, 2010; Naylor *et al.*, 2012). Therefore, an automatic method would reduce stress for the animals and save time for the farmer. Thus, the objective of the present study was to evaluate whether an IRC can be used to monitor the temperature of cows and calves because the IRC does not require contact with the animals and can be used on many animals at the same time. Furthermore, it may be able to provide real-time data, which is of great value for automatic detection of different physiological conditions in cows and calves (i.e. infectious diseases, parturition, oestrus).

In a recent Canadian study, the orbital region (eye plus 1 cm surrounding the eye) was used to detect calves with bovine respiratory diseases (Schaefer *et al.*, 2012). In that study, an infrared camera taking single pictures was installed at a fixed position near a calf watering system, similar to our study design. The researchers used the system to identify true positive and true negative animals from calves at risk of respiratory disease. Similar to the findings of our study, these researchers also advocated fixed installation of the infrared system and the use of a contactless method that does not disturb the animals.

Other previous studies have shown that infrared thermal measurements can be used as an early prediction system for infections in humans (Chiang *et al.*, 2008; Ng *et al.*, 2004), cattle (Rainwater-Lovett *et al.*, 2009; Schaefer *et al.*, 2004, 2012) and ponies (Johnson *et al.*, 2011). The disadvantages of these previously used camera systems included variability caused by hand-held devices and measurements based on single images. Therefore, it is important to ensure that the camera is located in a suitable position to capture data from the correct body region of the animal. This method also requires software or a person to analyse the pictures. The present study uses a thermographic video camera to measure the body surface temperatures of cows and calves. The advantage is that this method provides a large number of pictures per animal in a short period of time. This type of camera has already been used in a study of sows, where the IRC was compared with an infrared thermometer. The authors concluded that the eye and back of the ear were promising locations in terms of practicability and that the potential to use infrared techniques to detect an increase in the skin temperature appears promising (Schmidt *et al.*, 2013). This is confirmed by the present study. The results showed that it is possible to measure the infrared temperatures of body surfaces continuously with an IRC which saves the data as a video. However, there was a large range between the minimum and maximum temperatures for the regions, and many outliers were found. In order to obtain more reliable results with smaller temperature ranges, the study was conducted with the aim of maintaining a constant distance between the IRC and the body surface. The fixed position of the IRC, the use of a plate with a reference temperature, and the selection of the 10 highest values within the duration of each video recording (about 5 to 16 minutes) produced reliable results. Therefore, we agree with Johnson *et al.* (2011), who concluded in their study on ponies that the use of infrared thermography as a screening tool for febrile status may function best by collecting several rapid readings and then using the maximum temperature. However, in contrast to their preferred measuring point at the eye, the present study showed that it is sufficient to define an area around the body or head of the animal, and to determine the hottest point (hottest pixel of the video picture) in these areas, which can easily be done using a software program. So, for practical reasons, the head is a promising body region. However, besides the camera mounting system, other influencing factors such as animal parameters (coat, metabolism, etc.) and climatic conditions must be taken into account, as also mentioned by Knížková *et al.* (2007).

The results from our study showed that for the cows, when the REC temperatures neared the upper limit (>38.7 °C), the IRC temperatures were lower than those for lower REC temperatures. The reason could be a physiological reaction by the body when it is trying to cool down the body temperature via the skin as a method of regulation. Further research is necessary in order to find an explanation for this result.

The IRC temperatures for calves that were measured in the body area showed a higher level of precision than the IRC temperatures measured in the head area. Thus, the body area would be preferable for further investigations of the IRC temperature of calves. The body and head area of cows are equally suitable for IRC temperature measurements. However, the Bland-Altman plot also showed that, due to the lack of agreement between the IRC temperatures and the reference temperatures (REC), there might be difficulties in determining differences in body temperature in clinically unremarkable cows and calves. Studies on rabbits have already concluded that rectal measurements cannot be replaced in clinically unremarkable animals (Chen and White, 2006).

Therefore, it is important to evaluate febrile cows and calves in further studies in order to identify the individual changes in IRC temperature. The approach is to measure relative differences between one current measurement and the mean of previous measurements (normal temperature). A critical temperature difference must thus be defined in order to produce an automatic system with an alarm function. Therefore, the IRC must also be combined with an animal identification system at the milking or feeding station and with associated computer software. For early detection of a febrile animal, it would be essential for every animal to serve as its own control, as also noted by Schaefer *et al.* (2004).

Conclusions

The use of infrared thermography videos has the advantage of analysing more than one picture per animal. Additionally, it is possible to define special body areas and to use the maximum temperatures from each video image and body area. Infrared thermography videos might have the potential to serve as a monitoring system for body temperature in cows and calves.

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6.2. Early detection of metabolic disorders in dairy cows by using sensor data

R.M. de Mol[1], J. van Dijk[1], M.H. Troost[2], A. Sterk[3], R. Jorritsma[4] and P.H. Hogewerf[1]*
[1]Wageningen UR Livestock Research, P.O. Box 338, 6700 AH Wageningen, the Netherlands; [2]Rovecom, Elbe 2, 7908 HB Hoogeveen, the Netherlands; [3]Agrifirm, Landgoedlaan 20, 7325 AW Apeldoorn, the Netherlands; [4]Utrecht University, Yalelaan 7, 3584 CL Utrecht, the Netherlands; rudi.demol@wur.nl

Abstract

The transition period is a crucial period for the dairy cow. A negative energy balance results in an increased risk of metabolic disorders such as milk fever, ketosis and left displaced abomasum. Detection of these metabolic diseases may be improved by using sensors. The Dutch Smart Dairy Farming project has examined the potential of sensor systems. A detection model has been developed and tested. Sensors were installed on a practical dairy farm (300 cows, automatic milking system) for automated measurement of milk yield, milk composition (fat, protein), visits to the milking robot (rewarded and unrewarded), concentrate intake, visits to the concentrate feeder (rewarded and unrewarded), activity, rumination activity and body weight. It is known from the literature that most of these variables are influenced by metabolic disorders. Sensor measurements were aggregated to the daily level and used in the detection model to generate three types of alert: (1) level alert: the value was outside a confidence interval (based on a moving average and standard deviation for preceding values), or (2) trend alert: the change in successive values was different from what might be expected, or (3) index alert: given on specific days, such as the day of calving, in several situations, e.g. when the weight loss was much higher than average weight loss. An alert for metabolic disorder was generated when the number of alerts exceeded a predefined threshold. These metabolic alerts were compared with the reference data to estimate the model performance. The results from the detection model (sensitivity and specificity) depended on the model settings. The results confirmed the potential of a model-based approach for the detection of cows suffering from a metabolic disorder. However, it was difficult to reach an appropriate specificity level (99% or higher). Selecting a smart combination of variables could improve the results.

Keywords: detection model, transition period, sensitivity, specificity

Introduction

The transition period, in this study defined as the period between the start of the dry-off period until the sixtieth day of the new lactation, is a challenging period for the dairy cow. During early lactation, energy intake is usually lower than the energy requirement for milk production (which is high in early lactation) and maintenance. This results in a negative energy balance (De Vries *et al.*, 1999; Tamminga *et al.*, 1997; Van Knegsel *et al.*, 2007). The negative energy balance is associated with an increased risk of health disorders such as milk fever, ketosis and left displaced abomasum, which are often interrelated (Bigras-Poulin *et al.*, 1990; Ingvartsen, 2006; Ingvartsen and Moyes, 2013; Roche *et al.*, 2013).

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Cows are therefore at risk during the transition period and should be monitored closely. Due to increasing dairy farm sizes, however, farmers have less human-animal interaction and less time available per cow to observe abnormalities and potential health problems such as metabolic disorders (De Mol *et al.*, 2013; Gonzalez *et al.*, 2008; Mottram, 1997). Since sensors can gather a wide range of data from ongoing processes, sensor data can assist the farmer in his daily management by detecting changes, e.g. in level of activity and feeding behaviour, at an early stage (Gonzalez *et al.*, 2008; Van Asseldonk *et al.*, 1999). Raw data, however, is of limited value to farmers. It is important to develop models which can collect and process data in a way which provides farmers with practical management support (Berckmans, 2008; Frost *et al.*, 1997).

This study was carried out as part of the Smart Dairy Farming project. The aim of this project is to help the dairy farmer with management by developing models which convert data into practical information: alerts for cows which are probably ill or alerts for the whole herd, e.g. change of diet. This is done in order to increase the productivity and lifetime of dairy cows.

A literature study was conducted to investigate whether changes in the variables milk yield, feed intake, visits to the feeding stations, number of feedings, rumination activity, activity and body weight could be used for detection of the abovementioned metabolic disorders. The aim of this research is to build a model which can detect cows that are suffering from a metabolic disorder at an early stage. Early identification of metabolic disorders can be very helpful since treatment is generally more effective if applied early in the disease process (Soriani *et al.*, 2013). The model structure and the results found on a practical farm are presented in this paper.

Material and methods

Literature study

The causes and symptoms of metabolic disorders, as well as the applicability of sensor data in detection, were investigated in a literature search (Van Dijk, unpublished data). Milk fever (parturient hypocalcaemia) is a severe decline in blood Ca concentration around the time of calving, usually in the 24 hours after calving. A cow is suffering from ketosis if there is an excessive accumulation of ketone bodies in the blood. In the case of a left displaced abomasum (LDA), the abomasum is filled with gas and floating in the dorsal part of the abdomen; as a result, the feed passage to the intestines is partly or totally blocked.

Feed intake and rumination activity seem good indicators of milk fever. Feed intake, in particular, seems an early indicator. It seems that milk yield is not a good indicator due to the contrasting results reported. Days in milk (DIM) at diagnosis is 1 (±0.0). This is in accordance with other literature which reports that milk fever mainly occurs in the 24 hours after calving (DeGaris and Lean, 2009; Oetzel 2013; Roche and Berry, 2006).

For ketosis, all variables exhibit differences, at least on the day of diagnosis. However, for milk yield and feed intake, declines are already reported 28 days prior to diagnosis. For body weight, differences were reported seven days prior to diagnosis. 25.5 (±7.4) DIM was calculated as the average point of diagnosis, with the first case of ketosis at 16 DIM and the latest at 34 DIM. This is in accordance with other literature where it is reported that ketosis is mainly seen in the first eight weeks and especially in the first month of lactation (Andersson 1988; Baird, 1982; Ingvartsen, 2006).

For LDA, differences in milk yield, feed intake and body weight are reported on the day of diagnosis. However, changes in feed intake and body weight are already seen 14 days prior to diagnosis. Reduced milk yield is even reported 21 days prior to the day of diagnosis. 23.8 (±8.0) DIM was calculated, with the first case of LDA at 4 DIM and latest at 38 DIM. This is in accordance with other literature, which identifies the first month after calving as the major risk period (Cameron *et al.*, 1998; LeBlanc *et al.*, 2005).

It was found that changes in milk yield and feed intake, in particular, have been studied more (13 and 9 studies respectively) than changes in rumination activity, body weight and activity. Moreover, changes in feed intake and milk yield seem to be very suitable indicators of ketosis and LDA even several weeks prior to actual diagnosis. Changes in body weight have been studied less but also seem to be highly suitable. Almost all variables show a significant difference on the day of diagnosis, but milk fever seems to be particularly hard to predict prior to diagnosis. Ketosis and LDA seem to be more predictable.

Data collection

The data used for this study were collected on a commercial farm located in Koudum, Friesland (the Netherlands). Approximately 300 Holstein Frisian cows were milked on this farm, with an average milk yield of 9,017 kg/year with 4.3% fat and 3.6% protein. The cows were housed in a free-stall barn with individual cubicles. There were rubber strips on the concrete slatted floor. Cows were housed in two groups and milked by four automatic milking systems (AMS) (Lely, Maassluis, the Netherlands). Cows were allocated to a group depending on the AMS capacity, irrespective of lactation stage. During the summer cows could go outside to a small pasture with a heap of sand (to play with) and a pond (for refreshment).

Lactating cows were fed a complete diet *ad libitum* in the barn, including fresh grass in summer. Concentrates were provided in the AMS and in the concentrate feeders (Lely, Maassluis, The Netherlands). The amount of concentrates allowed per cow was set in accordance with a lactation scheme. Drinking water was available *ad libitum*.

The data collection period extended from January 2013 to March 2014. An overview of the available sensor data is shown in Table 1. All data were obtained per cow and measured automatically. The data had to be pre-processed in order to make it more applicable. First, some data had to be deleted due to its unreliability. All remaining data were converted into values per day per cow by interpolating, calculating an average or summing up. This was done either in the Microsoft Access database or in GenSat (sixteenth edition, VSN International Ltd). In addition to these variables, reference data were also available. Reference data included calving, transfer, disease, preventive actions, curative actions, drying off, in heat, insemination and pregnancy checks. These were recorded in the management system by the farmer and herd manager. All data were collected by TNO (Dutch Organization for Applied Scientific Research) and combined weekly in a Microsoft Access database (Microsoft, Redmond, WA, USA).

There were 326 lactations during the data collection period. During these lactations, 34 metabolic cases were recorded. Of these 34 cases, 25 were diagnosed as milk fever, 7 as ketosis and 2 as 'others'. A cow was diagnosed as suffering from a metabolic disorder if treated for it by the farmer, herd manager or veterinarian. If a cow was recorded as suffering from a metabolic disorder during the two days after a previous recording of a metabolic disorder, this second recording was not classified as a new case. This reduced the number of cases to 20 (milk fever), 5 (ketosis) and 1 (others).

Table 1. Sensor variables used in the research, the measurement unit (after aggregation to daily level) and the measurement method (all equipment supplied by Lely, Maassluis, the Netherlands).

Variable	Unit	Measurement method[1]
Milk yield	kg/day	AMS
Milk fat	percentage (per milking)	AMS
Milk protein	percentage (per milking)	AMS
Milking visits	number of rewarded visits per day	AMS
Concentrate intake	kg/day	AMS/concentrate feeder
Concentrates leftover	kg/day	AMS/concentrate feeder
Feedings	number of rewarded visits per day	AMS/concentrate feeder
Feeding visits	number of rewarded/unrewarded visits per day	AMS/concentrate feeder
Activity	-/day	collar sensor
Rumination activity	minutes/day	collar sensor
Body weight	kg	AMS/concentrate feeder

[1] AMS = automatic milking system.

Model formulation

The aim of this research was to convert the sensor data described above into practical information, i.e. alerts for the farmer which can be used in standard operating procedures (SOPs). Alerts were assigned to three categories (a summary is presented in Table 2):

1. Level alerts. Level alerts were related to daily values. A level alert was generated if a daily value differed from the expected value. This was done by first calculating a moving average and a confidence interval based on the standard deviation with an upper and lower limit for all indicators per cow. The trend for milk yield and body weight is also included. The time span used to calculate the moving average and standard deviation was seven days in the case of milk yield, visits to the AMS, concentrate intake and left over, feed visits and feedings, and fourteen days for activity, rumination and body weight. A distinction was made between outliers on one day and outliers on two successive days. The level alert for fat and protein was calculated differently: a ketosis alert was generated if the difference between fat percentage and protein percentage exceeded 1.5% and if at the same time the protein percentage was less than 3.25% (CRV, 2011).
2. Trend alerts. In order to detect values (trends) which were gradually decreasing in the opposite direction to that which would be desired or expected, trend alerts were calculated for milk yield and body weight. To calculate a trend, the difference between two successive days was first calculated. The moving average of this difference was calculated. For each variable, the number of days used to calculate this moving average was the same as that used for level alerts. A distinction between a one-day outlier and successive outliers was also made here. A trend alert was given when the trend was less than -1 in the first 28 days in lactation; a body weight alert was given when the trend was less than -10 in the first 80 days of lactation.
3. Index alerts. Index alerts were generated to detect cows at risk during the transition period. For activity and rumination, this occurred when the level on the day of calving was too high, and for body weight if it was too deviant at the start of the dry period or at the end of the dry period.

The dataset was not always complete due to malfunctioning or broken sensors.

Alerts were combined in two ways:

1. SumAlert. The number of alerts per day per cow was summed up. A SumAlert was consequently generated if the sum of that day exceeded a certain threshold value.
2. SmartSumAlert. some indicators were classified as more important and an alert for these indicators alone was sufficient to generate an alert. The variables used for these SmartSumAlerts were selected on the basis of their performance with respect to sensitivity and specificity, derived from results from the models and from literature. The selected alerts (bold in Table 2) were: milk yield, activity, rumination activity, visits feeding, concentrates leftover, double weight decline start lactation and activity day of calving.

Each case was either true positive (TP: one or more alerts generated) or false negative (FN: no alerts). Each healthy day was either true negative (TN: no alert) or false positive (FP: an alert generated). The performance of the model was expressed as sensitivity (percentage of detected cases: TP/(TP+FN)) and specificity (percentage of healthy days classified as such: TN/(TN+FP)).

Several settings were applied to the confidence intervals used to generate alerts, corresponding to 90%, 95 and 99% confidence. Different periods for which alerts were considered to be TP were also used, ranging from zero to fourteen days before diagnosis.

In order to be usable in practice, it was desirable for the results to have a specificity of at least 99%.

Results

The performance of all alerts generated using a Z-value of 1.96 and a five-day period is shown in Table 2. The same results are presented in Figure 1 as a receiver-operating-characteristic (ROC) plot where the false positive rate (100-specificity) on the x-axis is plotted against the sensitivity on the y-axis. In an ROC plot, a usable variable is located in the upper left triangle. Perfect classification is represented at a point (0,100), since in that case sensitivity and specificity are both 100% (Fawcett, 2006). The best performing alerts (due to their high sensitivity and specificity) are activity, activity day of calving, rumination activity, weight decline start lactation and alerts related to concentrates (visits feeding, number of feedings and concentrates left over).

The alerts were combined in SumAlerts and in SmartSumAlerts. The results for different sums and periods are shown in Table 3 and Figure 2 (all for Z-value 1.96). In general a larger number results in a lower sensitivity (and higher specificity), and a longer period results in higher sensitivity (with minor effects on specificity).

Discussion

A great variation was found in the performance of single alerts, indicating that some variables are more useful for detection of metabolic disorders. For all variables, nevertheless, most of the double alerts (where the daily value has to exceed the confidence interval on two successive days) seemed to be of limited use due to their low sensitivity.

In the literature, reduced milk yield is found to be a good indicator for ketosis and LDA. This was different in the current research. This was probably caused by the fact that 20 out of the 26 metabolic cases were diagnosed as milk fever, occurring in the first days of lactation when milk yield data were not yet available.

Table 2. Summary of alerts (alerts in bold are included in SmartSumAlerts) and performance for detection of metabolic disorders using a Z-value of 1.96 with a five-day period.

Alert type	Alert name	Name in Figure 1	Sensitivity (%)	Specificity (%)	100-specificity (%)
level	**Milk yield**	m1	13.3	97.07	2.93
level	Double milk yield	m2	0	99.78	0.22
level	Visits milking	v1	0	98.88	1.12
level	Double visits milking	v2	0	99.94	0.06
level	Ketosis	k	9.1	99.87	0.13
level	Concentrates intake	c1	38.1	97.60	2.40
level	Double concentrates intake	c2	0	99.73	0.27
level	**Visits feedings**	f1	79.0	95.34	4.66
level	Double visits feeding	f2	27.8	99.41	0.59
level	Number of feedings	n1	79.0	94.51	5.49
level	Double number of feedings	n2	33.3	99.29	0.71
level	**Concentrates leftover**	l1	79.0	96.51	3.49
level	Double concentrates leftover	l2	22.2	99.69	0.31
level	**Activity**	a1	85.7	97.01	2.99
level	Double activity	a2	35.7	99.56	0.44
level	**Rumination activity**	r1	61.5	92.27	7.73
level	Double rumination activity	r2	7.7	98.64	1.36
level	Body weight	b1	11.1	99.48	0.52
level	Double body weight	b2	0	99.93	0.07
trend	Milk decline start lactation	s1	23.1	98.18	1.82
trend	Double milk decline start lactation	s2	0	99.56	0.44
trend	Weight decline start lactation	w1	56.3	95.88	4.12
trend	**Double weight decline start lactation**	w2	42.9	96.76	3.24
index	**Activity day of calving**	ac	75.0	91.85	8.15
index	Rumination day of calving	rc	83.3	32.03	67.97
index	Body weight dry off	wd	44.4	77.97	22.03
index	Body weight end dry period	we	40.0	80.88	19.12

Alerts relating to concentrates showed good results. Reduced feed intake seemed to be a good indicator for or all metabolic disorders found in the literature, which corresponds with the findings from this research.

In the literature, decreased rumination activity appeared to be a good indicator of milk fever, and also for ketosis and LDA, although this has been investigated less. The level alert for decreased rumination activity indeed appeared to be a good indicator.

Activity is rarely investigated as an indicator for metabolic disorders and the few findings have been mixed. In this research, the level alert for activity was found to be a very good indicator with high sensitivity and specificity.

The level alert for weight did not perform well in this study, while the trend alert detecting an unwanted trend performed well. This is similar to reports in the literature for ketosis and LDA.

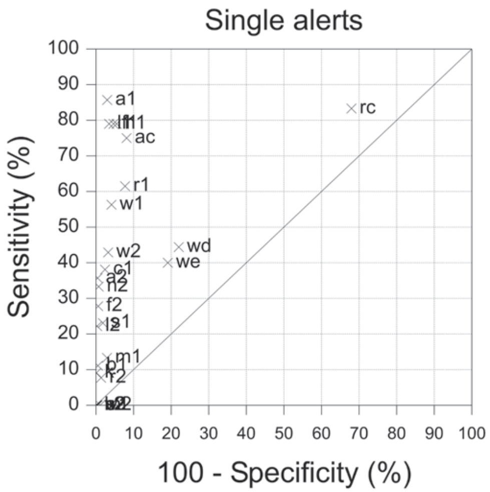

Figure 1. ROC-plot for the detection performance of single alerts for all metabolic disorders using a Z-value of 1.960 with a five-day period for diagnosis. Abbreviations of the single alert types are provided in Table 2.

Table 3. Performance of the combined alerts SumAlerts (top) and SmartSumAlerts (bottom) expressed as sensitivity (left) and specificity (right) for different periods and sums (all with X-value 1.96).

	period	Sensitivity					period	Specificity				
Sumalerts		1	2	3	4	5		1	2	3	4	5
	sum 0	73.1	65.4	53.9	42.3	30.8	sum 0	78.08	92.04	96.48	98.64	99.11
	2	92.3	80.8	80.8	69.2	57.7	2	78.21	92.13	96.56	98.7	99.17
	4	92.3	88.5	84.6	73.1	61.5	4	78.24	92.17	96.57	98.71	99.17
	1s0	100	96.2	88.5	73.1	61.5	10	78.21	92.16	96.57	98.71	99.18
Smartsum		1	2	3	4	5		1	2	3	4	5
	0	69.2	46.2	34.6	30.8	23.1	0	81.94	95.99	98.06	99.44	99.54
	2	88.5	76.9	69.2	53.9	34.6	2	82.04	96.07	98.12	99.49	99.56
	4	92.3	80.8	76.9	53.9	34.6	4	82.05	96.09	98.14	99.49	99.56
	10	100	84.6	80.8	53.9	34.6	10	82.04	96.1	98.16	99.5	99.57

Combining variables is worthwhile in order to improve the specificity. It is difficult to reach the desired specificity (at least 99%). In practice, the desired minimum value of sensitivity and specificity depends on multiple factors, such as type of disease, associated costs and farmer preference (Mollenhorst *et al.*, 2012). Some farmers prefer a higher sensitivity (so many sick cows are detected) at the expense of a lower specificity (farmer often gets a false alert) and some farmers prefer the opposite.

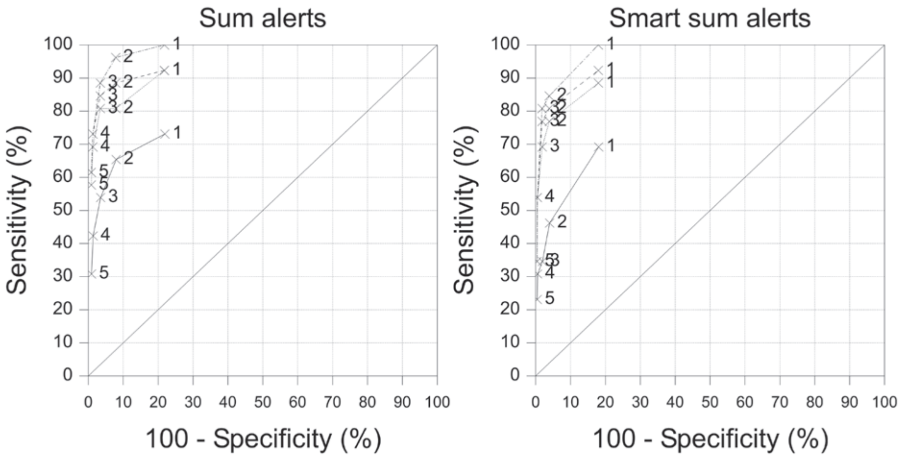

Figure 2. ROC plots for the detection performance of the SumAlerts (left) and SmartSumAlerts (right) for all metabolic disorders using a Z-value of 1.960 with different sums (1, 2, 3, 4, 5) and periods: 0 days (solid line), 2 days (dotted), 4 days (dashed) and 10 days (dotted/dashed).

SmartSumAlerts could sometimes achieve the same sensitivity as SumAlerts while achieving a higher specificity. This indicates that it is advisable to select certain indicators and that even farms with fewer sensors could benefit from using such models, since it appeared that it was not necessary to include all the indicators used in this study to obtain a reliable model.

A literature study investigated the number of days prior to diagnosis when certain variables could indicate that a cow was suffering from a metabolic disorder. These results showed that, for ketosis and LDA in particular, cows show some signs of sickness at least one week, but often even earlier, prior to diagnosis. The results from the current research, however, showed that cows can be detected a maximum of four days before diagnosis by the farmer.

Conclusions

A minimum specificity of 99% was set. For this restriction, a maximum sensitivity of 61.5% could be obtained. This indicates that this model cannot yet be used in practice and needs to be improved.

For the same time span before diagnosis, SmartSumAlerts could sometimes obtain the same sensitivity as SumAlerts while obtaining a higher specificity. This indicates that it is advisable to select certain indicators and that even farms with fewer sensors could benefit from using such models, since it did not seem necessary to include all the indicators used in this study to obtain a reliable model.

The effect of using different Z-values to determine the confidence interval, was investigated. As expected, increasing the Z-value resulted in a lower sensitivity and higher specificity for both single and combined alerts.

The best indicators, showing a high sensitivity combined with a high specificity, were indicators related to concentrates, activity, rumination activity and body weight loss at the start of lactation. These findings are quite similar to those reported in the literature.

The effect of using different time spans prior to diagnosis was investigated. Sensitivity increases until four days prior to diagnosis. This indicates that cows can be detected as suffering from a metabolic disorder at most four days earlier.

The results of this study confirmed the potential of a model-based approach for the detection of cows suffering from a metabolic disorder, although the models should be improved and tested on other data sets as well as in real time.

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6.3. Behaviour and performance based health detection in a robotic dairy farm

M. Steensels[1,2], C. Bahr[1], D. Berckmans[1], A. Antler[2], E. Maltz[2] and I. Halachmi[1]*
[1]M3-BIORES: Measure, Model and Manage Bioresponses, Department of Biosystems, KU Leuven, P.O. Box 2456, 3001 Heverlee, Belgium; [2]Institute of Agricultural Engineering, Agricultural Research Organization (ARO), the Volcani Center, P.O. Box 6, 50250 Bet Dagan, Israel; halachmi@volcani.agri.gov.il

Abstract

Correct separation of ill cows from the herd is important, especially in robotic dairy farms, where searching for an ill cow can cause disturbances in the routine of other cows. Nowadays, many sensors are available to help the farmer to monitor his cows. Therefore, the aim of this study was to apply a behaviour and performance based health detection model to post-calving cows on a robotic dairy farm in order to detect ill cows. The study was conducted at an Israeli robotic dairy farm with 250 Israeli-Holstein cows. All cows were equipped with a rumination and activity monitoring system that measured rumination time and activity in intervals of two hours. Milk yield, visits to the milking robot and body weight were recorded by the milking robot. For data analysis, a daily sum was calculated for activity, rumination time, milk yield and visits to the milking robot. For body weight, a daily mean was calculated. A tree-based model was developed based on a calibration dataset of historical data for the last year. The resulting model was validated against new post-calving data. The decision generates a probability of being ill for each new cow input. For classification, the cut-off threshold was set at 0.5. The model was applied once a week on the day the veterinarian performed the routine post-calving health check, which included testing all post-calving cows for ketosis and metritis. The veterinarian's diagnosis served as a binary reference for the model (healthy-ill). The validation dataset consisted of 66 cows. The tree-based model had a sensitivity of 66% and a specificity of 79%. Further analysis will indicate how the sensitivity of the model can be improved.

Keywords: post-calving cow health, tree-based model

Introduction

Early lactation is a sensitive period in the life cycle of dairy cows and is when the majority of health problems occur (Ingvartsen, 2006). Cows experience a negative energy balance after calving due to metabolic and hormonal changes, rapidly increasing milk production and an increasing nutrient demand after calving (Ingvartsen, 2006). Additionally, social stressors arise due to the change from the dry to the lactating cow group (Mulligan and Doherty, 2008). These metabolic and social stressors, in addition to the calving process, provide a fertile ground for post-calving health problems. Ketosis and metritis are common health problems in dairy cows in early lactation in Israel (Bar and Ezra, 2005).

Compared with cows milked in conventional parlours, cows using a milking robot have more freedom to control their daily activities and rhythms and have more opportunities to interact with their environment (Halachmi *et al.*, 2000b; Jacobs and Siegford, 2012). However,

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herd synchronisation with regard to lying, feeding and milking decreases (Halachmi, 2009; KetelaardeLauwere *et al.*, 1996; Winter and Hillerton, 1995). Correct separation of ill cows from the herd is important, especially in robotic dairy farms, where searching for an ill cow can cause disturbances in the routine of other cows (Halachmi, 2004; Halachmi *et al.*, 2000a).

A lot of sensors are available on farms with robotic milking. Automatic sensors provide detailed information about each cow, which was not easily obtained with previous management and milking systems (Spahr and Maltz, 1997). Automated detection of health problems might help the farmer and provide earlier warning, making appropriate treatment possible.

Health problems are associated with reduced activity (Chapinal *et al.*, 2010; Edwards and Tozer, 2004; Walker *et al.*, 2008), reduced rumination (DeVries *et al.*, 2009; Hansen *et al.*, 2003), reduced milk yield (Fourichon *et al.*, 1999; Rajala-Schultz *et al.*, 1999) and changes in weight (Maltz *et al.*, 1997). The objectives of this study were to develop and apply a mathematical model to detect post-calving health problems in multiparous dairy cows on a robotic dairy farm based on individual rumination time, activity, milk yield and weight measurements.

Material and methods

Animals and database building

Data were collected by the Agricultural Research Organization (ARO) – the Volcani Center on a commercial Israeli dairy farm in Yesodot. The herd consisted of 250 Israeli-Holstein dairy cows. The average annual milk yield was 11,500 kg per cow. The milking herd contained five production groups.

Disease occurrences were recorded using NOA, a dairy herd management program that includes health management. Diagnosis, treatment and dosage were recorded for each occurrence of a disease.

The farm veterinarian, who is part of Hachaklait Veterinary Services Ltd., the main cattle veterinary organization in Israel, routinely investigated all cows between 5 to 12 days after calving for ketosis and metritis once a week (on Sunday). For ketosis detection, all cows were checked with a Ketostix strip (Bayer Corporation, Leverkusen, Germany) which detects acetoacetate (AcAc) in urine samples. A cow was considered as ketotic when the Ketostix test result was higher than 1,470 μmolAcAc/l or 15 mg AcAc/dl. Metritis was checked by a rectal examination of the uterus. The criteria applied were size and tonus of the uterus and discharge appearance. A smelly, watery discharge was classed as medium metritis; severe metritis was present when the cow also had a fever. Slight metritis was diagnosed when the cow had an unusual discharge with enlarged uterus. All ill cows were treated after diagnosis.

The cows were housed all year round in fully roofed, laterally open cowsheds with dried manure bedding, which is the common dairy housing in Israel. The stocking density was about 20 m^2 per cow and cows could move freely within the cowshed.

The cows were milked in one of five robotic milking parlours (Lely Astronaut 3, Lely NV, Maassluis, the Netherlands). All cows were fed the same TMR according to NRC (2001) recommendations. The feed was distributed twice per day.

Sensors and software

All cows were equipped with a Lely Qwes HR monitoring system (Lely NV), which was fitted to their neck collar. The tag had 3 functions: (1) identification of the cow based on optical signal transmission; (2) measurement of the activity level of the animal in real time; and (3) recording of the rumination time of each individual cow in real time. The logger continuously recorded the activity and the time spent ruminating in 2-hour intervals.

Activity measurement was based on signal analysis of neck movements, and was expressed by a filtered activity index ranging from 0 to 255 units per 2 hours. The index was proportional to the number, intensity and direction of neck movements, and is associated with walking activity. Rumination time was based on analysis of the distinctive sounds of regurgitation and rumination recorded by a microphone. Rumination time was expressed as min/2 hours. All data were automatically transferred to the herd management software during each milking (T4C, Lely NV).

Milk yield, concentrate feed intake, visits to the milking robot and body weight were recorded by the milking robot during milking. Reports in Excel (MS Excel 2007, Microsoft, Redmond, WA, USA) were extracted from the herd management software. One report included rumination time and activity for all cows in 1-hour intervals. Another report included milk yield, visits to the milking robot and body weight per day for all cows.

Model calibration

A tree-based regression model was developed based on historic data for one year (April 2012 to March 2013). A previous study (Steensels *et al.*, 2013) indicated that farm-specific calibration could exclude inter-farm differences such as climate, distance to the milking parlour or management practices. During this time period, there were 35 ill (ketosis and/or metritis) and 76 healthy cows. The regression tree is based on the input variables (milk yield, activity, rumination, visits to the milking robot, body weight) and the output (diagnosis of the veterinarian). The tree is binary, which means that each branching node is split in two, based on the values of the input variables. The tree-based model (ctree, Matlab (Mathworks, Natick, MA, USA)) classified each cow into a category: ill or healthy. Table 1 shows the confusion matrix of the tree-based regression model. The accuracy of the tree-based model was 92%, the sensitivity was 86% and the specificity was 95% (Table 1).

Model application

This tree-based regression model served as the calibration dataset. The model was then applied to new calvings using the predict function in Matlab. Cows were monitored for the first 21 days

Table 1. Confusion matrix of tree-based model with 76 healthy and 35 ill cows – calibration dataset.

		Reference		
		Healthy	Ill	
Model	Healthy	72	5	0.94
	Ill	4	30	0.88
		0.95	0.86	0.92

after calving. New inputs were classified by the decision tree. The likelihood of being a member of a particular class is indicated in every end node, i.e. the probability of being ill is calculated.

Cows were randomly divided into two groups: control (CON) and treatment (TRT). The CON cows were brought to the veterinarian once in the period 5 to 12 days after calving, as in the normal routine. The TRT cows were only brought to the veterinarian when the model outcome indicated that the cow was ill or when the cow was at high risk of developing a disease.

Every Sunday, data were extracted from the farm computer and the model was applied to the new data. A list of cows that were up to 21 days after calving with their respective probability of being ill was then sent to the farmer. This was done a few hours before the veterinarian arrived, in order to give the farmer time to bring the cows that needed a check-up to the treatment pen.

Results

Between April and November 2013, 65 cows (34 TRT and 31 CON) calved and were included in the study. Metritis incidence was 50.0% in group TRT and 61.3% in group CON. This difference was not statistically significant (P=0.51) (Table 2). Ketosis incidence was 8.8% in group TRT and 6.5% in group CON. This difference was not statistically significant (P=0.98) (Table 2).

The confusion matrix is shown in Table 3. The overall accuracy was 72%, the specificity was 79%, and the sensitivity was 66%.

Table 4 shows the confusion matrices in detail for the CON and TRT. The performance of the model in relation to the TRT group, with a specificity of 85% and a sensitivity of 93%, is better

Table 2. Metritis and ketosis incidence in TRT and CON group.

	Metritis		Ketosis	
	No	Yes	No	Yes
TRT	17	17	31	3
CON	12	19	29	2
Total	29	36	60	5

Table 3. Confusion matrix of tree-based model with 34 healthy and 32 ill cows between 5 to 11 days after calving – validation dataset.

		Reference		
		Healthy	Ill	
Model	Healthy	26	11	0.70
	Ill	7	21	0.75
		0.79	0.66	0.72

Table 4. Confusion matrices of tree-based model of CON group (13 healthy and 18 ill cows) and TRT group (20 healthy and 14 ill cows) between 5 to 11 days after calving – validation dataset.

		Reference		
		Healthy	Ill	
CON				
Model	Healthy	9	10	0.47
	Ill	4	8	0.67
		0.69	0.44	0.55
TRT				
Model	Healthy	17	1	0.85
	Ill	3	13	0.93
		0.85	0.93	0.88

than the performance of the model in relation to the CON group, with a specificity of 69% and a sensitivity of 56%.

Of the 18 cows that were incorrectly classified, 4 cows that were diagnosed ill by the veterinarian and 5 cows that were diagnosed healthy by the veterinarian were correctly classified in the following model check, two days later. There was no significant difference between the model outcome and the diagnosis of the veterinarian.

Discussion

The model performance for the TRT group was better than that for the CON group. Several reasons could explain this. First of all, the exact timing of disease occurrence was not known – the disease might have developed earlier or was detected at a subclinical level, hence animal behaviour would not have been changed considerably. In optimal circumstances, the cows should be checked for ketosis and metritis every day after calving in order to identify the occurrence of ketosis or metritis more accurately. Cows that were not detected by the model would most likely be detected by the model during the next day or two and treated then. One or two days' delay is, however, undesirable. Nevertheless, the model still provides an alert in good time without the presence of the veterinarian. Ill cows which might be missed during the routine health check and therefore were not treated might recover spontaneously. Simensen *et al.* (1990) reported a spontaneous recovery in 40% of ketotic cows. However, the reduction in milk yield in ketotic cows that were not treated could be considerable (Rajala-Schultz *et al.*, 1999). In addition, very mild cases of metritis were still diagnosed as ill.

Second, there were several cases where the farmer overruled the decision of the model. The reason for this was that some cows were at high risk due to a difficult calving.

Third, TRT cows that appeared healthy in the model were not checked by the veterinarian and therefore assumed to be healthy. There is no guarantee that the veterinarian would also have found these cows to be healthy. Future studies should reveal whether these cows experienced a reduction in milk yield or fertility problems.

Fourth, there appeared to be an imbalance in the parity numbers of the CON and TRT groups. In the TRT group there were more 2nd parity cows than in the CON group (*P*=0.02), while there were more cows with parity 3 or more in the CON group than in the TRT group. The difference in parity numbers might affect the susceptibility to diseases. For example, in a study by Bar and Ezra (2005) the incidence of ketosis was 7.9% in second parity cows and up to 12.7% in older cows. This imbalance in parity should be taken into account in further studies.

There is always a trade-off between sensitivity and specificity. The cut-off threshold selected influenced the sensitivity and specificity of the model. The cut-off threshold for the model was set at 0.5. The accuracy of the model could be improved by optimizing the threshold. It is possible that every farm will need its own threshold (Steensels *et al.*, 2013). Future research should reveal the impact of applying a health detection model such as the one presented in this study on fertility, culling rate and milk yield.

Conclusions

A combination of existing farm data obtained during robotic milking, including rumination time, activity, milk yield, body weight compared to body weight at calving and number of visits to the milking robot, was used to develop and validate a tree-based model to detect post-calving diseases. When applying the model, the TRT group (accuracy 88%) showed better classification results than the CON group (accuracy 55%).

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6.4. Discussion: PLF for automatic detection of animal health in cows

I. Halachmi[1], A. Schlageter Tello[2], A. Peña Fernández[3], T. van Hertem[3], V. Sibony[1], S. Weyl-Feinstein[1], A. Verbrugge[3], M. Bonneau[4] and R. Neilson[4]*
[1]Agricultural Research Organization, P.O. Box 6, Bet-Dagan 50250, Israel;[2]Livestock Research Wageningen University, P.O. Box 338, 6700 AH Wageningen, the Netherlands; [3]M3-Biores: Measure, Model & Manage Bioresponses, KU Leuven, P.O. Box 2456, 3001 Leuven, Belgium; [4]European Federation of Animal Science (EAAP), Via G. Tomassetti 3, 1/A, 00161 Rome, Italy; halachmi@volcani.agri.gov.il

Preface

This chapter documents the questions and the answers that were expressed during the 2014 EU-PLF/EAAP joint-sessions. They were documented verbatim, but each questioner and responder were given the opportunity to rewrite/edit their questions and/or answers for more clarity. This discussion is related to Chapter 6.1 to 6.3.

Discussion

Question: Ilan Halachmi (ARO, Israel) – A question to the first presenter (Chapter 6.1). Which point in the body did you use to measure the temperature? We did similar experiments in the past, and we found that it was best to use the eyes of the animal and not the hair, to measure body temperature. Can you explain which exact point you used, and how you returned to this point every time?

Answer: Gundula Hoffmann (Leibniz Institute for Agricultural Engineering, Germany) – First, we visited the stable and made the video recordings. Then we returned to the office and analysed the videos on our computer. Every video is played and the software program gives me the maximum temperature of the head area, as well as the maximum temperature of the body area. These values are transferred to an MS Excel file, which I use in further analysis. We have a sampling rate of 9 measurements of temperature per second. Therefore, I decided to take the 10 maximal temperatures of the entire video to determine cow body temperature.

Question: Ilan Halachmi (ARO, Israel) – So if I understand correctly, the maximal temperature might be identified from different points in the body: sometimes it can be in the eyes, sometimes in the mouth, sometimes on the head, etc.

Answer: Gundula Hoffmann (Leibniz Institute for Agricultural Engineering, Germany) – Yes, that is correct. But when I look at the videos, I can see the hotspots in the body. It looks like it is always in the back of the ears or in the eye region. And when it is not the case, I don't think it is a problem, because when you look at the body temperature over time, today, yesterday and the day before, the cow has a higher temperature in another point, it would be the same in the next day. But if there is an inflammation coming up in another place, then you are probably right. But normally this is not the case, and we look at the hottest pixel in that area.

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Question: Jens Yde Blom (Lattec I/S, Denmark) – My question relates to the paper of Machteld Steensels on disease detection (Chapter 6.3). Being a veterinarian myself, I have the deepest respect for my colleagues in Israel, but how can you know that the gold standard is correct? I mean, what were the criteria for telling that a cow had ketosis?

Answer: Tom van Hertem (KU Leuven, Belgium) – For ketosis, they used the standardized Ketostix test and they check the urine of the cow. The Ketostix-test is a commercially available test that checks the amount of keton-bodies in the urine of the animal. This test is routinely used on the cows after calving by the veterinarians in Israel. For metritis, the veterinarians take a vaginal discharge, and they subjectively look at the colour and smell the discharge and score the degree of inflammation of the uterus. Both procedures are done on every cow on a routinely basis between 5 and 12 days after calving.

Answer: Ilan Halachmi (ARO, Israel) – The way we have designed the project, is based on the fact that the veterinarian checks every cow in the herd between 5 and 12 days after calving. So, we get a reference from the veterinarian, which is the same veterinarian for every farm over time. The veterinarian provides us with a reference, based on his own procedure. Unfortunately, he is not here to explain to you what this procedure exactly is. The veterinarian arrives to the farm, and he makes the decision on the illness. The vet does, not the farmer.

Question: Jens Yde Blom (Lattec I/S, Denmark) – You would probably have better sensitivities and specificities of your model if you had time series of your BHB-data, because the cow might not be sick on day seven, but she might be sick on day twelve.

Answer: Ilan Halachmi (ARO, Israel) – Cows that were detected as ill will continue with an inspection by the veterinarian. The routine is to check every cow, and then follow up with those cows that need special attention.

Question: Jens Yde Blom (Lattec I/S, Denmark) – One quick question on the first paper (Chapter 6.1). Did you take into account the wind chill factor and the ambient temperature in the barn where you measured the body temperatures?

Answer: Gundula Hoffmann (Leibniz Institute for Agricultural Engineering, Germany) – Yes, it is a good question. From literature we know it is important to look at the wind, climate and the dirty parts. We provided the software with the ambient temperature and the correction was made by the software. For the other factors we tried to minimise them as much as possible. The automatic milking system was inside the barn, and there was no sensible wind. We did the experiments only on one day, also in the calf feeder on one day. But if you do such a study over long time periods then you have to take this into account. I think to measure it as well, and then check if the data is making problems, so you can find out what is the cause.

Question: Steffi Wiedemann (Kiel University, Germany) – I also have a question to you Gundula (Chapter 6.1), because it is known that temperatures in cows and calves differ during the day. In the morning it is lower than during the day, and during the oestrus cycle there are also related differences in temperature. You have mentioned that you wanted to use the animal as its own control, so how do you plan to measure the temperature and use the cow as its own control when temperature depends on time of the day, and in your setup, the visit to the temperature measuring machine?

Answer: Gundula Hoffmann (Leibniz Institute for Agricultural Engineering, Germany) – We want to take this into account. We have the time point when the calf was in the calf feeder, and when the cow was in the automatic milking system. Future research will focus on this topic, to see if there is daily change in body temperature. I think another possibility is to take only morning or evening temperatures, and not mix them when we put this information in the software and see that we can manage it well. With sows, we did the study last year, and it was clear to see that there was a daily rhythm. Therefore, I think this will also be the case with cows and calves, meaning that we have to manage this as well.

Question: Chris Knight (University of Copenhagen, Denmark) – Gundala, you seemed a bit worried about the fact that skin temperature was going down in relation to high rectal temperatures (Chapter 6.1). Surely, there could be a physiological explanation for that. Core temperature and skin temperature would often differ, because the animal is trying to maintain core temperature, so it is trying not to lose too much heat or when it is fighting of an infection. And actually, it doesn't really matter in the point of view when we are following the animal over time. If we find something that is useful, it does not matter whether it was an up or a down signal. If you follow an animal over time and you see a rise and a fall, maybe that is very predictive.

Answer: Gundula Hoffmann (Leibniz Institute for Agricultural Engineering, Germany) – I am happy to hear this, because we were thinking about how to manage this. I think it is important to look at the individual animal. It would not be possible to find a threshold value for general purposes.

Answer: Chris Knight (University of Copenhagen, Denmark) – Don't do that. Forget about thresholds, look at the individual changes!

Question: Graham Gardner (Murdoch University Australia) – You alluded to a single image thermography system (Chapter 6.1), so I was just wondering about the comparison with this system (single image thermography), which I assume is going to be more complex and expensive relative to that system in terms of precision and accuracy. So, have you done that comparison and checked whether or not this system improved your precision and accuracy compared to a single image system?

Answer: Gundula Hoffmann (Leibniz Institute for Agricultural Engineering, Germany) – Do you mean: have we compared the video image to a single frame?

Question: Graham Gardner (Murdoch University Australia) – Have you compared the two systems?

Answer: Gundula Hoffmann (Leibniz Institute for Agricultural Engineering, Germany) – No, we did not do that.

Question: Graham Gardner (Murdoch University Australia) – And did you check and compare the cost of the systems?

Answer: Gundula Hoffmann (Leibniz Institute for Agricultural Engineering, Germany) – The cameras that we have installed cost between 2,000 and 3,000 Euro. It was a very simple system. You can buy more expensive systems. We might have to compare with other systems. But I don't think that it is that expensive, because you can buy one camera for the whole herd, which makes the cost per animal low.

Question: Frank Dunshea (University of Melbourne, Australia) – This question is for the third speaker (Chapter 6.3), or perhaps for anyone else who is interested. You mentioned that parity can be a risk factor for disease, such as whether they had twins. Is there any way that you could build this kind of information into your model to make it more accurate or more predictive?

Answer: Tom van Hertem (KU Leuven, Belgium) – I understand your question. It is possible to bring this information into the model, because all this data is available in the management software. If you can extract it from there, you can use it in your model. So these features can still be added to the model that was presented here.

Answer: Ilan Halachmi (ARO, Israel) – This project was part of a precision feeding tool that was based on the cows' individual dry matter intake. The cow body weight, which goes up in pregnancy, is an integral part of the model. So actually, we showed here part of it: the health part of the model. We are using the same concept for precision feeding in this farm based on the body weight, which is also part of Machteld Steensels' model.

Question: Miel Hostens (University of Ghent, Belgium) – Two of you used Lely (Chapter 6.2 and 6.3). If I talk to producers, and you talk about rumination data, they start doubting it, because sometimes I doubt that if anybody has ever checked to see if we are looking at data from these companies. But did anyone ever check if these data rely on a good basis for rumination time? If you start comparing Lely versus DeLaval, they will have different averages. That is my first question.

Answer: Rudi de Mol (Wageningen UR Livestock Research, Netherlands) – We did not compare these sensors yet, but in our farm, we use two different systems. We use Lely for one half of the cows, and the other half has the new NedApp-system. So on that farm we might see differences between both groups. And there are some students in our group that are working on the validation of these systems, especially on the NedApp system because that is new. I don't know if the Lely system has been validated.

Question: Kees Lokhorst (Wageningen UR Livestock Research, Netherlands) – Are you expecting that this validation should be published in scientific journals, or in another way? Please respond before Tom will respond

Answer: Miel Hostens (University of Ghent, Belgium) – In my opinion, it should be published. If I were a company, of course, I would not publish it. That is normal. But everybody looks at graphs and data, and we just pick out the data as researchers and we think that these data are correct. Then we are start correlating to diseases where we don't even have good definitions. So we lose a lot of information in the meantime. And I am always interested in raw data, but that is actually my pure scientific way of thinking.

Answer: Tom van Hertem (KU Leuven, Belgium) – Lely sells the Israeli SCR rumination tags. We did not check the validity of the data ourselves, but we know that Schirmann *et al.* tested the rumination tag of SCR, and compared the sensor data to the rumination time measured by hand. She did this validation of the sensor in 2012, if I am correct.

Answer: Ilan Halachmi (ARO, Israel) – We, the ARO, tried the SCR sensor in our facilities during the development process and later on. The SCR-tag was tested quite a lot in the Volcani Center, ARO, in Israel.

Question: Miel Hostens (University of Ghent, Belgium) – But that is only one of the five or six commercially available sensors.

Answer: Ilan Halachmi (ARO, Israel) – I know the validation of those sensors has been done. For Afimilk it is the same, but different type of sensors. The sensors of these two companies are well tested.

Answer: Kees Lokhorst (Wageningen UR Livestock Research, Netherlands) – And we are not even discussing whether you have the test results and how it will be used in practice, so there might also be some differences.

Question: Leen Vandaele (ILVO Belgium) – I would like to put forward the difficulty of choosing a gold standard. In the case of Andres' presentation (Chapter 2.4), but also for the presentation on ketosis detection (Chapter 6.3). Mobility scoring is very difficult, you pointed to that and this is also confirmed by colleagues of ILVO working on lameness detection. The same goes for the Ketostix, which was used as a reference in the study on ketosis. There are many studies that have validated the Ketostix in a comparison with blood parameters and not all results were convincing. When calculating sensitivity and specificity, everything comes down to your gold standard. So I am struggling a little bit with this. Before we can develop a good sensor, we need good standards. I would like some comments on this from today's presenters.

Answer: Andrés Schlageter Tello (Wageningen UR, Netherlands) – In the special case of lameness, and my personal opinion, we should focus on more molecular markers of lameness than these subjective scoring methods. So I completely agree with you that the gold standard is the weak point in the sensor development for Precision Livestock Farming.

Comment: Claudia Bahr (KU Leuven, Belgium) – Thank you. I think you are right about the gold standard. But I also think we can always claim that an automatic system stands and falls with its gold standard. What we have is what we have. So if we really want to move forward in technology, we sometimes have to take the gold standards that are available today. I think that this is what many researchers who develop new technologies struggle with. But finally they have to make compromises. And unfortunately, humans make mistakes, and machines probably will make the same mistakes, because they are developed with gold standards created by humans.

Answer: Kees Lokhorst (Wageningen UR Livestock Research, the Netherlands) – The advantage is, if we have a more or less agreed upon a gold standard – because that is an agreement on what to use – and by looking at this in a timeframe and see how it develops, it becomes a little bit more relative. And then the importance of which level (of the gold standard) becomes less important. That is my vision.

Answer: Andrés Schlageter Tello (Wageningen UR, the Netherlands) – I can only speak about lameness, because that is what I know most about. We can use lesions as a gold standard if we want to use something, which is not easier, but less subjective to score. But I think the problem of lameness detection is that we are focussing on analysing locomotion. I don't think that analysing locomotion, although automatic measurements can make it more reliable, is the correct approach for hoof lesion detection.

Answer: Chris Knight (University of Copenhagen, Denmark) – I am just afraid that we are losing track here. If we start comparing veterinarian versus machine, the vet will be superior to machines in many aspects. But there is one aspect in which the machine will always be superior compared to the vet, and that will be that the vet will visit the farm once, look at the cow once, whereas a machine will potentially monitor the cow every day, or even multiple times per day. I don't really care if the sensor under or overestimates the ruminating time of the animal, as long as the deviations are detected. Isn't that more important? And when we talk about precision, I seriously consider this as a wrong word. We are chasing something that is not what we need. In the past we also did not have precision and some of the times, best guess is just as good as precision. I suspect that is what is disturbing me here in this discussion.

Answer: Ilan Halachmi (ARO, Israel) – I would like to reply to this point of the gold standard and precision. We don't really care about the reference, because we look at the individual animal, if there is a change in the individual animal behaviour or its performance, then we get an alarm. This alarm will go to you, to the veterinarians and to the farmer, to decide what to do. We only look at what is happening to the animal, and if there is a reliable (not small variation) change, then we start to react. We have a problem with cow body weight for example, with large fluctuations after calving and becoming more stable afterwards. We take one measurement that we trust, and see how it changes as a function of time, and then we don't care about gold standard or reference. I look at the individual animal and look at the way it has changed over time.

Question: Miel Hostens (University of Ghent, Belgium) – I just want to comment on the data set. I understand what you are saying. But on the other hand, I think Leen (Vandaele) is right when she says that we should watch out. For example, for years, I think 20 years now, we have been collecting data on fertility – that is the best example. What did we conclude from the data? That there was low heritability for fertility, range was 0.04-0.05. Right now, because there are new scientists looking at the data again with a different view and different aspects, and what do we see suddenly? The heritability coefficients increase to 0.15, which is becoming more interesting. What happened to fertility in practice? It declined! The whole world started to invent oestrus detection systems, but geneticists said: 'Just do the correct thing! Focus on the right data, and we will do the rest for you.' I heard earlier a very nice presentation somewhere in this conference that we should collect the right data, and from the right data, we can have good genetic selection and improve our herd. So just collecting data without knowing if it is good data, because there is still the issue of the gold standard, seems not correct to me. And probably the answer will lie somewhere in the middle. But I am a little bit afraid of saying that we should not care about the gold standard, because then I think we will end up just like we did with fertility. Hereby I conclude my comment to the comment of Chris (Knight).

Answer: Vivi Thorup (INRA, France) – Yes, I have a comment to the comment on the comment of Chris. I am working both on lameness and the energy balance of cattle, and I think it is an important question. I used Lely weight in my research, and they are not just linear weights. It is not simple, the weighing of the cow, but there is an algorithm behind it to calculate the 560 kg cow weight. Therefore, I think you have a point. Don't just assume that the data you get from the sensor is the raw data, because it certainly isn't. So, this is good point! Also on the gold standard. I think that we still need them, but the history of the cow is just as important.

Part 7. Precision livestock farming in milk quality and milk contents

7.1. Real-time analyses of BHB in milk can monitor ketosis and its impact on reproduction in dairy cows

J.Y. Blom, J.M. Christensen and C. Ridder*
Lattec I/S, Slangerupgade 69, 3400 Hillerød, Denmark; jmc@lattec.com

Abstract

Traditionally, cow-side tests that monitor sub-clinical and clinical ketosis are limited to one sample in the postpartum period. This paper presents the first results of ketosis detection and reproductive performance in three dairy herds utilising Herd Navigator^{tm}, where milk samples are automatically analysed for β-hydroxybutyrate (BHB) at least once daily in the postpartum period. Apart from ketosis, the system also monitors reproduction, mastitis and milk urea levels in real-time. Farm 1 (278 cows, DK) and 3 (126 cows, CA) were milked in DeLaval VMS and cows in farm 2 (151 cows, NL) were milked in a 2×10 parlour barn. BHB and progesterone (P4) were measured on a daily basis in Herd Navigator, and data processed in the systems biomodels. BHB was measured 4-60 days from calving (DFC) and P4 from 20 days before end of voluntary waiting period. The number of ketosis alarms varied from farm to farm, ranging from 3 to 38 alarms per 100 calvings. Early (≤10 DFC) and later alarms (>10 DFC) did not differ among herds. Incidence rates for postpartum anoestrus varied from 4-23 alarms per 100 calvings, and was closely related to the incidence rate for ketosis. The analysis of reproductive performance revealed that ketosis, cystic ovaries and postpartum anoestrus highly influence the conception rates and length of breeding period, irrespective of length of the voluntary waiting period. With the use of Herd Navigator, inferior cows performance can easily be monitored on a real-time basis, and factors contributing to improper ketosis and reproductive management can be identified and corrected to improve farm performance.

Keywords: ketosis, postpartum anoestrus, progesterone, β-hydroxybutyrate, conception rate, daily monitoring

Introduction

Ketosis is a common metabolic disorder in high-yielding dairy cows. Negative energy balance in early lactation, fat mobilization in the absence of sufficient energy supply or reduced energy uptake from the feed ration will be followed by rises in ketone body concentrations (acetone, aceto-acetate and beta-hydroxybutyrate (BHB)). The disease is reported with herd incidences ranging from 2 to 20% (Ingvartsen, 2003). However, evidence from the literature points to a vast underreporting of the disease. Bovine ketosis typically occurs in early lactation. Clinical signs include reduced appetite, decreased milk yield, loss of weight, hypoglycaemia and hyperketonaemia. The importance of the disease is evident from its detrimental effect on reproduction (prolonged anoestrus, failure to conceive), and the milk yield depression that can amount to 400 kg during the lactation (Ospina *et al.*, 2011).

In recent years there has been an increased focus on monitoring subclinical ketosis, defined by a milk BHB threshold value of 0.12 mM (variation among investigators between 0.10 and 0.15 mM). Therefore, measurement of BHB in newly calved cows is part of many herd health programs

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worldwide. Manual sampling and analysis of blood, milk or urine samples is time-consuming and not without discomfort for cows. Furthermore, single-point measurements will not fully elucidate the true status of the cow, as BHB levels can vary considerably from day to day. Therefore, classifying a cow as ketotic or not on the basis of a single BHB measurement can be misleading, although studies have shown high sensitivities and specificities in trials on cows when compared to blood measurements (Oetzl, 2007)

In order to safely monitor the development of BHB concentrations, frequent measurements of BHB should be taken during the early post-partum period. The labour and time required for manual sample taking and analysis are therefore limiting for a practical approach. Also, the application of a simple threshold-based classification of cows as ketotic and non-ketotic has its limitations, as baseline values of BHB may vary among cows due to the dietary composition (Nielsen *et al.*, 2009). The obvious solution to manual sampling is to develop and use automated sensor systems that can sample and analyse relevant data and compute these before presenting the results to the farmer.

Demand for on-farm automated sensor systems

With the advent of larger dairy herds and automated milking, there is an increased need for the farmer to be able to monitor cow health and reproduction. This has led to the development of a number of systems for monitoring milk quality and udder health. Sensors to measure these parameters in milk are now available to farmers either on-line (electrical conductivity, colour, somatic cell count, fat, protein and others) or off-line (California mastitis test, bacterial culture, somatic cell count). Further, in-line sensors to measure fat, protein and lactose are available. A number of sensor systems based on cow activity have been developed to monitor heat, locomotion and rumination activity. Recently, systems to monitor rumen pH have also been developed.

One major obstacle to most sensing systems is that they are stand-alone systems, and therefore the farmer has to combine the output from these systems with other available data in order to make a management decision. Many systems also deliver huge amounts of unprocessed data, which leaves the user with laborious data filtering work. Bewley (2013) stated that the ideal sensor system should explain the underlying biological process then translated it into management action (standard operating procedures or SOPs), should be cost effective, flexible, robust and reliable, delivering information that is readily accessible to the farmer, should be suitable for commercial application (works in real life), and should also be subject to continuous improvement and feedback loops.

Rutten *et al.* (2013) reviewed sensors to support health management on dairy farms and validated systems based on how they fit into four functionality categories (Figure 1). Interestingly, based on a review of a vast number of publications describing sensors to monitor mastitis, reproduction, locomotion and metabolism, they found that most systems did not meet the level 3 and 4 requirements, i.e. the crucial point where monitoring is converted into decision making.

The Herd Navigator™ (DeLaval, Tumba, Sweden) was developed in an attempt to offer the dairy farmer a fully automated system which would collect, analyse and present data from frequent milk samples relating to substances that can provide information and decision support on ketosis, mastitis, reproduction and protein feeding.

The approach taken during development was that disease is not a yes/no issue. Diseases and disorders develop gradually, and therefore early warnings (Figure 2) allow for additional diagnostics, less aggressive medication, less tissue and metabolic distress, and less discomfort for the cow.

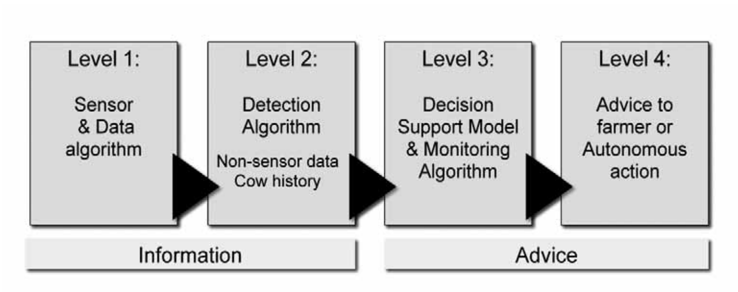

Figure 1. Framework for sensor information in dairy farm management (adapted from Rutten *et al.*, 2013).

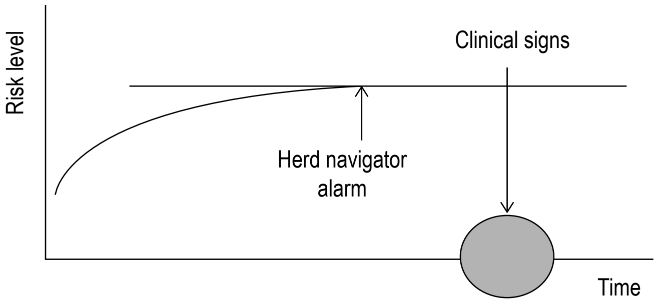

Figure 2. Concept for use of time series data for the detection of disease. As the risk of disease goes beyond a set threshold, the system will alert the farmer of an upcoming disease event before clinical signs are present.

The Herd Navigator system has a sensor system based on dry stick technology. Samples are taken from the onset of lactation, and at a frequency determined by the algorithms for each of the four parameters measured in the system. The frequency of sampling is higher in high-risk periods and, for ketosis and mastitis monitoring, the default sampling frequency is set to at least one sample per day at the beginning of the lactation.

Decision support module

The next step for the ideal system is to provide the user with timely alarms, and to provide the user with advice on how to handle the at-risk cow.

In Herd Navigator, only risk values which pass a certain threshold will appear in the daily alarm report. The threshold can be set by the user, and the alarm can have a SOP attached to it. Figure 3 shows the ketosis alarm list. As can be noted, the farmer and his advisers have chosen a specific treatment protocol for ketosis alarms in cows that are ≤10 days from calving ('Ketosis Treatment 1'), which can easily be followed by anyone responsible for management.

Monitoring algorithm

For continuous tracking of changes in health status, an automated system should also include a monitoring algorithm. The Herd Navigator system can provide lists of alarms, and also graphical

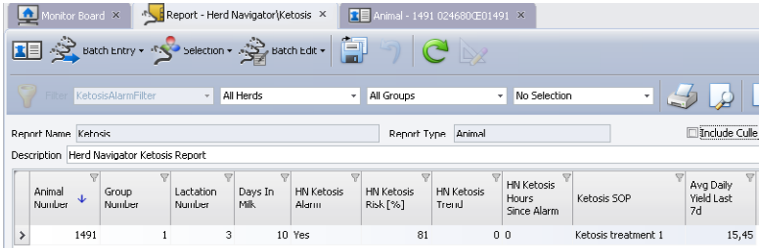

Figure 3. Alarm list for ketosis in the Herd Navigator system. As treatment protocols can differ according to stage of lactation, more than one protocol can be applied.

monitoring tools, as can be seen from Figure 4. The figure shows herd-level changes over time (or lactation stage) for a low, medium and high risk of ketosis.

Detection of ketosis using time series data for beta-hydroxy-butyrate

The biological model in Herd Navigator was designed to receive BHB data at regular intervals from day 4 to day 60 from calving (DFC), thus building a time series of BHB data. During the first 20 days of lactation a sample will be taken at least once a day. The ketosis model (Nielsen *et al.*, 2005; Figure 5) closely follows the general architecture of the biomodels used in Herd Navigator. The model calculates the risk of ketosis (from 0 to 100%) based on repeated measurements of BHB. The output risk of the model is sent to the Herd Management System. The output risk (OutRisk) is a sum of the indicator-based risk and additional risk factors. Another output is a sampling frequency feedback ('Days to Next Sample', DNS).

Calculation of the indicator based risk of the model is initiated by processing measurements in a State Space Model (Norberg *et al.*, 2008). Probabilities for four different states are calculated, and a smoothed value of BHB, based on prior measurements, is also calculated. A prerequisite for calculating the indicator based risk is to establish a baseline for BHB, i.e. a level that is considered normal for the individual cow at a certain time during lactation. The reason for this is that BHB is produced in the rumen epithelium as a normal process when butyrate is absorbed from the rumen (Heitmann and Fernandez, 1986). Therefore, BHB is a natural metabolite which may vary in concentration depending on diet. Thus, in the ketosis model it is necessary to estimate the baseline for BHB and subtract that from the measured BHB concentration.

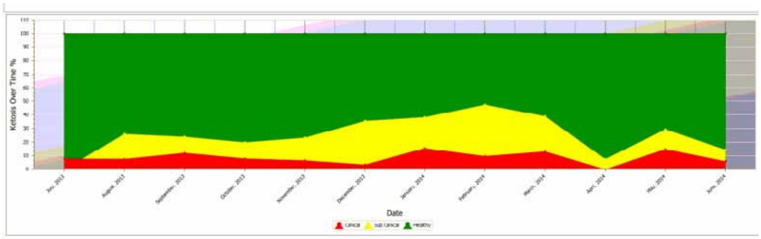

Figure 4. Herd ketosis monitoring tool in the Herd Navigator.

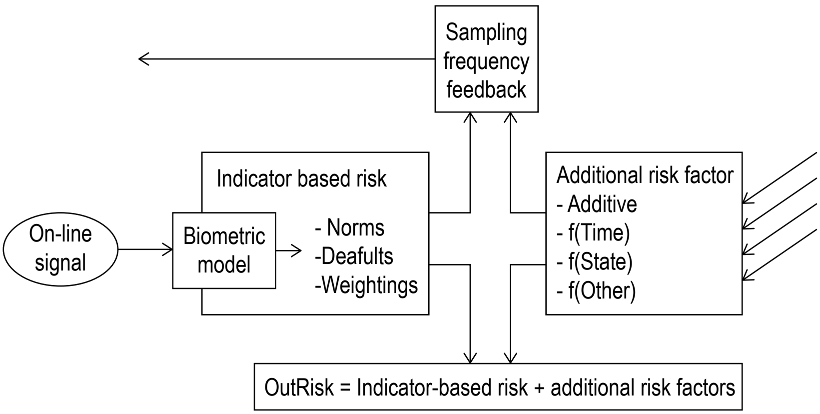

Figure 5. Overall structure of the ketosis model in the Herd Navigator.

For a given cow at the start of lactation, the baseline is initially set to the present smoothed level, provided that the level is ≤0.10 mM. The use of a baseline with a maximum value of 0.10 mM assumes that concentrations >0.10 mM are associated with a physiological imbalance which mediates subclinical or clinical ketosis. Further, it is assumed that the baseline level cannot increase during lactation; therefore, the baseline can only be adjusted down to lower values by subsequent smoothed BHB values. As soon as BHB is measured after calving, the baseline will adjust itself according to the individual cow (unless the level is >0.10 mM). Because the baseline is based on smoothed values (Level), it is unlikely that a single low BHB value of, for instance, 0.01 mM, will cause a low baseline.

Monitoring of ketosis by use of time series beta-hydroxy-butyrate data – an example

To demonstrate the use and benefits of monitoring BHB for ketosis management, and the influence of BHB on reproduction, a prospective study was performed using Herd Navigator data from 2012.

Materials and methods

Farm 1 (278 cows, Denmark) and farm 3 (126 cows, Canada) were milked in a DeLaval VMS (Voluntary Milking System) and cows in farm 2 (151 cows, the Netherlands) were milked in a 2×10 parlour barn. BHB and progesterone (P_4) were measured on a daily basis in Herd Navigator, and data were processed in the system's biomodels (Friggens and Chagunda, 2005; Nielsen *et al.*, 2005). BHB was measured 4-60 DFC and P_4 from 20 days before the end of the voluntary waiting period. All data analyses were performed in Matlab (ver. R2012a; MathWorks, Inc., Natick, MA, USA).

Results and discussion

The number of ketosis alarms, and hence ketosis events, varies from farm to farm as can be seen from Table 1, which shows key figures for ketosis. Early (≤10 DFC) and later alarms (>10 DFC) did not differ between herds.

Table 1. Key figures for ketosis detection in three Herd Navigator herds.[1]

	Farm 1	Farm 2	Farm 3
Milk yield per cow/year, kg	10,900	8,900	10,500
No. of BHB samples/year	8,948	3,116	3,411
Per cent BHB samples beyond 0.12 mM ('BHB load')	1.8	14.2	10.3
No. of ketosis alarms per 100 calvings	3	29	38
No. of early alarms (≤10 DFC)	5 (48%)	26 (48%)	24 (51%)
No. of later alarms (>10 DFC)	7 (52%)	28 (52%)	35 (49%)
Start of sampling of P_4, DFC	30	20	60
No of post-partum anoestrus alarms per 100 calvings	23	20	4

[1] BHB = beta-hydroxybutyrate; P_4 = progesterone; DFC = days from calving.

The distinction between early (≤10 DFC) and later (>10 DFC) alarms relates to evidence that the early alarms are most probably caused by dry period management, and should be handled differently from energy deficiency ketosis (alarms appearing >10 DFC). The frequency of post-partum anoestrus is dependent on the start of measurements for P_4, as the frequency of post-partum anoestrus was very low in herd 3, although the BHB load was high.

From Figure 6 it can be seen that ketosis has a considerable impact on reproduction, as the conception rate for 1st insemination was 40% in herd 1 and 15% in herd 2, which has a high BHB load. For herd 3 the conception rate for 1st insemination in ketosis alarm cows was 26%.

Conception rates for ketosis, follicular cyst cows and post-partum anoestrus can be seen in Figure 7. The conception rates for all conditions show that with larger BHB loads, the reproductive results are inferior to those in healthy cows. This is in agreement with other studies (Chapinal *et al.*, 2012; Walsh *et al.*, 2007).

In conclusion, frequent sampling and analysis can be used effectively to monitor ketosis in dairy herds, and is useful for the implementation of health management programmes as ketosis is a major causative factor in reproductive failure.

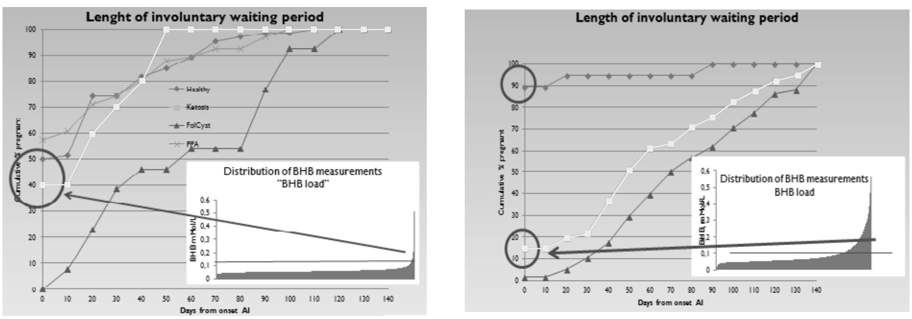

Figure 6. Length of involuntary waiting period (from end of voluntary waiting period to conception) for farm 1 (A) and 2 (B). Healthy cows (♦) become pregnant earlier than ketosis alarm cows (■), and the difference is considerably larger in the ketosis problem herd (B).

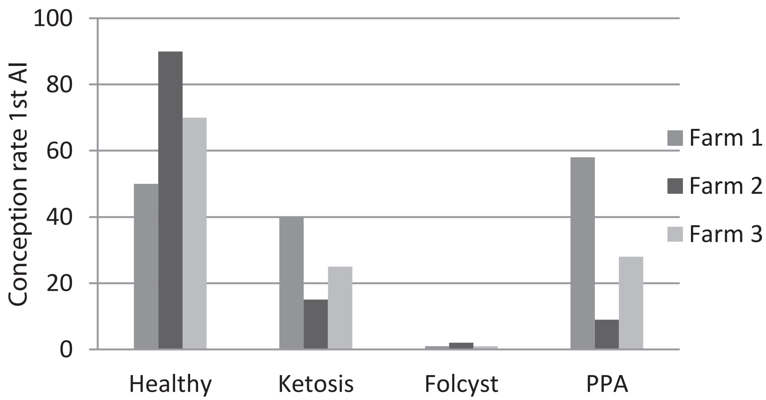

Figure 7. Conception rates (%) for first[t] inseminations as related to prior condition of the cow in the three herds (Folcyst = follicular cyst, PPA = post-partum anoestrus).

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7.2. Assessing the pregnancy status of dairy cows by mid-infrared analysis of milk

A. Lainé[*], H. Bel Mabrouk, L-M. Dale, C. Bastin and N. Gengler
University of Liège, Gembloux Agro-Bio Tech, Passage des Déportés 2, 5030 Gembloux, Belgium;
aurelie.laine@ulg.ac.be

Abstract

In dairy cattle, unlike other species, performance recording schemes make it possible to provide advisory tools which integrate information across the whole population. Mid-infrared (MIR) analysis of milk provides a spectrum for each individual cow's milk sample. The MIR spectrum represents the whole milk composition and can be used to assess the status of the animal (e.g. health, pregnancy, feeding). The main objective of the European project OptiMIR (INTERREG IVB North West Europe Programme) is to develop innovative advisory tools based on the MIR data collected by milk recording organizations. One of the objectives is to develop a tool to assess the pregnancy status of cows. The tool uses an innovative comparison of observed spectra with expected spectra predicted from a set of spectra with a known cow status, in this case open. Development was carried out using Walloon milk recording data. A training dataset (348,191 spectral data from 49,849 cows) was used to obtain residual spectra (i.e. difference between observed and expected spectra). Based on the fact that the pregnancy status of all cows was known, a predictive discriminant function was constructed using 7,524 residual spectra randomly selected from the initial dataset. The discriminant function was then applied to the rest of the dataset (24,278 residual spectra) for validation. When considering the period from 21 to 50 days after insemination, the error rate was about 7.5% with a specificity of 95.3% and a sensitivity of 87.2%. These results showed a high potential for directly using the MIR spectrum of milk to detect a change in the pregnancy status of dairy cows. This methodology can also be applied to predict other types of physiological status changes (e.g. udder health related) and can be used on other types of biomarker data (i.e. collected from on-farm sensors). Similarly, integration of on-farm information on expected pregnancy status could improve the off-farm tool presented here.

Keywords: mid-infrared analysis, milk spectrum, pregnancy, biomarker data

Introduction

Mid-infrared (MIR) spectroscopy is the method of choice which is used internationally for the quantification of milk composition, i.e. for quantification of the major milk components such as fat, protein and lactose, but recently also for quantification of fine milk components such as fatty acids (De Marchi *et al.*, 2014). MIR spectroscopy is used to predict components both for samples taken as a part of large-scale milk recording and for milk payment systems. This is a rapid and non-expensive method which provides an MIR spectrum which is a unique fingerprint of the whole milk composition. An MIR spectrum represents the absorption of infrared light through the milk samples at wavelengths between 900 cm^{-1} and 5,000 cm^{-1} (Coates, 2000).

For many years, milk recording organizations have used major milk components predicted by MIR to provide advice to dairy farmers, e.g. fat to protein ratio and urea for feeding management. The

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objective of the European project OptiMIR (INTERREG IVB North West Europe Programme) is to investigate the potential for direct use of the MIR spectrum of milk instead of MIR-predicted milk components to provide new management tools for the dairy sector.

In a previous component of the OptiMIR project consisting of surveys, farmers and milk recording organizations prioritized fertility, and especially pregnancy diagnosis, as key elements in the management of dairy farms. Currently the most common pregnancy diagnosis methods are ultrasound scans and transrectal palpation which must be carried out by a veterinarian or another qualified person between 30 and 90 days after the insemination date. These methods involve a certain cost, might by risky and have a given efficiency (Purohit, 2010).

Therefore, the aim of this study was to investigate the potential of MIR analysis of milk to identify changes in the pregnancy status of dairy cows. The long-term objective of this research is to develop a transferable strategy in the context of the milk recording system which can distinguish open cows from pregnant cows after insemination and within the first 50 days after insemination.

Material and methods

Overall principle

The general approach of this study was to perform comparisons between an observation, i.e. the milk spectrum from a given cow on the day in milk when we want to test the pregnancy, and an expected observation, i.e. the expected milk spectrum on the same day in milk if this cow was not pregnant. Hence, the expected milk spectrum was modelled, based on an analysis of relevant effects on spectral data from open cows only. A similar strategy was used by Sloth *et al.* (2003) in order to assess the udder health status of dairy cows by adjusting some milk components in a subset of healthy observations. Residuals, i.e. differences between observed and expected milk spectra, were then used to obtain a predictive discriminant equation for observations from open and pregnant cows.

Data used in this study were collected in the context of the official milk recording programme of the Walloon Region of Belgium, managed by the Walloon Breeding Association (AWE, Ciney, Belgium). These data consisted of test-day observations with production information (e.g. milk yields, fat percentage, protein percentage) collected from 1 November 2011 to 1 November 2013 and related to animal information (e.g. identification, number of lactations, dates of calving, dates of inseminations). Moreover, milk MIR spectra for each test day are routinely obtained and were usable.

Editing

The pregnancy status of the cow on each test day was then added to the database. In order to obtain the pregnancy status (i.e. pregnant or open) for each cow and test day from the database, the following algorithm was established. The theoretical date of the successful insemination was calculated for each cow according to the theoretical gestation time of the breed (e.g. 282 days in Holstein cows) and the known re-calving date. The nearest observed date of insemination within an interval of 20 days around the theoretical date was identified as the actual successful date of insemination. Based on that, all test days occurring before this date were recorded as 'open' and test days occurring after were recorded as 'pregnant' until the end of the lactation. If any doubts existed or if an irregularity in the recorded dates (e.g. irregularity in oestrus) was observed, those test days were recorded as 'unknown' in order to ensure the quality of the dataset. Finally, only observations with a known pregnancy status, 'open' or 'pregnant', were kept for the rest of the study.

Pre-processing of data

Records associated with milk yield, fat content and protein content which were outside the range recommended by ICAR norms (ICAR, 2012) were considered as outliers and removed from the dataset. Moreover, spectra with a value for standardised Mahalanobis distance that was greater than 3 compared to the mean for our dataset were also considered as outliers and removed from the dataset (Shenk and Westerhaus, 1990). Finally, only observations from 5 to 365 days in milk (DIM) were kept.

MIR spectra of milk are recorded as raw information and needed to be pre-processed mathematically in order to extract relevant information. In this study, only the first derivative was calculated as the difference between a spectral value at data point X and the spectral value at data point X+5 in order to set all spectra at a common baseline (McParland *et al.*, 2011). To avoid introducing noise, informative areas of the spectrum which are routinely used to predict fatty acid contents in milk (Soyeurt *et al.*, 2006) were selected.

The edited dataset contained a total of 348,191 spectra, of which 188,347 were from pregnant cows and 159,844 were from open cows. The dataset included 49,849 cows from 920 herds.

Modelling of the expected open spectra

A subset of open cows only was constructed and a mixed model was created using relevant effects. Expected open spectra were then estimated for all the spectra in the database (pregnant or open) as in Equation1.

$$\hat{y}_{ijklm} = parity_i + \mathrm{breed}_j + monthTD_k + (cDIM \times DIM) + (cDIM2 \times DIM^2) + animal_l + anlact_m + (cDIManimal_l \times DIM) + (cDIM2animal_l \times DIM^2) \quad (1)$$

Where:

$\hat{y}_{ijklm}$	expected value of spectra for the l^{th} animal in its m^{th} lactation at the i^{th} parity for the j^{th} breed and at the k^{th} month of test day;
$parity_i$	fixed effect of parity *I;*
breed_j	fixed effect of breed *j;*
$monthTD_k$	fixed effect for the k^{th} month of test day;
$cDIM$	regression coefficient for the days in milk (DIM);
$cDIM2$	regression coefficient for the squared DIM;
$animal_l$	random effect of the l^{th} animal;
$anlact_m$	random effect of the l^{th} animal in its m^{th} lactation;
$cDIManimal_l$	random regression coefficient for the DIM and for the l^{th} animal;
$cDIM2animal_l$	random regression coefficient for the squared DIM and for the l^{th} animal.

Residual spectra

For the complete edited dataset, residual spectra were defined as the result of the difference between the observed spectrum and the expected open spectrum calculated above. These residual spectra represent all factors that were not taken into account in the calculation of the expected spectra (errors, and unaccounted factors including the pregnancy status).

Predictive discriminant analysis

In order to differentiate spectra obtained from open cows from spectra obtained from pregnant cows, a predictive discriminant function was applied to a training dataset including spectra recorded after 20 days in milk and recorded from 20 to 120 days after insemination, whether successful or not. Assuming that there was an equal proportion of pregnant or open cows after the first insemination, the dataset was adjusted so that it had the same proportion of residual spectra from pregnant and open cows. The training dataset included a total of 7,524 residual spectra and discriminant analysis was performed using the PROC DISCRIM procedure from SAS (SAS Institute, 2009).

The predictive discriminant function obtained from the training dataset was then applied to a validation dataset constructed with observations from lactations that were not present in the training dataset. This validation dataset only contained observations occurring from 20 to 120 days after insemination, whether successful or not (24,278 residual spectra). The error rate of classification was calculated as the number of data misclassified divided by the number of observations in the validation dataset.

Results were expressed in terms of specificity and sensitivity. Specificity is defined as the ability of the equation to correctly predict the non-event (open cows) from all observations which are known to belong to open cows. Sensitivity is defined as the ability of the equation to correctly predict the event (pregnant cows) from all observations known to belong to pregnant cows.

The potential for using residual spectra was demonstrated by establishing another discriminant equation from the same training dataset but using raw spectra, and applying it to raw spectra from the validation dataset. Error rates of classifications, sensitivity and specificity were calculated using the method described above.

Results and discussion

Predictive discriminant function applied to residual spectra

The error rates of classification for the validation dataset using the predictive discriminant function constructed on the basis of residual spectra was 6.4%. Specificity was 95.3% and sensitivity was 93.5%. The sensitivity, which is the proportion of observations from pregnant cows correctly identified as pregnant, is lower than the specificity, which is the proportion of observations belonging to open cows that were correctly identified as open. This may be due to the smaller number of data available in this classification group. Indeed, the algorithm assigning the pregnancy status to each observation (pregnant or open) did not allow the open status to be assigned more than 48 days after an insemination date. Therefore, this study could not yet be validated for observations beyond this limit.

Error rates of classification, expressed by groups of 10 days after the insemination date, and number of data in each group are shown in Table 1. Results expressed as sensitivity and specificity are also presented in Table 1. The greater the number of days after the insemination date, the more the sensitivity and specificity converge. This indicated that classification improves as the number of days after insemination increases. This is expected as the more advanced the gestation, the greater the physiological impact of the gestation on the cow and therefore the greater the changes in milk composition. The results for 21 days after insemination show over 95% correct classification,

Table 1. Number of data and error rates of classification for residual spectra by groups of 10 days after an insemination date (IDATE).

Days after IDATE	n Open (%)	n Pregnant (%)	Error rates	Specificity[1]	Sensibility[2]
21-30	592 (22.2%)	2,071 (77.8%)	3.2%	96.8%	82.2%
31-40	489 (18.9%)	2,093 (81.1%)	10.5%	93.1%	88.7%
41-50	154 (6.8%)	2,126 (93.2%)	8.8%	96.1%	90.8%

[1] Specificity: proportion of data for open cows which are correctly classified as open; it relates to data from cows that have been inseminated unsuccessfully.

[2] Sensitivity: proportion of data for pregnant cows which are correctly classified as pregnant; it relates to data from cows following successful insemination.

which is a very competitive result when compared with conventional pregnancy detection (e.g. ultrasound). For instance, the efficiency of ultrasound is close to 95% but it can only be performed 30 days after insemination and its costs are not negligible in view of the fact that a visit from the veterinarian visit is needed.

Predictive discriminant function applied to raw spectra (not adjusted for systematic factors)

When the discriminant function was constructed and applied to raw spectra, meaning spectra that were not adjusted for systematic factors using the model presented in Equation 1, and not residual spectra, the error rate was around 47%. Since, the probability of achieving a correct classification is 50% in the case of a two-group classification, the raw spectra were not useful in making this kind of prediction.

Conclusions

Results have shown a high potential for direct use of the MIR spectrum of milk to detect a change in the pregnancy status of dairy cows. This strategy is now being tested under field conditions. The methodology can also be applied to prediction of other physiological disorders, such as udder health issues. Moreover, the MIR technology and the milk spectrum have many potential applications in the development of management tools for dairy farmers. Similarly, integration of on-farm information on expected pregnancy status could improve the off-farm tool presented here.

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7.3. Evaluating progesterone profiles to improve automated oestrus detection

C. Kamphuis[1], K. Huijps[2] and H. Hogeveen[1,3]*
[1]Chair Group Business Economics, Wageningen University, Hollandseweg 1, 6706 KN Wageningen, the Netherlands; [2]CRV, Wassenaarweg 20, 6843 NW Arnhem, the Netherlands; [3]Department of Farm Animal Health, Faculty of Veterinary Medicine, Utrecht University, Yalelaan 7, 3584 CL Utrecht, the Netherlands; claudia.kamphuis@wur.nl

Abstract

Adoption of automated heat detection technologies is increasingly popular in the dairy industry. Generally speaking, farmers invest in only one technology on the assumption that this system will find most, if not all, cows in heat. It is, however, known that these technologies do not find all cows in heat. It has been suggested that automated heat detection may improve when sensor data are combined, where this involves combining different sensor measurements, e.g. linking activity with rumination data. So far, the option of combining different technologies has not been studied for the obvious reason that no commercial farms are using technologies from several suppliers. The Smart Dairy Farming (SDF) project, a Dutch initiative, brings together technology providers, knowledge institutions and dairy farms to improve the longevity of dairy cows by developing innovative tools to improve animal health, reproduction and feeding strategies. The SDF project offers a unique opportunity to research whether combining different sensing technologies improves automated heat detection. To do this, progesterone profiles were created by daily measurement of progesterone in milk from 31 cows, over a 24-day period, at two farms participating in the SDF project. One automated heat detection technology is used on both farms, and each farm has a second, different, technology running simultaneously. Heat alerts generated and farmers' observations were compared with progesterone profiles. The data were used to provide insight into the following issues: do heat detection technologies provide alerts for cows in heat; when do they alert for heat events; how do farmers use the information from the heat detection technologies; and whether the exact timing of true heat may be improved by combining heat alerts. Finally, possible explanations will be studied for those heat events that remain undetected by both oestrus detection systems and farmers' observations.

Keywords: oestrus events, heat detection, heat observation

Introduction

Infertility, together with lameness and mastitis, is one of the top three cow health issues associated with economic losses in the dairy industry (Juarez *et al.*, 2003). Fertility issues are one of the main reasons for involuntary culling of cows (Gosselink *et al.*, 2008). Farmers generally aim for their cows to have a calving interval of one year as this interval has been considered to be economically optimal (Inchaisri *et al.*, 2011). To achieve this one-year calving interval, it is important to inseminate cows as soon as possible after calving. The optimal period for first insemination is between 40-70 days after calving (Inchaisri *et al.*, 2011). To inseminate cows at the right time, it is important for farmers to detect cows that are in heat by looking for visual signs of oestrus-related behaviour, for example the willingness to stand while being mounted (Eradus *et al.*, 1992).

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Visual detection of these signs requires experience, diligent attention and time (Harris *et al.*, 2010). However, these requirements can be challenging with the ongoing trend towards increased herd sizes. Accordingly, the adoption rate for automated heat detection systems is increasing. It is estimated that 20% of Dutch dairy farms currently have an automated heat detection system working on their farm (Huijps, personal communication; CRV, Arnhem, the Netherlands). These automated heat detection systems work reasonably well, with sensitivities ranging between 80 to 90% in combination with a specificity of 90% or higher (Rutten *et al.*, 2013). However, these performance indicators also indicate that these systems do not find all cows in heat and that they generate false positive alerts. For those working with these systems in the field (farmers), it can be hard to distinguish true positive alerts from false alerts.

A normally functioning hormonal cycle in a cow generally takes 21 days. The corpus luteum performs a vital function in this cycle. The corpus luteum produces the hormone progesterone, which plays the main part in this fertility cycle. Under normal circumstances, maturation and degradation of the follicle and corpus luteum is a smooth process, but occasionally ovulation can be delayed or the follicle does not 'burst' properly and forms a cyst. Even the activity of smaller cysts is sufficient to block a cycle that has already begun and thereby all other fertility events, including the behavioural changes associated with oestrus. With some cows the ovaries have started to regress and show no signs of activity (follicle atresia). A weakened corpus luteum with too little progesterone production may cause a lower intensity and shorter duration of oestrus in high-yielding cows (Lopez *et al.*, 2004). As a consequence it is even more difficult to inseminate high-yielding cows at the right time (at oestrus) and maintain an economically optimum calving interval. To date, it is unclear whether cows with suboptimal progesterone patterns play a role in the generation of false positive alerts or missed oestrus events.

The relationship between progesterone profiles and the alerts generated by automated heat detection systems was evaluated in this study.

Materials and methods

Two farms located in the northern part of the Netherlands and participating in the smart dairy farming project (www.smartdairyfarming.nl) were enrolled in this study. Farm characteristics are summarised in Table 1. Progesterone profiles were created by measuring the progesterone concentration in milk samples. Milk samples were collected once daily from 31 cows (12 on Farm A and 19 on Farm B; Table 1) over a 24-day period.

Selection of cows

To be enrolled in this study, cows had to be between 40 and 70 days in milk (DIM) and not yet inseminated. Because a limited number of cows on Farm B had heat detection system B, the selection criteria for DIM were adapted slightly for this farm. Cows with heat detection system B which were slightly under 40 DIM at the start of the study were also eligible for inclusion.

Progesterone measurements

A milk sample was collected from every cow enrolled in the study on a daily basis. On Farm A, herd staff were instructed to collect a milk sample at every morning milking. This sample was collected from residual milk. Because Farm B milked robotically, automated milk sampling devices were connected to two out of four units and programmed to collect a mixed milk sample from every first

Table 1. Farm characteristics of two farms participating in the project.

Farm	A	B
Herd size	450	250
Milking system	conventional	robotic (4 units)
Milk yield/cow/year	9,509 kg	9,777 kg
Data collection period	21 February – 16 March 2014	22 March 2014 – 14 April 2014
Progesterone sampling	morning, after milking	first milking of the day, mix
Cows enrolled	12	19
Cows with system A[1]	12	-
Cows with system B	12	8
Cows with system C	-	19

[1] Commercially available automated heat detection systems (A, B and C).

milking of the day. All milk samples collected were refrigerated until further analysis. Milk samples were analysed for progesterone three times a week (Monday, Wednesday and Friday) using an on-farm measuring device (Hormonost – Microlab Farmertest, Biolab, Unterschleissheim, Germany). Every day that milk samples were analysed, milk samples for that day and the previous one or two days were tested. For every individual cow the progesterone profile was created in Microsoft Excel. Progesterone positive heat moments (P4heat) were determined by four individuals. Only P4heats with consensus about the day of heat (>3 individuals indicated the same day as P4heat) were included in the study. These P4heats were considered as the gold standard.

Heat alerts from automated heat detection systems and farm staff observations

Three automated heat detection systems were used in this study (system A, B, and C). All three systems are commercially available systems and all three of them included, amongst other information, activity data to generate heat alerts. For the purpose of this study, further detailed information about underlying data and/or detection algorithms was deemed unnecessary and is, therefore, not included. The heat alerts from the different systems were available for every individual cow. Alerts from system A and system B were available for cows on Farm A. Alerts from system B and system C were available for cows on Farm B (Table 1). Additionally, farmers recorded the day when they had observed cows in heat due to behavioural changes associated with oestrus.

Analyses

Heat alerts generated by the different automated heat detection systems together with farmers' observations were visually compared with progesterone profiles and P4heats using SAS (version 9.3, SAS Institute Inc., Cary, NC).

Results

The average DIM of the 31 cows during the data collection period was 62 (Farm A: 57; Farm B: 65). The average DIM when the study commenced was 50 (Farm A: 44; Farm B: 53). On completion of the study, the average DIM was 73 (Farm A: 67: Farm B: 76). The selection criteria did not included parity, although parity of a cow may have an effect on the levels of progesterone. Table 2 presents the distribution of parity among the cows selected. Cows at Farm A were older (parity range: 2-7, average parity 5.5) than cows at Farm B (parity range: 1-7, average parity 2.4).

Gold standard heats, and heat alerts and observations

A total of 30 P4heats from 31 cows were detected; one cow on Farm B had no P4heat. The number of heat alerts generated by the systems were 14, 12, and 31 for system A, B and C, respectively. Farm staff recorded 15 observed heats. Nine P4heats (30%) received an alert from at least one of the automated heat detection systems on the exact same day, whereas three (10%) P4heats were observed by the farmer on the same day. To allow for a potential mismatch in setting P4heats, the time window was widened to plus/minus 1 day of the P4heat. This resulted in 17 P4heats that were detected by at least one heat detection system (57%) and nine P4heats (30%) that were visually observed by the farm staff. Outside this 3-day time window (day of P4heat plus/minus one day) alerts were generated by all three automated heat detection systems. These alerts were considered to be false positives and totalled four, five and 18 for automated detection system A, B and C, respectively. Farm staff also recorded six heat observations outside this 3-day time window, which also were considered to be false positives.

Heat alerts generated and heat observations were represented graphically in relation to the day of P4heat in order to achieve greater insight into the timing of alerts and observations, where the day of P4heat was set at day 0 (Figure 1). Most of the alerts (48 out of a total of 57; 84%) and visual observations (13 out of 15; 87%) were plus/minus three days round the day of P4heat (day 0; Figure 1). System A generated the most alerts on exactly the same day as P4heat (day 0), while system C generated the most alerts around the P4heat day (Figure 1). System A detected five out of the 12 P4heats (41.6%) on Farm A, whereas three out of the 12 P4heats (25%) were correctly identified by system B when a plus/minus 1 day time window was applied. Only one of the three P4heats correctly identified by system B was not detected by system A. System C detected nine out of the 18 P4heats (50%) on Farm B, whereas two out of the 18 P4heats (11%) were detected by system B, again when a plus/minus 1 day time window was applied. Both P4heats detected by system B were also detected by system C.

Progesterone profiles

Figure 2 demonstrates the average progesterone profile around the day of P4heat (day 0), which is as expected. Average progesterone profiles were also created for cows that were not detected by at least one automated heat detection system (black dashed line; Figure 2) and those that were detected using a plus/minus 1-day time window around the day of P4heat. There is no apparent difference in average progesterone profile between these two groups of cows.

Table 2. Parity distribution per farm.

Parity	Farm A	Farm B	Total
1	0	8	8
2	1	5	6
≥3	11	6	17
Total	12	19	31

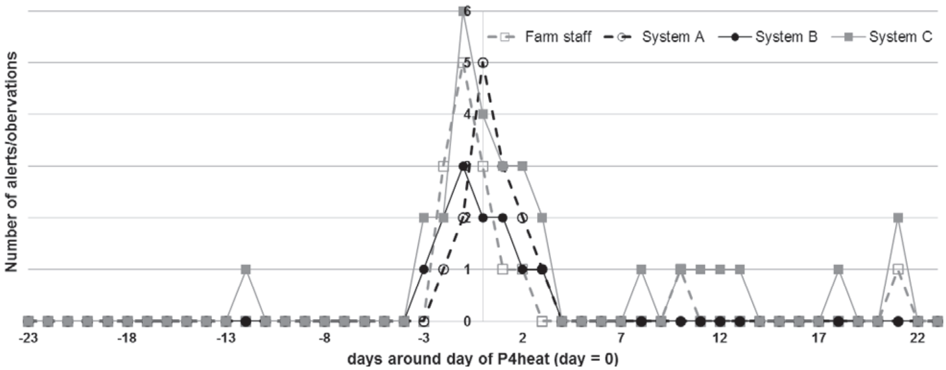

Figure 1. Number of alerts generated by automated heat detection systems and number of recorded visual observations by farm staff in relation to the day of P4heat (day 0).

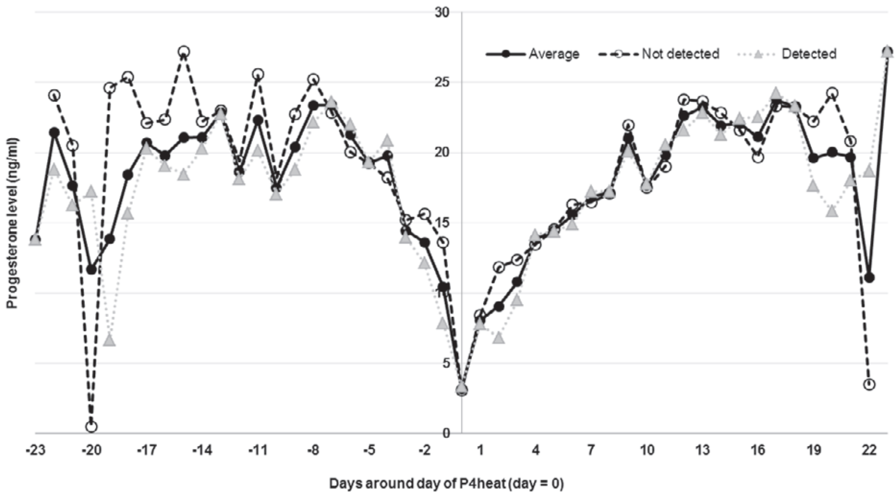

Figure 2. Average progesterone profile around the day of P4heat (black solid line), and average progesterone profiles for those cows that were not detected by an automated milking system within plus/minus 1 day of the day of P4heat (black dashed line), and those that were detected by at least one automated detection system within plus/minus 1 day of the day of P4heat (grey dotted line).

Discussion and conclusions

The study provides insight into progesterone profiles of dairy cows in relation to heat alerts generated by automated heat detection systems and in relation to heat observed by farmers. All three automated heat detection systems performed less well than expected, compared with results reported by Rutten *et al.* (2013) and by Kamphuis *et al.* (2012). The latter study reported a sensitivity of 76.9% and a specificity of 99.4% using a similar 3-day time window. Moreover, the number of heats observed by farm staff was lower than expected. Both farmers mentioned that they rely on their automated heat detection systems, but this study demonstrates that they only observed nine P4heats out of 17 P4heats (52.9%) that were correctly identified by the systems. There seems to be no difference between the two farms as farm staff on Farm A observed 25% of the P4heats, whereas this was 33.3% on Farm B. An explanation for this low detection rate by farm staff may lie in the fact that the false positive alerts that are generated by these systems cause farmers to use their own selection criteria to decide which alerts to trust and check. This selection of alerts to be checked may result in too many heats being missed. A similar result has been found for automated mastitis detection systems: farmers tend to check less than 3% of all mastitis alerts visually. As a consequence, farmers miss 74% of mastitis cases that were initially detected by the automated systems (Hogeveen *et al.*, 2013). Another explanation may be that these automated heat detection systems work 24/7 and therefore can provide an alert for a heat event during the evening and night. Farm staff will learn about these alerts the next morning but in the meantime the cow may already have reduced her changes in behaviour or returned to her normal behaviour. Consequently farm staff may fail to visually identify the cow in heat, resulting in a missed heat event.

The heat alerts generated by the automated heat detection systems seem to be more accurate than farm staff's observations, but the number of false positive and false negative alerts is high for both the systems and farm staff. The detection systems generate most alerts around a P4heat day, but results indicate that the alerts are not accurate enough. The alerts generated at day 18 and 21 by system C and farm staff are now regarded as false positive alerts but could be signals for an upcoming true positive alert as it is known that some cows have shorter hormonal cycles.

Combining the alerts from the two different systems results in one additional true positive alert at Farm A and no additional true positive alerts at Farm B. This indicates that combining different automated heat detection systems may have limited benefits. It might be interesting, however, to use the raw sensor data measured by these systems in combination with the generated alerts, which may be useful in researching improved heat detection systems in the future.

Progesterone profiles did not differ between cows that were detected and those that were not detected by automated heat detection systems. This suggests that P4heats that are missed by the automated systems were not caused by abnormal progesterone profiles. Currently, profiles are not specified for different parities. It is possible that profiles might differ in regularity. This could be an interesting topic to study in the future.

In conclusion, all three heat detection systems performed less well than expected. Since farm staff missed about 50% of the P4heats correctly identified by the detection systems, performance of these systems in the field reduced even further. Most heat alerts and observations appeared in a 3-day time-window days around the day of P4heat, but none of them was accurate enough. Combining outputs from different heat detection systems showed to have limited benefits in this study. Progesterone profiles appeared not to affect oestrus behaviour, and thus, not to indirectly affect performance of detection systems. Future research should confirm results from this small study, and perhaps should use successful inseminations as golden standard to crank up numbers rather than using progesterone measurements.

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7.4. Discussion: PLF in milk quality and milk contents

I. Halachmi[1], A. Schlageter Tello[2], A. Peña Fernández[3], T. van Hertem[3], V. Sibony[1], S. Weyl-Feinstein[1], A. Verbrugge[3], M. Bonneau[4] and R. Neilson[4]*
[1]Agricultural Research Organization, P.O. Box 6, Bet-Dagan 50250, Israel;[2]Livestock Research Wageningen University, P.O. Box 338, 6700 AH Wageningen, the Netherlands; [3]M3-Biores: Measure, Model & Manage Bioresponses, KU Leuven, P.O. Box 2456, 3001 Leuven, Belgium; [4]European Federation of Animal Science (EAAP), Via G. Tomassetti 3, 1/A, 00161 Rome, Italy; halachmi@volcani.agri.gov.il

Preface

This chapter documents the questions and the answers that were expressed during the 2014 EU-PLF/EAAP joint-sessions. They were documented verbatim, but each questioner and responder were given the opportunity to rewrite/edit their questions and/or answers for more clarity. This discussion is related to Chapters 7.1 to 7.3.

Discussion

Question: Michael Pearce (Zoetis, Belgium) – Is there a relationship between ketosis and the milk production? How is it related with the BHB (beta-hydroxybutyrate) load (Chapter 7.1)?

Answer: Jens Yde Blom (Lattec I/S, Denmark) – For sure there is a relationship. The lower production detected with our tool can be related with the change in the load in BHB. This could be explained simply as the lack of more energy for milk production.

Question: Susanne Klimpel (GEA Farm Technologies GmbH, Germany) – How did you identify if your day of progesterone (Chapter 7.3) was the first day it was above the threshold?

Answer: Claudia Kamphuis (Wageningen University, the Netherlands) – We took milk samples every day for 24 consecutive days and we analysed all these samples every 3 days using the manufacturer's instructions. We had four persons who, independent from each other, established the progesterone heat based on the results. Moreover, we went back to the technology supplier of these analysing tool to check whether we were right. And they confirmed our set days of progesterone.

Question: Karen Helle Sloth (GEA Farm Technologies GmbH, Germany) – Around 10 years ago, a veterinarian in a PhD study showed that the changes in progesterone were related with ovulation. The results showed that maybe progesterone is not the best predictor to detect heat in cows. It is good for detecting that there has been a heat period but not to say exactly when it happened.

Answer: Claudia Kamphuis (Wageningen University, the Netherlands) – Progesterone has been used since a long time as the 'gold-standard'. We chose to use it as well. To overcome the latter aspect, that progesterone perhaps doesn't pin point the exact oestrus time, we allowed a time-window in which the automated system could alert for oestrus.

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Question: Mattia Fustini (University of Bologna, Italy) – One possibility for the difference between the results of the experiment and the ones in literature is that the Microland commercial test for progesterone probably is not the best.

Answer: Claudia Kamphuis (Wageningen University, the Netherlands) – This could be an explanation, but I cannot confirm this.

Question: Daniel Berckmans (KU Leuven, Belgium) – Choosing the gold standard is always a difficult issue, but it is expected that the farmer should be really familiar with this process. How do you explain that the farmers went so wrong?

Answer: Claudia Kamphuis (Wageningen University, the Netherlands) – That was something that surprised us too. I can think of two main reasons. The first one is that farmers are not checking all the alerts from the system, and the second one is related to the fact that the system monitors 24/7 and if an alert comes out at 2 a.m. the farmer is going to miss it.

Question: Kristof Hermans (University of Ghent, Belgium) – It is normal that the farmers miss some of the alerts because usually cows show signs of heat at night time when the farmer is sleeping. But your system monitors all day so the results for detecting heat should be really high (Chapter 7.3).

Answer: Claudia Kamphuis (Wageningen University, the Netherlands) – From literature we know that at least 10% of the cows do not show signs of heat, so we are going to miss those ones, no matter at what time. But several studies that also used progesterone as the gold standard, show that the level of detection should be around 80%. We cannot explain why results in our study are so different from those previously conducted ones.

Question: Kristof Hermans (University of Ghent, Belgium) – The conception rate was 90%, which is really high. It is possible that a lot of inseminations were missing? Usually farmers only fill in when the insemination for conception succeeded and a lot of data is missing. One should expect a high rate when the BHB load is low and a lower rate when it is high (Chapter 7.1).

Answer: Jens Yde Blom (Lattec I/S, Denmark) – For herds in general, when we get an alarm for heat from the Navigator system in the afternoon, the cow will be inseminated during the morning of the day after tomorrow, 36-48 hours after the alarm. We updated these results with what we saw in the field, so they are referring to what we use. The results of the study show that the potential of high conception rates in dairy cows are not compromised in any way. Also, a drop in progesterone is equal to heat. We can state that after performing a study over a sample of around 400,000 cows. The problem is that a drop in progesterone is not always equal to an ovulation within the next 36 hours.

Question: Hans Spoolder (Wageningen UR Livestock Research, the Netherlands) – In cyclic cows, the length of the period during which progesterone levels are low is variable. Is the timing of ovulation similarly variable?

Answer: Jens Yde Blom (Lattec I/S, Denmark) – Yes, in an average cow the drop can last for 3-4 days. Based on our data, I would say that if an average cow in an average herd is not compromised, it should have an ovulation 48 hours after the drop in progesterone below the threshold.

Question: Hans Spoolder (Wageningen UR Livestock Research, the Netherlands) – Based on the fact we have a variation in the success rate of inseminating cows, I was thinking that with a combination of different factors we could give a better indication of when the ovulation is taking place.

Answer: Claudia Kamphuis (Wageningen University, the Netherlands) – I was a little bit surprised when I saw the low performance rates, but I think we can improve them using more data from the farms and using the raw data from the different systems. We are still looking for the right combination of factors.

Answer: Jens Yde Blom (Lattec I/S, Denmark) – With the Navigator bio-model we are also able to use activity data, which allow us to modulate the alarms. If we have an activity alert, we can combine that with the progesterone one and try to give a more precise alert on when to inseminate the cow.

Question: Niels Rutten (Utrecht University, the Netherlands) – The Navigator system (Chapter 7.1) allows the farmer to have information in advance regarding ketosis. What should the farmer do with this information? Usually the farmers do not like false alerts and if they (the farmers) do not detect the illness, they will not trust in the system any more.

Answer: Jens Yde Blom (Lattec I/S, Denmark) – The system is giving information in advance about ketosis to the farmers; in the beginning the farmers did not believe that there was so much ketosis in the herd, because there was no sign of it. However, learning from the lactation curves they realised that ketosis was indeed present in the herd. What we are implementing in this system is an alarm system in combination with a standard operating procedure or treatment protocol to follow in alarm cows. Our experience is that if you do this, the farmers will use it and will follow the procedures. One farmer said that they did not need the system because they routinely treat all cows for ketosis, but from a cost perspective, giving the treatment to all cows is a very costly way of dealing with the ketosis problem.

Answer: Tove Asmussen (Raw Milk Connect, Denmark) – We are talking so much about treating the sick cows and I think the biggest advantage of these systems should come from focusing on prevention, once you start having a high proportion of disease cows, how to proceed with the healthy ones comes up in the same situation.

Part 8. Precison livestock farming in rumen sensing, feed intake and precise feeding

8.1. Dairy farm evaluation of rumen pH bolus data: identifying the benefits

T.T.F. Mottram[1,2*]
[1]*Royal Agricultural University, School of Agriculture, Cirencester, GL7 6SJ, United Kingdom;* [2]*eCow Ltd., King St Business Centre, Exeter, EX1 1BH, United Kingdom; toby.mottram@rau.ac.uk*

Abstract

Ruminal pH is an important parameter for nutritional status particularly of dairy cows and studies using rumenocentesis showed 25% of cows have rumen pH values below 5.5 pH. Since 2005, boluses measuring pH continuously and using wireless telemetry have been used for research purposes, mainly in fistulated cows. This paper reports the use of 120 rumen pH telemetry boluses on 30 farms in South West England in 2013/2014. The farms were selected to represent a range of farm types from continuous grazing, through mixed grazing and concentrate feeding in a robotic milker to total mixed ration fed continuous housed cows milked three times a day. The data were collected by a nutritionist visiting the farm regularly with a handset to download data, analysing feed and talking to the farmer about events that affected rumen pH. The pH data were recorded in the reticulum which has a pH level approximately 0.25 pH units above that in the ventral sac from which rumenocentesis was conducted. Fewer than 5% of the recordings were below 5.75, indicating that sub-acute ruminal acidosis was not common in this sample of cows. The variety of responses to the rumen data will be presented as narrative case studies; they include one farmer saving 70 pence per cow per day by removing a minor food ingredient which raised mean rumen pH from the diet and increasing the amount of night time feeding without affecting milk yield. In a grazing situation one farmer changed his fence moving routine, which optimised rumen pH and raised milk yields. Several farms detected irregularities in rumen pH which were probably caused by changes in feed offered to the cows by different staff. Optimal pH values in different feeding systems will be discussed but the most important parameters to create pH targets for dairy farmers appear to be the daily range of pH, the mean daily pH, the number of feeds per day and detection of management changes.

Keywords: dairy cow, rumen pH, wireless, telemetry, temperature, nutrition, husbandry, management

Introduction

Reports of rumen wireless telemetry pH measurement boluses used in research have been available since Mottram *et al.* (2008). However, there have been no reports of the use farmers and their advisers make of rumen pH and temperature data. Existing methods for detecting sub-acute ruminal acidosis (SARA) in commercial cows are based on either rumenocentesis or through use of a sampling tube (Tajik and Nazifi, 2011). Both methods are invasive and can only gain one data point from an unknown location within the rumen, whereas the rumen pH was highly variable in time with up to 2.5 pH range through the day and varying spatially by up to 0.5 pH units from top to bottom within the rumen (Gasteiner *et al.*, 2010). The wireless telemetry bolus was intended to replace these crude techniques with a continuous recording of data from a fixed location within the rumen-reticulum, thereby overcoming the variability in data. The study described here had the

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intention of checking both the operability of the bolus in farm conditions and the use the farmer and his nutritionist made of the data.

Materials and methods

The boluses used were the farmBolus from eCow Ltd. (Exeter, UK). The farmBolus was 115 mm long by 26.5 mm diameter weighing 200 g. The sensor end was made of stainless steel which inverts the bolus into a normally sensor down position in cows with a normal shaped reticulum. The electronics was encapsulated with a cold poured resin coat that has proved resilient against rumen liquor in trials and obviates the need for vulnerable seals. The sensor was a combined electrode pH probe routinely used in applications in industry. The temperature probe was embedded in the stainless steel end cap, which has machined holes to allow rumen liquor to flow past the sensor tangentially without permitting direct impact of stones or grit on the glass sensing bulb.

The weight of the bolus allowed it to remain in the reticulum for the life of the cow. The bolus contained no toxic materials at doses harmful to the cow. The bolus measured pH and temperature every 60 s, took an average value every 15 minutes and stored up to 2,700 lines of data in a .csv format for date, time, pH, temperature, battery V, which was 96 lines of data per day stored over 28 days of data. If data was not collected the file on the bolus was overwritten from the beginning.

The bolus was administered by mouth with a standard bolling gun. The only restriction on operation was that a period of 2 hours should be allowed before reading for it to migrate to the reticulum. The bolus has a temperature switch which causes it only to activate when the temperature is above 31 °C, which enables a long shelf life. As with all pH sensors the device needs to be calibrated before use and the calibration is accurate for four weeks in normal storage. Once in the cow, drift is said to be less than ±0.1 pH unit per 30 days but this is impossible to verify in non-fistulated animals. The radio frequency used was in the free to use ISM band. In this study we wanted to compare the utility of two available frequencies 433 MHz and 868 MHz and identify any operational issues with the different frequencies.

The nutritionist visited the farms of an adapted mobile phone handset and stood near the cow on the left front side to download the data. The farmer inserted boluses in 2-3 cows, often during the ante-partum period to allow monitoring through the transition phase and early lactation.

Over 120 boluses were shipped to 30 farms in South West England in a collaboration between Mole Valley Farmers, eCow Ltd. and the Royal Agricultural University. The farms were selected to represent a variety of systems found in this area, from grass-based low input/output systems to very high-yielding continuously housed TMR systems.

Results and discussion

The main conclusions from the field testing were that monitoring rumen pH gives unique insights into farm management practice and that when matched to the events and circumstances on each farm, the data can trigger major management changes to improve rumen stability.

Case 1. Farm with low pH

This farm of 350 cows used a home-mixed diet which used bread meal for fast-release energy. The herd yield was over 12,000 litres and cows were milked three times a day. Total mixed ration (TMR) was offered daily. Three boluses were inserted in lactating cows on 1 May. The boluses showed a strong daily cycle with high pH at night and regularly dips below pH 5.8, usually in the evening (Figure 1). This is the closest case we had to SARA as described in the literature. The vertical lines are midnight of each day.

Removing the bread meal from the TMR very quickly brought the pH above 5.8 and also reduced the night-time peak, indicating that cows were eating little and often (Figure 2). There was no effect on milk yield but feed cost was reduced by 70 pence per cow per day.

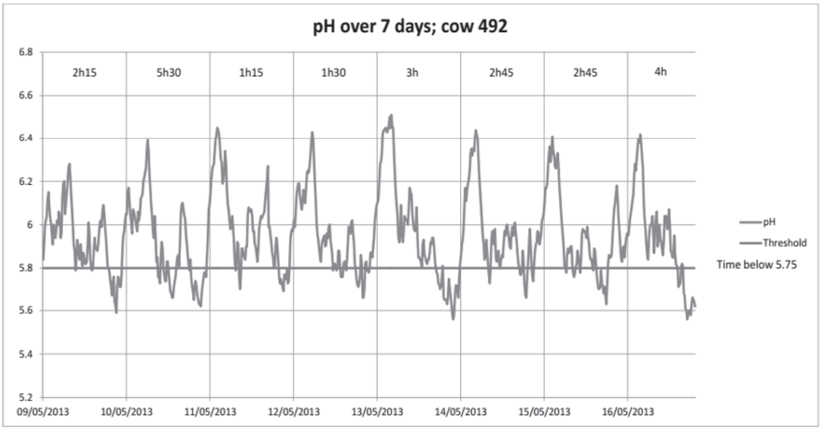

Figure 1. The numbers above each day are the hours below pH 5.8.

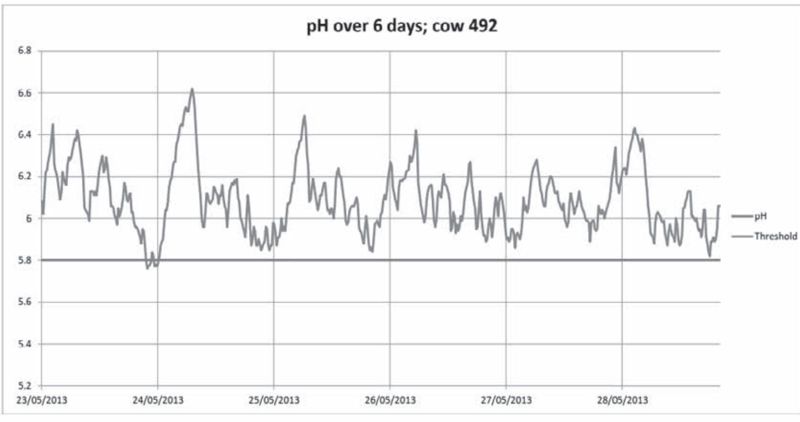

Figure 2. The same cow during and after feed change, showing how rapidly the rumen pH changed to a less dangerous level.

Case 2. Farm with grass as the main feed

Some commentators assume that grass is the natural feed for cows, that may be so, but not all grass is the same. On this farm which was predominantly grazed, there was a major difference between pastures. Between 9/06/13 and 12/06/13 this cow was on new 'high sugar' grass ley and then returned to one sown many years ago (Figure 3).

Case 3. Robotic milking

We had several robotic milking farms and they all showed a very consistent pattern with regular shallow dips in rumen pH and a narrow range (0.4) of pH during the day (Figure 4).

Case 4. Concentrate and grass

This is a very traditional method of feeding and milking. The cows are fed at milking and then go out to grass, leading to a twice a day cycle of rumen pH rise and fall with a daily range of 0.6 pH units (Figure 5).

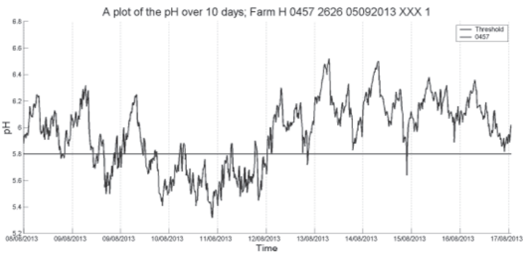

Figure 3. Digestible grass from a new high sugar ley can depress pH into the acidosis zone

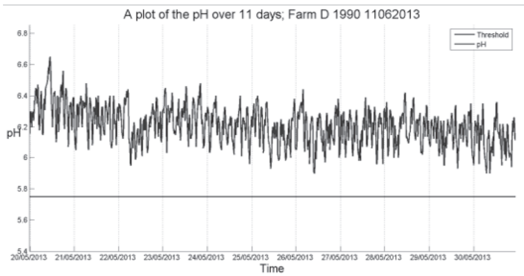

Figure 4. An example of little and often concentrate feeding driven with plenty of activity at night.

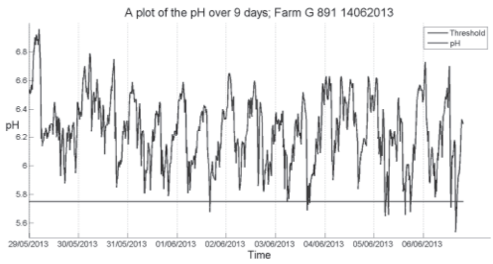

Figure 5. Twice daily dip in pH caused by the milking cycle.

Case 5. Rumen buffer – is it always necessary?

Veterinarians are convinced that high-yielding cows automatically have SARA but we see no evidence of this in this study. Farmers are advised to feed acid buffer. Our data suggest that this is not always the case and a diagnostic should be performed before this expensive addition to diet is recommended (Figure 6).

The main findings from this study are that few cows have a pH below 5.8 in the reticulum and by implication SARA was not found in this study. Each farm has specific management challenges and rumen pH monitoring permits farmers to make decisions better and earlier than waiting for milk yields to drop or health to deteriorate. The next stage is to determine optimum pH patterns and levels under different feeding regimes, but by inspection it would appear that the main parameters to manage are mean daily pH level, daily pH range, speed of drop after a feed (energy density of ration) and the number of feeds per day.

The benefits of rumen pH are reductions in feed costs and a reduction in risk by identifying the immediate effects of management changes.

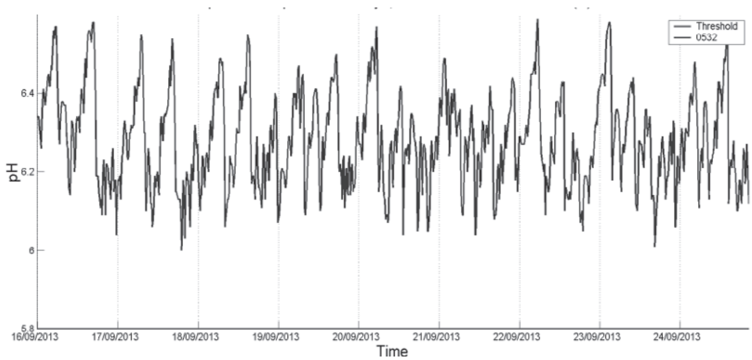

Figure 6. This farmer was using rumen buffer; removing it made virtually no difference to pH levels.

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8.2. Biopara-Milk: a whole cow simulation model for the prediction of rumen pH

V. Ambriz-Vilchis[1,2], R.H. Fawcett[2], D.J. Shaw[1], A.I. Macrae[1] and N.S. Jessop[2]*
[1]Royal Dick School of Veterinary Studies and the Roslin Institute, University of Edinburgh, Easter Bush Veterinary Centre, Roslin Midlothian EH25 9RG, United Kingdom; [2]Bioparametrics Ltd., The Cottage SRUC Building, West Mains Road, Edinburgh EH9 3JG, United Kingdom; ambrizvilchis@gmail.com

Abstract

Low rumen pH has deleterious effects for the dairy cow: it can alter feed intake, microbial metabolism and feed digestion and cause diarrhoea and laminitis. Amongst other factors rumen pH is affected by diet and so a way to predict the consequences of different feeding regimes on rumen pH would be beneficial. Mathematical modelling is a helpful tool to model the complexity of the rumen and to predict multiple responses of the rumen environment to different diets. Biopara-Milk is a whole cow model, simulating the digestive system and predicting performance and circadian pH dynamics. Intra-ruminal boluses are capable of measuring pH dynamics in non-fistulated animals. The aim of this study was to compare Biopara-Milk pH predictions against those obtained with rumen pH boluses in lactating dairy cows. Fourteen dairy cows were offered a partial mixed ration diet with concentrate fed to yield. Cows were orally administered an intra-ruminal bolus in order to measure rumen pH. Model input data included: detailed information on the feed-stuffs (chemical composition and degradation kinetics) and the animals (bodyweight, condition score, lactation potential, milk composition, week of lactation and lactation number, eating behaviour) and were input into Biopara-Milk. Correlation coefficient (r), concordance correlation coefficient (CCC) and the limits of agreement (LoA) method were performed to determine the relationship between the rumen pH flux obtained with the boluses and the predictions from Biopara-Milk. Average pH values per hour were obtained with both methods and r and CCC for the rumen pH data were acceptable (r=0.93, $P<0.05$ CCC=0.85; n=24,). The LoA showed that disagreements between the two methods were evenly distributed across the range. Estimates obtained with Biopara-Milk were 0.02 (95% C.I.=-0.33 and 0.29) lower than those obtained with the rumen pH boluses. The results showed the capabilities of Biopara-Milk to predict rumen pH dynamics in dairy cows.

Keywords: dairy cow, modelling, rumen pH

Introduction

In the dairy industry, the use of new technologies to measure physiological, behavioural and production parameters can improve management strategies and performance. An example of this is the use of boluses to measure rumen pH. Low rumen pH in dairy cattle can have deleterious effects, such as erratic feed intake, compromised microbial metabolism and feed digestion, and direct negative effects on the health of the dairy cow. Amongst other factors, pH is influenced by feeding regimes. Mathematical modelling is therefore a helpful tool to describe the complexity of the rumen and to predict multiple responses of the rumen to different diets. Biopara-Milk (Bioparametrics Ltd., Edinburgh, UK) is a whole cow model which simulates the ruminant digestive system and, predicts performance and circadian pH dynamics. The aim of the present

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study was to compare Biopara-Milk pH predictions against those obtained with the rumen pH boluses in lactating dairy cows in a commercial farm environment.

Material and methods

Fourteen multiparous dairy cows were selected and balanced for days in milk (DIM) (mean ± standard error of the mean) and parity (median lactation number (L)=4). The cows were randomly allocated to two different groups: Group 1 (G1: DIM 103±5.0, L=5) and Group 2 (G2: 105±4.6, L=4), with seven cows in each group. To facilitate management routines and video recordings, the groups were housed in contiguous pens that shared identical characteristics: area of feed and water troughs, cubicle/stalls with rubber mattresses top-dressed with sawdust three times a week. Cows were offered a partial mixed ration (PMR) consisting of grass silage 46.2% (fresh weight PMR proportion), wholecrop wheat silage 18.0%, crimped maize 6.7%, dairy meal 24.1% and molasses 5.1%, with additional concentrate fed to yield in the milking parlour. Water was supplied *ad libitum*, and the cows were milked twice daily (a.m. and p.m.) as per standard farm practice. To record rumen pH, cows were orally administered an intra-ruminal bolus (eCow Limited, Devon, UK). All individuals were clearly identified with a unique number or letter by colour spray (Arco Limited, Hull, UK) on either the side of the thorax and/or neck so they were easily viewed and recognized. Cows were given two weeks to adapt to the diet and facilities. All measurements were taken in the third week. Cow behaviour was recorded using sixteen video cameras (Panasonic WV BP120, Panasonic, Bracknell, UK) with 1/3' fixed iris lenses (Panasonic WV-LF4R5C3AE, Panasonic). The cameras were positioned throughout the shed so that all cows were viewed and easily identified (by their unique number or letter) at any given time. The area under observation was naturally lit during daylight hours and infrared lighting was used for night time recording. The cameras recorded 24 h per day. On an average day, 3 h of cow behaviour were missed as the cows left the pens to be milked (around 5 a.m. and 3 p.m.). Behavioural measurements were analysed and recorded using The Observer® software (Noldus Information Technology, 2004, Wageningen, the Netherlands) by one trained observer using the video tapes recorded during the measuring week. Behaviours (eating, drinking, idling and ruminating) were recorded according to the ethogram shown in Table 1. Behaviours were recorded continuously (Martin and Bateson, 1994; Mitlohner *et al.*, 2001) and were defined as being mutually exclusive categories, the daily time budget (eating) was used as input for Biopara-Milk model.

The model: Biopara-Milk

This is a whole animal simulation model developed from basic and sound principles of rumen function, microbial growth, feed digestion and passage rates, and animal physiology (taking into account: maintenance, growth, lactation (stage and parity number), pregnancy, and body

Table 1. Behavioural ethogram.

Behaviour	Definition
Eating	head over or in the feed trough
Drinking	head over or in the water trough
Ruminating	time the cow spends chewing a regurgitated bolus until it swallows it back
Idling	no ruminating, eating or drinking behaviour

reserves). At its simplest level, the model uses the ingredients in a diet or partial mixed ration and predicts the daily intake of that diet taking into account any constraints imposed by animal size and rumen volume. The nutrient supply to the animal from the daily feed intake is then predicted by application of appropriate passage rates of material from the rumen (liquid, small and large particles for forages, small and large particles for concentrates) and extent of fermentation within the rumen (each feedstuff has up to seven fermentation rates). Milk yield and/or body weight change (separately for protein and lipid) are then predicted from the amount and pattern of absorbed nutrients. Rumen pH is predicted for a 24 hour period, based on the amounts and pattern of feed consumed and fermentation and passage rates. Rumen pH predictions are derived from a dynamic process by continuously estimating the concentration of bicarbonate in the rumen: i.e. its production and usage (Dijkstra *et al.*, 2012; Kohn and Dunlap, 1998) (Figure 1). Bicarbonate is produced, firstly, from saliva at three different rates: resting, eating and ruminating (Bailey, 1961), secondly by the addition of bicarbonate to the diet, and lastly by the absorption of volatile fatty acids (VFA) through the rumen wall as it results in varying amounts of bicarbonate production from CO_2. The amount of bicarbonate produced depends on the animal's size. The bicarbonate is used as a result of its interactions with hydrogen ions, and from its movements from the rumen at liquid and solid passage rates. Salivation produces bicarbonate and urea, at a low and constant rate from resting and from eating, and at a high rate for a short period of time from rumination.

Biopara-Milk is a simulation model that calculates outputs every six minutes throughout the day. Every simulated day, the outputs are checked and if necessary, the rumen fill is adjusted upwards (there is a maximum) or downwards for the next simulated day. A steady state is reached by 20 days.

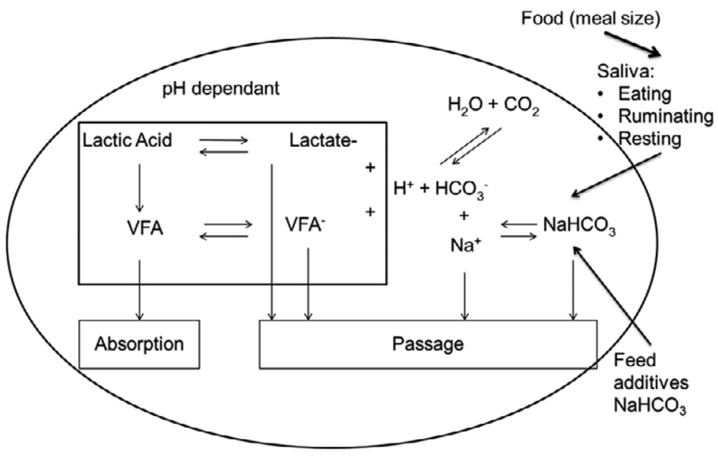

Figure 1. Factors affecting rumen pH: bicarbonate concentration, production and usage.

Model inputs

Animal parameters

Current liveweight (kg), condition score (1-5 scale), lactation potential (305 days yield), milk composition (butter-fat % and protein %), lactation number (heifers, second lactation and third or more lactations) and eating behaviour. Eating behaviour can be entered in five different ways: automatic or Biopara-Milk uses a predetermined meal pattern of eight meals, six meals, four meals or set meal times, i.e. from 3 to 11 meals can be set during a 24-hour period.

Feed-stuffs

Biopara-Milk uses libraries containing a detailed description of all feeds, forages, minerals, compounds and premixes. A detailed description of the feed ingredients is required, including fermentation rates and lags for carbohydrates and protein measured by the *in vitro* gas production technique (Menke and Steingass, 1988). The gas production parameters are routinely predicted by near infrared spectroscopy for most of the forages commonly found in northern temperate climates. The parameters required for the model are: dry matter, ash, oil, sugar, starch, neutral detergent fibre, protein and fermentation products (VFA, lactic and ammonia) obtained by AOAC International methods and degradation parameters for carbohydrates and protein (lag and rates).

Model outputs

Biopara-Milk predicts dry matter intake, milk yield and rumen pH dynamics. Data on the animals and feed characteristics obtained from the feed trial were used to run the Biopara-Milk model. Predictions obtained for each individual animal were used to make comparisons between observed and predicted rumen pH values per hour. A modification of the standard limits of agreement (LoA) methodology was used to take account of the multiple observations per individual (Bland and Altman, 1986, 2007), and to explore the agreement between the predicted and observed pH values. To further assess this relationship and to avoid temporal pseudoreplication due to repeated measurements from the same individual animal, the correlation coefficient (r) and concordance correlation coefficient (CCC) were obtained from pooled data for the means of pH per hour for all individual cows. All statistical analyses were performed using R (R Core Team, 2013), using the modified version of the LoA with repeated measures as modified by (Nutter, 2008) and CCC using the 'Epi.R' package (version 0.9-58). Statistical significance was taken as $P<0.05$.

Results

Reliable pH values per hour were obtained with the intra-rumen boluses from nine of the fourteen cows. Figure 2 shows the circadian pH dynamics per cow obtained with the rumen pH boluses and with Biopara-Milk.

The LoA method (Figure 3) showed an evenly distributed scatter of measurements with no discernible patterns; the disagreements between the two methods were evenly distributed across the range. There were no tendencies for the differences between predicted and observed pH values to become larger or smaller as the averages increased. The pH predictions obtained with Biopara-Milk were on average 0.02 (95% CI -0.33 and 0.29) lower than those recorded with the boluses.

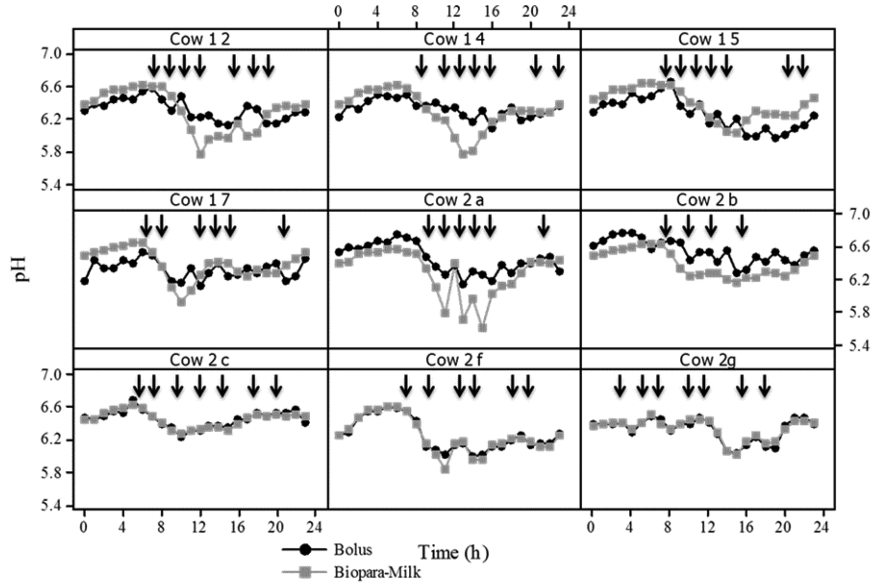

Figure 2. Circadian pH dynamics obtained with Biopara-Milk and by intra-ruminal boluses per cow. The arrows represent feeding patterns (each individual meal).

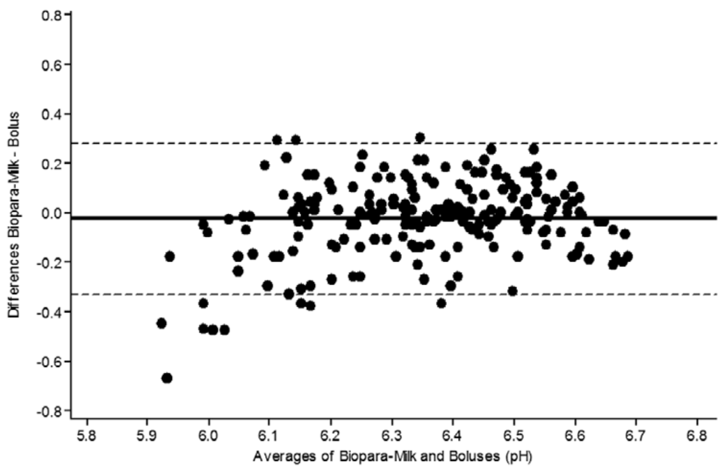

Figure 3. The limits of agreement method with multiple observations per individual. The plot shows pH values per hour per cow obtained with the pH boluses and with Biopara-Milk. The lines represent the main difference between the two methods (central solid line, -0.02) and the limits of agreement higher (upper broken line 0.29) and lower (lower broken line -0.33).

Figure 4 shows the pooled data for the means of pH per hour from all the cows obtained with both Biopara-Milk and the rumen boluses. Biopara-Milk rumen pH predictions were highly correlated to those recorded with the rumen boluses (r=0.93, P<0.005, CCC=0.85, n=24).

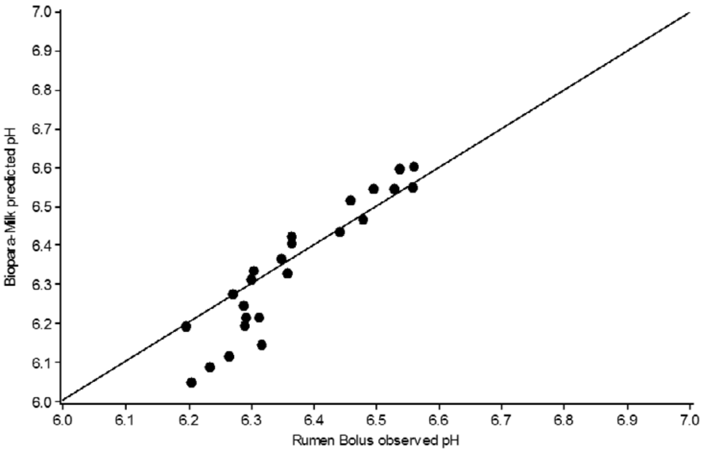

Figure 4. Pooled data for rumen pH per hour for all cows obtained with Biopara-Milk and the rumen pH boluses.

Conclusions

Modelling allows the simulation of several aspects of dairy cow physiology, and such simulations can be used to evaluate the effect that feeding regimes have on ruminant physiology and production. Evaluation of the results of such simulation exercises is of benefit as a means of testing assumptions regarding rumen physiology and environment. Measurement of rumen pH dynamics from rumen boluses can be used to evaluate the suitability of such models. Predicting rumen pH dynamics involves many assumptions: firstly, the rumen bicarbonate levels depend on salivary input (variation in saliva production rates between resting, eating and ruminating), passage rate, absorption of VFA and level of bicarbonate in the feed; secondly, the production of acid depends on the diet and its degradation, microbial metabolism, passage and absorption, and lastly, the calculation of resultant bicarbonate levels per hour. Given an accurate description of the animals and the feed consumed, Biopara-Milk is capable of accurately predicting pH dynamics in dairy cows. The simulation exercise has shown the capabilities of Biopara-Milk to predict pH dynamics in dairy cows. Future work will explore the use of Biopara-Milk as a diagnostic tool for rumen pH related diseases such as sub-acute rumen acidosis.

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8.3. Feeding concentrate in early lactation based on rumination time

M.V. Byskov[1], M.R. Weisbjerg[2], B. Markussen[3], O. Aaes[1] and P. Nørgaard[4]*
[1]Knowledge Centre for Agriculture, Cattle, Agro Food Park 15, 8200 Aarhus N, Denmark; [2]Department of Animal Science, AU Foulum, Aarhus University, Blichers allé 20, 8830 Tjele, Denmark; [3]Laboratory of Applied Statistics, University of Copenhagen, Universitetsparken 5, 2100 Copenhagen, Denmark; [4]Department of Veterinary Clinical and Animal Sciences, University of Copenhagen, Gronnegaardsvej 3, 1870 Frederiksberg C, Denmark; mvl@vfl.dk

Abstract

Precision feeding of dairy cows facilitates optimization of milk production. Accordingly, the objective was to study the effect on milk production when stepping up concentrate at 3 rates in early lactation according to individual daily rumination time (RT). Data was collected in 3 commercial dairy herds with Holstein cows, where daily RT was recorded by rumination sensors (Qwes HR™). Cows were fed a partially mixed ration and concentrate at the milking robot. Concentrate was stepped up over the first 28 and 17 days in milk for primiparous and multiparous cows. Cows were assigned to either an experimental group (EXP) or a control group (CON) immediately after calving. In addition, all cows in the EXP and CON were assigned to either a high, medial or low rumination group according to their individual RT. Cows in the EXP assigned to the high (E_H), medial (E_M) or low (E_L) rumination group were stepped up to 6, 4 or 3 kg concentrate during the experimental period. Concentrate was stepped up to 4 kg during the experimental period for all cows in the CON, regardless of whether the cows were assigned to the high (C_H), medial (C_M) or low (C_L) rumination group. In total, 40 and 41 primiparous cows and 66 and 66 multiparous cows in the EXP and CON finished the trial. Primiparous cows in the EXP showed higher ECM yield than primiparous cows in the CON (26.1 vs 25.6 kg per day). The same applied to primiparous cows in the E_L compared to C_L (25.6 vs 25.1 kg per day). No effect on milk production was found for multiparous cows. In conclusion, adjusting the concentrate allocation rate in early lactation based on RT shows a potential effect on ECM yield for primiparous cows.

Keywords: forage:concentrate ratio, milk production, precision feeding, rumination time

Introduction

Feeding cows in early lactation requires the feed to be optimized to promote high milk production, and to cover the requirement for both structural fibre and energy in order to prevent digestive disorders. Studies have found substantial variations in dry matter intake (Ingvartsen and Friggens, 2005), milk production and mobilization between early lactating cows within the same herd (Bossen and Weisbjerg, 2005). Furthermore, Soriani *et al.* (2012) found that cows in early lactation fed the same ration expressed great variation in rumination time (RT), indicating a large variation in the intake of physically effective structural fibre (Nørgaard *et al.*, 2010). Accordingly, there is a potential for precision feeding of cows in order to accommodate the nutrient requirements for each individual cow (Ingvartsen and Friggens, 2005; Ingvartsen *et al.*, 2003). However, since cows in modern dairy production systems are mainly fed mixed rations, precision feeding must be performed by separate concentrate feeding (Bach, 2013; Maltz *et al.*, 2013), which is commonly

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used in automatic milking systems (AMS). In early lactation, concentrate is allocated to all cows at a fixed increasing rate within the first 3 to 4 weeks of lactation in order to facilitate a gentle transition to high energy-dense feeding after parturition. Therefore, the variation in the intake of partially mixed ration (PMR), provided *ad libitum*, between cows determines the energy density of the compiled feed that each cow consumes. Consequently, a high PMR intake results in dilution of the concentrate supply, creating a less energy-dense compiled ration and vice versa. Hence, both situations entail individual deviation from the optimal energy density of the diet. This increases the risk of nutritional imbalance, impaired health, and lower milk production. Consequently, the ability to adjust concentrate allocation to individual feed intake in early lactation could potentially overcome this problem. However, no equipment is available to record individual intake of PMR in commercial dairy herds. An indirect method of recording feed intake might be to record individual daily RT, since the intake of forage NDF drives RT (Adin *et al.*, 2009; Yang *et al.*, 2001,). It is already possible to record daily RT using of a rumination monitoring system (RMS) (Byskov *et al.*, 2014). Therefore, adjusting the concentrate allocation according to individual RT values appears to be possible. Consequently, the objective was to study the effect on milk production when stepping up concentrate at 3 rates in early lactation according to individual daily RT.

Materials and methods

Recording rumination time

Daily RT was recorded by the RMS (Qwes HR, SCR Engineering, Netanya, Israel). Rumination time is recorded by a sensor placed dorsally on the left side of the cow's neck, where it identifies RT from the sound pattern of rumination behaviour. Rumination is recorded as minutes of rumination activity within 2-hour intervals, and daily RT is totalled from the twelve 2-hour intervals in 24 hours, starting at midnight.

Herds, cows and experimental facilities

The trial was conducted in 3 commercial Holstein dairy herds (herd I, II and III) during the period from September 2012 to February 2013. Cows were housed in loose housing systems with cubicles and a slatted or solid floor, having free access to PMR and water provided *ad libitum*. The cows were milked in AMS and supplemented with concentrate within the AMS. The herd size ranged from 140 to 360 lactating Danish Holstein cows. Each cow which calved during the experimental period entered the trial on the day of parturition, with 34, 57 and 122 cows completing the trial from herd I, II and III respectively. The distribution was 81 primiparous and 132 multiparous cows in total.

Experimental design and diets

Immediately after parturition, both primiparous and multiparous cows were continuously assigned to one of the two trial groups; the experimental group (EXP) and the control group (CON). In total, 40 and 41 primiparous cows and 66 and 66 multiparous cows in the EXP and CON finished the trial. Based on the level of RT from day 4 to 7 after calving, 3 rumination groups were created for each herd and for both primi- and multiparous cows, representing high, medial, and low RT. All cows in the EXP and CON were assigned to one of the three rumination groups according to their individual RT. The experimental period covered the period when concentrate was increased, also referred to as the step-up period. In the experimental period, concentrate was stepped up over 28 and 17 days, for primi- and multiparous cows, respectively. All cows in the CON were also assigned to the three rumination groups, however, they were all stepped up to 4 kg of concentrate, with a daily concentrate allocation rate of 0.09 and 0.12 kg/day for primi- and multiparous cows, respectively. The C_H was for cows in the CON in the high rumination group; the C_M was for cows in the CON in the medial rumination group, and the C_L was for cows in the CON in the low rumination group. For cows in the EXP and in the high rumination group, the concentrate amount was stepped up to 6 kg (E_H), with a daily concentrate allocation rate of 0.18 and 0.28 kg/day for primi- and multiparous cows. For cows in the EXP and in the medial rumination group, the concentrate amount was stepped up to 4 kg which was the same as for all cows in the CON (E_M). For cows in the EXP and in the low rumination group, the concentrate amount was stepped up to 3 kg (E_L), with a daily concentrate allocation rate of 0.05 and 0.04 kg/day for primi- and multiparous cows.

Statistical analysis

The differences between the EXP and CON groups and between the treatment groups in terms of milk production was analysed by using the MIXED procedure in SAS 9.2 (SAS Institute Inc., Cary, NC, USA). The model consisted of:

$$Y_i = \mu + a(EG_i) + b*DIM_i + c(EG_i)*DIM_i + d*DIM_i^2 + e(EG_i)*DIM_i^2 + f*M4_i + A(cow_i) + B(herd_i) + C(cow_i, DIM_i) + \varepsilon_i$$

where Y_i = dependent variable; μ = overall mean; $a(EG_i)$ = fixed effect of trial group (EXP vs CON); $b*DIM_i$ = linear term of DIM; $c(EG_i)*DIM_i$ = trial group dependent linear term of DIM_i; $d*DIM_i^2$ = quadratic term of DIM_i; $e(EG_i)*DIM_i^2$ = trial group dependent quadratic term of DIM_i; $f*M4_i$ = linear term of milk production at 4 DIM; $A(cow_i)$ = random effect of cow; $B(herd_i)$ = random effect of herd; $C(cow_{i,}\ DIM_i)$ = exponential correlated term of the repeated recordings within each cow; and ε_i = random error term. The effect of treatment group (E_H, E_M, E_L, C_H, C_M and C_L) on milk production was analysed with a similar model using treatment group instead of trial group. Individual comparisons between treatment groups were performed using the CONTRAST statement in the MIXED procedure.

Results

The results showed that primiparous cows in the EXP had significantly higher energy-corrected milk (ECM) yield than cows in the CON, with ECM yields of 26.1 and 25.6 kg/d, respectively (P=0.02). No effect of trial group on ECM yield was found for multiparous cows (P≥0.2). Comparison between treatment groups showed that primiparous cows on the E_L had significantly higher ECM yield of 25.6 compared to 25.1 kg/d for the C_L (P=0.05). Again, no effect of treatment group was found for multiparous cows.

Conclusions

Allocation of concentrate to early lactating cows according to the daily RT increased ECM yield by 0.5 kg/day for primiparous cows. Furthermore, allocating a lower concentrate amount to primiparous cows with low RT increased ECM yield by 0.5 kg/day. The allocation of concentrate to multiparous cows based on daily RT appears not to affect RT. In conclusion, it seems plausible that there might be a positive effect on ECM yield for primiparous cows. However, larger scale studies, using more cows and extending the trial period are needed in order to confirm the results.

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8.4. Ability to estimate feed intake from presence at feeding trough and chewing activity

C. Pahl[1], A. Haeussermann[1], A. Grothmann[2], K. Mahlkow-Nerge[3] and E. Hartung[1]*
[1]Christian-Albrechts-University Kiel, Institute of Agricultural Engineering, Max-Eyth-Strasse 6, 24098 Kiel, Germany; [2]Agroscope Research Station ART, Tänikon, 8356 Ettenhausen, Switzerland; [3]Chamber of Agriculture Schleswig-Holstein, Futterkamp, 24237 Blekendorf, Germany; ahaeussermann@ilv.uni-kiel.de

Abstract

Monitoring of feeding and rumination behaviour can provide useful information for dairy herd management. The feeding behaviour of dairy cows can be recorded by different techniques, such as indoor localisation, weighing troughs, or chewing sensors. Among feeding characteristics, individual feed intake of cows is of utmost interest, but weighing troughs have high space and cost requirements so they are only used in research. The objective of the present study was to evaluate whether records on feeding time or chewing activity or a combination of both contain enough information to estimate feed intake with sufficient accuracy. Feed intake and feeding time per cow were recorded by means of weighing troughs (Insentec, The Netherlands). Simultaneously, chewing activity of seven cows was recorded by MSR-ART pressure sensors (ART, Tänikon, Switzerland) during five to eight measuring days per cow. Feeding and chewing behaviour were evaluated in time slots (1 min) and additionally assigned to feeding bouts for further analysis. Over all cows, the two systems classified 92.2% of the recorded one-minute time slots concurrently as feeding and chewing activities. On average, cows spent 270±39 min per day at the feeding troughs and chewed for 262±48 min per day. The average feed intake was 49.6±5.1 kg per day. Feeding time per day was divided into 9.7 bouts during which cows fed for an average 27.8±21.7 min per bout and chewed for 27.0±23.1 min per bout. The correlation between fresh matter intake and feeding time was 0.891 and the correlation between fresh matter intake and chewing time was 0.780 over all cows. Hence, both systems delivered suitable information for estimating feed intake.

Keywords: dairy cow, sensor, behaviour, rumination, weighing trough

Introduction

Knowledge about the feeding behaviour, namely feeding time, feed intake and feeding rate, of dairy cows can provide useful information for dairy herd management. In addition to traditional methods such as visual observation or video recording (Krawczel *et al.*, 2012), systems for automatic monitoring of feeding behaviour which do not need an operator have been developed and the disadvantages of former systems, such as high time and work input have been overcome. Automated monitoring systems enable continuous collection of information on the feeding behaviour of individual dairy cows in loose housing systems over long-term periods, and the feasibility of such methods has been confirmed in several studies (Chapinal *et al.*, 2007; DeVries *et al.*, 2003).

Changes in the feeding behaviour of dairy cows have been identified as serious indicators for health disorders (Bareille *et al.*, 2003). Reduced dry matter intake (DMI) often heralds upcoming health disorders several days before they become acute and thereby facilitates early detection,

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but changes in feeding behaviour during health disorders are not limited to feed intake and also include feeding time and feeding rate (González *et al.*, 2008). Different health disorders caused specific effects, but in the case of ketosis, in particular, a decrease in feeding time, feed intake and feeding rate (g fresh matter/min) occurs several days before detection by farm staff (González *et al.*, 2008). Furthermore, the level of feed intake is of particular importance when calculating need-based feed composition.

The feeding behaviour of individual dairy cows can provide useful information for enhancement of animal welfare by early detection of upcoming health disorders (González *et al.*, 2008). As well as feed intake, additional feeding characteristics such as feeding time or feeding rate improve the informative value of feeding data. Despite the proven suitability of weighing troughs and electronic identification systems for monitoring of feeding behaviour, the former are not suitable for commercial farms and are used predominantly in dairy research. Automated systems like weighing troughs have higher space requirements than conventional feeding systems and are quite expensive. In consequence, benefits such as early detection of health disorders resulting from research work (González *et al.*, 2008) are not transferred into practical dairy management and there is a need for methods which are easier to implement. Therefore, the objective of the present study was to analyse whether feed intake could be estimated with sufficient accuracy from feeding time, chewing time and rumination time. Furthermore, the improvement in the accuracy of estimating feed intake from a combination of variables was analysed. In the same context, the temporal accordance between feeding time and chewing time, measured with two different types of sensor, was evaluated.

Materials and methods

The study was conducted at the federal state research farm LVZ Futterkamp (Schleswig-Holstein Chamber of Agriculture, Germany). The farm milked around 190 German Holstein cows with an average herd yield of 10,700 kg milk/305 days (3.9% milk fat and 3.2% milk protein) during the trial period. Seven cows were included in the trial and between five and eight measurement days per cow were incorporated into the analysis. Data recording was scheduled in August and September 2011.

Animals, housing and feeding

Primiparous (first lactation; n=3) and multiparous (≥second lactation; n=4) cows were included in the trial and cows were 145-294 days in milk on the date when the trial started. The cows in the study were kept in one of two separate compartments, each with 36 cow places, 18 feed weighing troughs (Insentec, Marknesse, the Netherlands) and two water troughs (Insentec). The two compartments were part of a cubicle housing system with a solid concrete floor, which was cleaned by folding slides. Cows were fed total mixed rations (TMR) containing 51-57% maize silage, 22-32% grass silage, 9-21% concentrate, 1% straw and additives. The feed ration was slightly changed during data records of individual cows and varied between cows at the beginning, middle and end of the study. The composition of the TMR fed was calculated to achieve a daily milk yield of 33 kg. The energy content was 6.9-7.1 MJ NEL/kg dry matter (DM) and the crude fibre content amounted to 15.9-16.4% of DM. The basic components varied because of changes in management of the research farm. Both TMR and water were provided *ad libitum*. Fresh TMR was fed twice per day at 06:00 h and 16:00 h. Cows were milked in a milking parlour between 05:00 h and 07:00 h in the morning and between 15:00 h and 17:00 h in the afternoon.

Data recording

Feeding behaviour was monitored with two different systems: weighing troughs for recording feeding time and fresh matter (FM) intake, and pressure sensors (ART-MSR, Agroscope Reckenholz-Tänikon, Switzerland) for recording chewing and rumination time. The weighing troughs were locked when in a passive state, opened after identifying the entering cow by means of a transponder, and closed after the cow had left. The system recorded time of day, visit duration and feed intake for each visit to the feed trough and stored the data together with the number of the visiting cow. Presence at the trough was classified as feeding time if the visit duration was longer than 20 s within one minute.

Raw data for chewing and rumination were recorded with ART-MSR sensors which consisted of a noseband sensor, fixed to the cow's head by a halter, and a modular signal recorder MSR 145 logger (Nydegger *et al.*, 2010). The raw data were evaluated using R-based software (R, Boston, MA, USA). Due to low pressure values, data from cow 54 were also evaluated with a low amplitude classification. The raw data contained 600 measurement readings per minute and the software RumiWatch Converter (ART, Tänikon, and ITIN+HOCH, Liestal, Switzerland) was used to aggregate chewing and rumination activity per minute. The activity within one minute was summarised and classified according to the prevailing activity (0 = other, 1 = ruminating, 2 = chewing).

The following variables were included in the evaluation:
- feeding time (min; weighing trough): duration of presence at trough, including presence at trough without measurable feed intake;
- feeding time corrected (min; weighing trough): duration of presence at trough with measurable feed intake (weight loss >100 g/visit), excluding zero values (trough presence without measurable feed intake);
- feed intake (kg; weighing trough): weight loss (> 100 g/visit) of trough content during presence at trough;
- feeding intake rate (kg/min; weighing trough): feed intake per minute of feeding time corrected;
- chewing time (min; ART-MSR sensor): minutes classified as chewing activity;
- chewing intake rate (kg/min; weighing trough, ART-MSR sensor): feed intake per minute of chewing time;
- rumination time (min; ART-MSR sensor): minutes classified as rumination activity.

Data analysis

Feeding and chewing activity were grouped into bouts whereby feed trough visits were used as the determining variable. Feed trough visits were aggregated to one bout if the time intervals between single visits were not longer than 5 min. A bout ended 3 min after the last feed trough visit of the current bout. Chewing and rumination activity were assigned to the current bout if they took place during the bout or at least no longer than 3 min after the last feed trough visit of the current bout. In all other cases they were assigned to the next bout.

Feeding time, feed intake, chewing time and rumination time were totalled for each bout. Feeding activity occasionally contained time during the visit to the feed trough during which no feed intake was measured. Feeding time was analysed including and excluding these zero values.

The program used for statistical analysis was PASW 18.0 (IBM, Armonk, USA). Differences between groups of primiparous and multiparous cows were analysed using the Mann-Whitney test. Correlation coefficients between variables were tested using the Pearson correlation test (P<0.01). Coefficients of determination were calculated with a linear regression model. Feed intake served as a dependent variable and feeding, chewing and rumination time alone or in combination as independent variables.

Results

The average daily milk yield varied between 27.5 kg and 42.8 kg per day per cow. Feed intake averaged between 46.2 kg and 54.0 kg FM per day per cow. Cows spent on average 270±39 min per day at the weighing troughs, and feeding time corrected for zero values was 243±43 min per day. The average chewing time was 262±48 min per day per cow, while rumination time was 534±58 min per day per cow. Feeding, chewing and rumination time per day did not vary between primiparous and multiparous cows. The average intake rate was 211 g/min for feeding and 190 g/min for chewing. The daily intake rate varied between 120 g/min (04:00 h to 05:00 h) and 299 g/min (15:00 h to 16:00 h) for feeding, and between 88 g/min (01:00 h to 02:00 h) and 238 g/min (16:00 h to 17:00 h) for chewing.

The number of bouts per cow per day ranged between 8.4 and 11.8 and averaged 9.7. Most feeding bouts started between 06:00 h and 07:00 h (12%) and between 17:00 h and 18:00 h (8%). The fewest bouts were initiated between 02:00 h and 06:00 h (total 2.5%). The average feeding time per bout was 27.8±21.7 min while average chewing time per bout was 27.0±23.1 min. Cows consumed 5.2±4.5 kg FM per bout on average. No differences between primiparous and multiparous cows were identified for feeding time per bout, chewing time per bout and feed intake per bout. Feeding time corrected per bout and chewing rate per bout were higher in primiparous cows than in multiparous cows; for feeding rate the opposite was true (P<0.05).

The temporal accordance between the weighing trough and the ART-MSR sensor for classification of corrected feeding time and chewing time per minute ('one-min time slot') is presented in Table 1 for the cow with the highest and the lowest accordance. The highest accordance between both systems was achieved in cow 110 as 94.1% of the recorded one-min time slots were classified identically as feeding/chewing (11) or no feeding/no chewing (00; Table 1). The lowest accordance was obtained for cow 910 with 89.6% of time slots classified identically. In six of the seven cows both systems classified more than 90% of the time slots in the same way. On average, more time slots were designated as chewing by the ART-MSR sensor and as not feeding by weighing troughs (10) than vice versa (01). The absolute number of classifications as chewing exceeded those as feeding in five of seven cows.

Table 1. Accordance (%) between weighing trough and ART-MSR sensor for classification of cow activity as feeding time corrected and chewing time.

Classification[1]	00	10	01	11	00 + 11	10 + 01
Best (cow 110; n=10,095 min)	74.2	2.5	3.4	19.9	94.1	5.9
Worst (cow 910; n=11,557 min)	76.3	8.2	2.2	13.3	89.6	10.4
Average (n=70,697 min)	77.2	5.3	2.5	15.0	92.2	7.8

[1] 00 = no chewing/no feeding; 10 = chewing/no feeding; 01 = no chewing/feeding; 11 = feeding/chewing.

Correlations between feed intake and feeding time per bout (r=0.891) and feed intake and chewing time per bout (r=0.907) were highly significant ($P<0.01$) for each cow (Table 2). Correlations between feed intake and feeding time per bout were similar to correlations between feed intake and chewing time per bout, except for cow 54. This resulted in a lower correlation between feed intake and chewing time per bout for the complete group of cows. Feed intake and rumination time per bout were correlated significantly ($P<0.05$) but correlation was only of medium strength (r=0.337, cow 991; r=0.362, cow 994). The exclusion of time spent at feeding troughs without feed intake (feeding time corrected) improved the correlation coefficients per bout for individual cows and for the group.

The ability to estimate feed intake was tested with a linear regression model using feeding and chewing time as input variables. The coefficient of determination (R^2) per cow ranged between 0.699 and 0.940 when feeding time included time slots without measurable feed intake and between 0.874 and 0.950 for corrected feeding time (Table 2). In general, the contribution of chewing time to feed intake estimation was equal to or slightly higher than that of feeding time, indicated by higher correlation coefficients. However, chewing time was more susceptible to the results for individual cows, as exemplified by cow 54. For this cow a high correlation between feed intake and chewing time was achieved if low amplitude classification was chosen but not for the common classification. The additional consideration of rumination time led to a slight increase in the coefficient of determination (chewing, rumination and feeding time, cows 994 and 991: R^2=0.743 – R^2=0.950).

Discussion

Feed intake in dairy cows is influenced by many factors (Ingvartsen and Andersen, 2000). The cows involved in the current study were kept under constant environmental conditions, but varied in terms of actual milk yield, stage of lactation, and slightly in feeding ration. Cows were neither suffering from apparent health disorders nor affected by management activities, e.g. hoof trimming, during the trial. As the present study represents a random sample of five to eight

Table 2. Correlation (r) and coefficient of determination (R^2) for the relationship between feed intake per bout (dependent variable) and feeding and chewing time per bout (independent variables; singly and combined).[1,2]

	Cow 12	Cow 54	Cow 110	Cow 111	Cow 910	Cow 991	Cow 994	Group
r (feeding time)	0.937**	0.938**	0.938**	0.932**	0.907**	0.950**	0.800**	0.891**
r (feeding time corrected)	0.960**	0.942**	0.942**	0.950**	0.946**	0.966**	0.932**	0.917**
r (chewing time)	0.937**	0.532** [0.958**]	0.955**	0.929**	0.917**	0.966**	0.824**	0.780** [0.907**]
R^2 (chewing and feeding time)	0.922	0.898 [0.928]	0.913	0.874	0.848	0.940	0.699	0.785 [0.825]
R^2 (chewing and feeding time corrected)	0.934	0.908 [0.929]	0.914	0.904	0.907	0.950	0.874	0.833 [0.844]

[1] ** means correlation on significant level ($P<0.01$).

[2] [ ]: evaluation of chewing time with low amplitude classification in cow 54.

observation days per cow, effects such as season or health disorders were not included. Both variables, feeding and chewing time, demonstrated potential for estimation of feed intake. For broader application, however, the correlation must be confirmed and validated using a larger data base which enables as yet unconsidered effects to be included.

In general, stationary electronic feed monitoring systems are validated by comparison to records from direct visual observation (Bach *et al.* 2004; Chapinal *et al.* 2007; DeVries *et al.* 2003). The current study differs from the cited works as the duration of presence at a stationary feeding trough system was compared with chewing time recorded by a mobile pressure sensor. The number of one-minute time slots per cow that were classified non-uniformly was between 5.9 and 10.4% (Table 1); there are several possible explanations for this. Cows may be logged in to weighing troughs while just idling or browsing the ration. Correction of feeding time for feed trough visits without feed intake reduced non-uniform classification in the study. Feed thrown out of the trough may become inaccessible to cows but might be monitored as feed intake, although this was unlikely because the weighing troughs had high side panels which normally prevented the cows from throwing out feed. It was much more likely that ART-MSR sensors would classify time slots as chewing and that weighing troughs would classify time slots as not feeding (10) than vice versa (01, Table 1). Cows can exhibit chewing activity when they are beside the troughs because they may simply continue chewing after having left the weighing troughs. Furthermore, continuous grooming or licking of other cows (>10 s) might have caused pressure shifts which led to classification as feeding (N. Zehner, personal communication). Altogether, the accordance between the two monitoring systems was high (>92%).

Feed intake was correlated with feeding and chewing time for multiparous cows, which was very similar to the findings of Dado and Allen (1994; r=0.89). By contrast, the results for primiparous cows differed between Dado and Allen (1994; r=0.40) and the current study (r>0.90). The prediction accuracy for estimating feed intake based on corrected feeding time only was already high and varied between $R^{2=}0.869$ and R^2=0.934 for individual cows. Combining chewing time with feeding time improved prediction accuracy, but the increase was low (0.2-3.1%). In five of the seven cows, corrected feeding time delivered higher prediction accuracies than chewing time (Table 2). When compared to the original, i.e. non-corrected, feeding time the prediction accuracy obtained from chewing time was higher in six cows. When feeding time was considered instead of corrected feeding time there was a slight decline in prediction accuracy in six of the seven cows and a remarkable deterioration in one of the cows, namely cow 994. Cow 994 displayed by far the highest percentage of feeding time without feed intake out of the total feeding time (20.3%). Consequently, the amount of feeding time without feed intake had an effect on prediction accuracy. For cows with low percentages of feeding time without feed intake the original, i.e. non-corrected, feeding time appeared to be nearly as appropriate as the corrected one. The relationship between feed intake and rumination time was less strong. As there is normally a time delay between feed intake and rumination of the cud, the assignment to bouts was probably not appropriate.

Conclusions

In the current study, feeding time, feed intake and feeding rate measured by weighing troughs and chewing and rumination time measured by ART-MSR sensors were evaluated for seven cows each. The results showed a high accordance between time of feed trough visit and time of chewing activity. Feeding time and chewing time per bout were strongly correlated with feed intake per bout and explained a large amount of variation in feed intake data. By contrast, rumination time appeared to be less suitable for estimation of feed intake. Prediction accuracy improved slightly when feeding and chewing time were combined. Both variables separately showed potential for estimation of feed intake but were also susceptible to results from individual cows. Future studies will need to broaden the data base in order to get obtain more information on variations due, for example to lactation, health status, season or management, and to include and cope with individual cows.

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8.5. Discussion: rumen sensing, feed intake & precise feeding

I. Halachmi[1], A. Schlageter Tello[2], A. Peña Fernández[3], T. van Hertem[3], V. Sibony[1], S. Weyl-Feinstein[1], A. Verbrugge[3], M. Bonneau[4] and R. Neilson[4]*
[1]Agricultural Research Organization, P.O. Box 6, Bet-Dagan 50250, Israel; [2]Livestock Research Wageningen University, P.O. Box 338, 6700 AH Wageningen, the Netherlands; [3]M3-Biores: Measure, Model & Manage Bioresponses, KU Leuven, P.O. Box 2456, 3001 Leuven, Belgium; [4]European Federation of Animal Science (EAAP), Via G. Tomassetti 3, 1/A, 00161 Rome, Italy; halachmi@volcani.agri.gov.il

Preface

This chapter documents the questions and the answers that were expressed during the 2014 EU-PLF/EAAP joint-sessions. They were documented verbatim, but each questioner and responder were given the opportunity to rewrite/edit their questions and/or answers for more clarity. This discussion is mainly related to Chapters 8.1 to 8.4, but also to the other parts of the book, as well as 'repeatability of rumination time in individual dairy cows'(P. Løvendahl *et al.*, unpublished data) and 'precision feeding' (I. Halachmi, unpublished data).[7]

Discussion

Question: Igor Stokovic (University of Zagreb, Croatia) – I have a question for Jeffrey Bewley (Chapter 1.1). You said that we should change management and PLF (Precision Livestock Farming) to get good results. Then again, if we are changing the management, what is the point of changing PLF? Can you divide those two? Maybe if you change the management you don't need to change PLF or vice-versa?

Answer: Jeffrey Bewley (University of Kentucky, USA) – Good question; that's a hard question. I don't know if there is a specific answer to the question, but certainly PLF and management can't be separated. If we try to separate them, it won't work. We have to think about how to manage the entire system and not PLF as separate from the system and we have to think about the cow and the people in the system. So by nature they are intertwined. And there are opportunities where the information we get from the system may improve the overall system. When we learn something from rumen pH or lameness detection or whatever, then that can help us in changing the way we manage the system. So the day to day deviations that identify the problems are only one part of the advantages in using these technologies. The other part is how do we use that information and what do we learn from it to help the entire operation. Hopefully we can use that knowledge to tweak, to better understand what we can do to better manage the operation. The other side of that is, people are very difficult to understand, even more so than cows. In the end, I think we're really talking about people and some people don't want to change. And that's okay. It's not my job as an extension specialist or consultant to make people change. My job is just to educate about what we know and what we don't know. But people are the difficult part of the whole equation to figure out.

[7] Unpublished results referred to in this discussion are available on the EAAP website under session 10: http://www.eaap.org/Previous_Annual_Meetings/2014Copenhagen/index.html.

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Answer: Anonymous – To just add to that, in one of the farms, which was a 900 cow unit, there were a lot of people on staff. They found out that when one of the herdsmen was feeding (the cows) the pH drops weren't as great as when everyone else was feeding them. It was then discovered that he was putting some concentrates in the back of his car, to take home to give to his own cows. So, it's about people and not just about the cows.

Answer: Ilan Halachmi (ARO, Israel) – I would like to add that we have to adapt our management to the possible technologies, like any other business. When there is a new technology, the management must adapt to that technology: the faster, the better.

Question: Igor Stokovic (University of Zagreb, Croatia) – Or change the manager?

Answer: Ilan Halachmi (ARO, Israel) – You can find a person who can use the technology …

Question: Philippe Faverdin (INRA, France) - I have heard a lot of talk about the feeding behaviour and the interpretation of the feeding behaviour. Feeding behaviour is hard to understand, it has many variables which are affected by dynamic parameters. How do you intend to extrapolate all the information from your sensors for those factors?

Answer: Ilan Halachmi (ARO, Israel) – We already estimate feed intake in a few models, additional sensors will make it more reliable. I know that different feeds influence the milk, the body weight, and behaviour. They are incorporated into our models. They worked before when we only had milk, milk content and body weight and they will better if we have more sensors.

Answer: Peter Løvendahl (Aarhus University, Denmark) – I am interested in genetics, thus I am more interested in the individual differences among cows and less in the herd behaviour.

Answer: Peder Nørgaard (Copenhagen University Denmark) – Sensors need to improve in order to help in a more precise and practical way.

Answer: Anonymous – Rumen pH for example, can help in models, to assess feed intake. Management is the key to enhance performance better then genetics.

Question: Marija Klopčič (University of Ljubljana, Slovenia) – Could genomic selection replace sensors?

Answer: Peter Løvendahl (Aarhus University, Denmark) – It is a combination of both that will give progress.

Answer: Ilan Halachmi (ARO, Israel) – Sensors would not replace genomics. But with the sensors, you may find those cows that are more efficient and follow them. So this is the way you can use the sensors if the model is accurate.

Question: Arjen van der Kamp (Lely International, the Netherlands) – What do you think the farmers are expecting from PLF? There is a lot of nice research and I am not commenting on that, but what do you think the farmers are wanting?

Answer: Claudia Kamphuis (Wageningen University, the Netherlands) – I think they are looking for the perfect system – which I think just does not exist. PLF systems are tools, not solutions as such.

Answer: Marcia Endres (University of Minnesota, USA) – They are looking for a system to help them increase efficiency and productivity and that doesn't cost a lot of money, that they can afford. That can be difficult.

Answer: Jens Yde Blom (Lattec I/S, Denmark) – Maybe we should start at another point. Perhaps the question should be: are we technology or user driven? That is a very interesting question. Why don't we ask the farmers before we do anything? Because, basically, a lot of the items we are actually investigating now are derivatives of technology used in other industries. The question is where can we relieve the farmers so that he can do a more efficient job?

Answer: Dries Berckmans (SoundTalks, Belgium) – Farmers want a simple system, easy to understand.

Answer: Jeffrey Bewley (University of Kentucky, USA) – Farmers want simpler and better life for themselves and for their cows: that's in the big picture. Another thing is that I think it is good to ask farmers what they want, because I think we can go in the wrong direction but then there are times when farmers don't know what they *should* want. So there is always that balance we have to think about.

Answer: Anonymous – I have talked with a lot of farmers and it's really about what decisions they can take. So rather than how much information they can get, they're more interested about what decisions they can take.

Answer: Peter Løvendahl (Aarhus University, Denmark) – Once the technology is there, you learn to live with it and even like it. But what I think we can do in research is to investigate to see if it works.

Answer: Rachel Gabrieli (Ministry of agriculture and rural development, Israel) – I think extension services in each country should serve as the link between researchers and farmers.

Answer: Anonymous – The farmer prefers advice that they have paid for, and not advice from the service extension.

Answer: Rachel Gabrieli (Ministry of agriculture and rural development, Israel) – I think it is not good to privatise extension services, because when they are government employed, they are objective and not driven by other third-party influences. The role of extension services is to be an objective and balanced link between farmers and research. If it doesn't work like this then it should be made to work like this.

Keyword index

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