Developing precision livestock farming tools for precision dairy farming

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Implications

Dairy cows stay longer in production when compared with any other farmed animals. Moreover, each animal unit is of a high economical value to the farmer. Therefore, for the dairy cow and, consequently, for the farmer, it is important to detect problems as soon as possible and to take action on an individual animal level. Precision livestock farming (PLF) systems offer a real-time monitoring and management tool for the farmer. They provide early warning to the farmer, so when something goes wrong during production, the farmer can immediately act on the information. Precision livestock farming requires real-time algorithms that are able to detect problems while the process is ongoing. To successfully develop such algorithms in an efficient way, some basic principles must be respected in the methodology being applied. This paper gives a systematic approach in using the interaction between taking field data, applying a gold standard, and using labeling techniques to develop real-time algorithms that allow real-time monitoring and management of individual cows. The paper presents the application of this process to the development of a real-time lameness detection system.

Key words: feature variables, gold standard, labeling, principles of PLF

The Dairy Industry and Precision Livestock Farming

For centuries, milk and dairy products have been an important source of dietary energy, protein, and fat for the global population. Currently, milk is the EU’s number one agricultural product, accounting for circa 15% of agricultural output in terms of value (European Parliament, 2015). The EU dairy sector is supported by 650,000 specialized dairy farmers and 18 million milking cows and has a labor force of about 1.2 million people (European Parliament, 2015). However, since the abolishment of milk quotas in 2015, farmers are facing increased pressures to exploit the economies of scale by increasing the size of their herds. With larger numbers of cows per farm, farmers no longer have the same time traditionally had to care for their animals. Therefore, the application of technology is becoming more important for EU dairy farmers than ever before.

Precision livestock farming (PLF) represents the application of modern information and computer technology (ICT) for the real-time monitoring and management of animals. In dairy production, PLF systems can be important tools to complement and support the skills of the farmer in the monitoring and assessing cow health and welfare. Automated PLF systems enable dairy farmers to manage larger herds on a more time-efficient manner (Rutten et al., 2013). Automated systems exist to monitor behavioral activities for detection of lameness (Kashiha et al., 2013) and eustrus (Dolecheck et al., 2015). However, there are far fewer studies on the design/implementation of cow behavior monitoring for other important health events such as metabolic diseases or mastitis.

When developing PLF systems for real-time monitoring of dairy cow health, welfare, and productivity, the development process should be done within a framework specifically designed for living organisms. A core principle in this regard is that any living organism can be considered a CITD system, which stands for complex, individually different, time-varying, and dynamic (Berckmans and Aerts, 2006; Quanten et al., 2006). A living organism is much more complex than any mechanical, electronic or ICT system. The complexity of information transmission in a single cell of a living organism is for example much higher than in most man-made systems (e.g., today’s most powerful microchip). It is obvious that all living organisms are individually different. The general approach in biological research and the management of biological process (e.g., medical world, livestock world) in industry and society is still to compare groups of living organisms by looking for statistical differences between group averages using experiments. However, there is not a single living organism that lives or acts as the purely theoretical average of a group since all living organisms are individually differ-
ent in their responses. Moreover, the time varying character of a living organism means that a living organism’s response to a (environmental) stimulus or stressor might be different each time it happens. Of course, living organisms are dynamic systems. A living organism is constantly looking for a good energy balance and, as a consequence, is continuously changing its physical condition and mental status.

The CITD nature of living organisms has an important impact on the type of algorithms we need to develop. It implies that algorithms to monitor these time-varying individuals must continuously adapt to the individual and/or use principles that can be used in real time in the field application to adapt to the time variation of that individual. Paying attention to this core principle requires that the development of PLF happens within multidisciplinary teams comprising bio-engineers, animal scientists, physiologists, veterinarians, ethologists, engineers, and ICT experts. When developing PLF tools, we are often aiming to create early warning systems, so it is wise to focus on the first signs that can be monitored in a non-invasive and contactless way in an animal. When the animal experiences less-than-ideal conditions, it will exhibit an initial response in terms of behavioral changes, and these first signs should be picked up by the PLF sensing technology, such as a sensor or real-time sound and/or image analysis. Therefore, the use of field data to develop real-time algorithms involves some steps that should be properly understood to make successful algorithms.

This paper will present principles of algorithm development by taking an example of real-time monitoring of lameness of dairy cows by using real-time image analysis. Lameness can be considered a deviation in gait resulting from pain or discomfort from hoof or leg injuries or disease (Flower and Weary, 2009). The prevalence of lameness can be estimated as 34% of the cows in Denmark, 12% in Poland, 16% in Germany, and 31% in Austria. It can be stated that lameness is the number one problem regarding animal welfare in milking cows, and in the literature, more than 200 possible causes have been named. Therefore, the development of a robust algorithm for lameness detection is very important for dairy farmers.

The first objective of this paper is to describe some basic principles to realize a more efficient development of PLF of algorithms for monitoring and improving dairy production. The second objective is to achieve some agreement in the terminology used during algorithm development to improve communication between specialists from different disciplines.

**Framework for Precision Livestock Farming Tool Development**

**Field data or bio-signals**

The basic methods used in PLF involve continuously measuring responses directly on the animal rather than from the environment surrounding the animal. Since animal responses can be fast, it is useless to carry out a survey just once a year, once a month or week, or even twice a day depending on the specific objective. Therefore, we need a continuous monitoring/management tool. The word “continuous” must be interpreted in relation to the dynamic response time of the variable being monitored, like in this case, lameness of cows.

In the example of monitoring lameness, we use image analysis for collecting real-time field data, known as “bio-signals.” One of the advantages of image analysis is the fact that there is no need for physical contact, and so there is no risk of influencing the animal response while making the measurement and no need to recover sensors from living animals. Furthermore, costs are reduced since one camera can monitor a very large group of animals as each of them will pass under the camera every day (Figure 1).

**Linking field data, target variable, gold standard, feature variable, and labeling**

The **field data** consists of a lot of numbers originating from the sensors (e.g., 240 samples per second for an accelerometer) or images (e.g., 25...
In each of the processes involved in developing a real-time PLF algorithm, we have to take some steps in which we combine different types of variables to produce a generic method for developing algorithms. In the example case, we aim to develop a real-time lameness monitoring system for cows by using real-time image analysis of the camera-produced images of the animals. This means that in this example, the target variable directly relates to the final objective of the algorithm. In the example of a lameness monitoring system, this means that the variable is a quantity indicating the degree of lameness of the cow.

**Gold standard**

The first question is whether we have a reliable gold standard to quantify the target variable, in this case the real health status of a cow regarding lameness. Do we have a generally accepted way of measuring the lameness status of a cow? A gold standard or reference point can be defined as a state-of-the-art scientific measurement or method that enables us to draw a conclusion relating to the final objective of the algorithm or the status of the target variable, in this case, the degree of lameness of a cow. A gold standard might be an expensive and complex method, but the most important point is that this gold standard should be accepted by scientists as the state-of-the-art measurement or method that will quantify the target variable in a reliable way. In the case of lameness of cows, a gold standard might be the score a human expert gives to quantify the degree of lameness of the cow.

In most cases, the gold standard cannot easily be applied to real-time measurements, and consequently, has a much lower sampling frequency than the real-time solution that we are looking for. In the case of a score by a human expert, it is technically unrealistic to consider continuous scoring every day on enough cows. This can be done once a week, for example, which is already an ideal case, for a large farm with many animals. Having worked on the development of this PLF approach and methodology since 1991 (Aerts, 1991) we can say that, in most cases, establishing an accurate gold standard is one of the most difficult elements of developing PLF algorithms. In case that we do not know a clear gold standard for the target variable we aim for, we will not proceed for this target variable.

In collaboration with other teams in the world, we had built up several datasets to collect field data for cow lameness where, at the same time, a gold standard (see further) was applied. We collected videos from walking cows at three different farms: 155 recordings on 70 cows with weekly gait scoring for all recordings; 4,200 recordings on 58 cows per dataset with gait scoring every 2 wk; and finally, more than 9,000 recordings from 965 cows over a 15 wk period with weekly gait scoring.

This shows that the result is a huge amount of data, and the transmission of so much data takes time, energy and money. Sending data wirelessly in real time involves energy and costs; we should, therefore, avoid transmitting too much data and develop real-time algorithms that calculate information from the data at the lowest possible level, enabling us to transmit information rather than data.

**Feature variable**

The idea of the real-time monitoring system assumes that we can find another variable that can give an early warning of lameness in a cow; this variable is called the feature variable. In the example of lameness monitoring, the idea was to use different variables calculated from the image of the animal to find out which is the best feature variable that would indicate the lameness in an early stage. The hypothesis was that the gait analysis of an image of a cow gives the baseline for that individual cow and that a significant deviation from that baseline in time would be shown by the dynamic variation of the appropriate feature variable calculated from the image.

The feature variable is the variable that is calculated from the field measurements on the animal, which are captured by, in this case, the image information. The idea is that the feature variable can be measured or calculated at a high sampling frequency or continuously in relation to the dynamics of the process, in this case, lameness of the cow. The PLF algorithm aims for real-time calculation of the target variable so that there

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**Table 1. List of the tested 13 feature variables to monitor lameness in cows in real time.**

| Automatic measured feature variables | Step Overlap: Position of hind leg - position of front leg |
|--------------------------------------|----------------------------------------------------------|
| Swing time: Amount of time the hoof is released from the floor | Stride time: Amount of time the cow takes for a full stride cycle (≈ 1 step with each hoof) |
| Stance time: Amount of time the hoof has contact with the floor | Step length: Distance between two subsequent placements of same hoof |
| Back arch: Arch of back measured with 3 points | Touch angle: Angle of the lower leg (from fetlock joint to tarsus or carpus joint) when the hoof touches the floor (from vertical line) |
| Release angle: Angle of the lower leg (from fetlock joint to tarsus or carpus joint) when the hoof releases the floor (from vertical line) | Active appearance model: Deformable model, fit on contour in the image Robust Global (holistic) |
| Asymmetry step overlap | Swing time/Stance time |
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is no need to store any raw field data, or in this case, all the image signals measured at a rate of 25 Hz, in the monitoring system.

Since it was not clear that human scoring was based on a well-defined single-target variable, we have tried 13 different feature variables (see Table 1).

**Labeling**

In this example, when collecting the bio-signals or field measurements on the animal, we obtain the image data produced by the animal (see Figure 2). To develop an algorithm that can detect the deviation from a healthy gait behavior automatically, we again need a reference point that indicates the point in time when the field data shows these deviations from normal gait. To develop an algorithm for lameness detection, it is not sufficient to know at what moment the way of walking is different; we need to know when exactly a step starts and when it ends. This information must be obtained by careful audio-visual analysis of the field data using some kind of methodology: for example, a human observer on the scene who carries out audio-visual scoring of lameness or visual analyses on the scene in reality. Another method is for a human to carry out off-line visual marking of video images: image per image to mark deviations from “normal” walking gait. This might be less expensive and easier but is it as accurate as on-the-spot observations (in the livestock house)? A main objective is to get insight in the feature variable, understand the dynamic behavior of the feature variable, and understand the biological meaning of the feature variable. This activity is called labeling: detailed manual audio-visual analyses of the

**Figure 2.** A gold standard for lameness is the human score to quantify the degree of lameness.

**Figure 3.** The first objective of the algorithm must be to estimate or calculate the value of the feature variable (1 of the 13 feature variables calculated from the image) from the measured field data (the measured images the cow shed). The second objective of the algorithm is to link the value of the feature variable (1 or more of the 13 variables calculated from the image) to the target variable (the lameness status of the cow as scored by the human expert).
feature variable from the measured field data to be used as a reference point for algorithm development to calculate the feature variable (Figure 3).

This accurate labeling of field data is very labor intensive: manual labeling of a 48-h video, involving marking start and stop points (e.g., in an image) for only seven different activities can easily take a few man-months! Each single image or data sample has to be analyzed to identify the beginning or end of one of the activities. To label, for example, the beginning and end of each deviation in normal gait, all the low quality images (sunlight, shadows, dirty lenses, moving background, etc.) in image data that were captured at a sample frequency of 25 Hz requires a serious investment of man-hours. Research teams specializing in labeling have developed tools that enable this time-consuming hard work to be performed more efficiently. It has been demonstrated that visual labeling of cow lameness on the scene in the livestock house is not very straightforward (Ismayilova et al., 2013). It is clear that the accuracy of labeling will be of crucial importance in developing accurate algorithms. If the accuracy of labeling is unknown, a new problem arises with regard to how to develop an accurate algorithm. An algorithm can never be more accurate than the used gold standard or the used labeling technique. Gold standard and labeling activities are two different things that should not be mixed up; this is evidenced by the fact that the objectives relating to the target variable and feature variable are different, and that all these variables vary over time, creating a need for real-time calculation of the feature variable.

Algorithm Development and Testing

When data are collected, we print them as a function of time and apply labeling to obtain reference data for the feature variable. The labeling has now marked exactly which feature variable she/he can see in the image and when a variation of the value starts and ends in all of the field data. We can now develop/run the first part of the algorithm, which calculates the values of the feature variable for each image. The next step is to develop the second part of the algorithm, namely to compare the dynamic behavior of the feature variable with the results of the gold standard to complete the algorithm for automatic detection of the lameness (Figure 4).

The algorithm must enable calculation of the feature variable in real time from the field data to detect the individual variation in feature variables. Whatever type of physical or mathematical simulation we use in the lab, experience shows that the hard work starts when the algorithm is implemented in a real livestock houses. The main reason for this is that animal-related processes in a commercial livestock house are much more complex than anything we can simulate in the laboratory. In the case of real-time lameness monitoring, validation of these algorithms in the field, conducted in a test farms in practice, demonstrated that the algorithms developed were able to classify the lameness correctly in 86% of cases (Van Hertem et al., 2014). The final results in terms of performance of these
algorithms can be expressed quantitatively using the criteria: sensitivity, specific, and overall accuracy (Exadaktylos et al., 2008).

**Conclusions**

Making algorithms work in real-life conditions is a hard job that all developers will experience before successfully developing a reliable and accurate real-time monitoring system. Producing journal publications and patents is clearly far easier than creating cheap, reliable, and accurate PLF tools. As described, the application of a good method is an important tool to create algorithms.

Technology nowadays offers exciting opportunities to develop automatic monitoring and management products to help farmers remain competitive in the face of the many requirements and skills that society imposes on them. Technology, however, is just a tool that supports many others. Development of suitable systems needs much more intensive collaboration between people from different disciplines, which appears to be difficult because each discipline, each team, and many individuals are just hunting for more research money instead of focusing on making more progress in their field of research or the sector where their knowledge should be applied. This paper has been aimed at defining some terms that will help to facilitate communication between scientists from the different disciplines that are needed to create useful PLF tools.

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**Literature Cited**

Aerts, J.M. 1991. Ontwerp van een experimentele opstelling voor het toepassen van on-line modelleringstechnieken op levende organismen. Ph.D. thesis, Katholieke Universiteit Leuven.

Berkmans, D., and J.M. Aerts. Integration of biological responses in the management of bioprocesses. Master Course in the Masters of BioSystems and of Human Health Engineering at the KU Leuven.

Dolecheck, K.A., Silvia, W.J., Heersche, G., Chang, Y.M., Ray, D.L., Stone, A.E., Wadsworth, B.A. and Bewley, J.M., 2015. Behavioral and physiological changes around estrus events identified using multiple automated monitoring technologies. Journal of dairy science, 98(12), pp.8723-8731.

European Parliament. 2015. The future of the EU dairy sector after the end of milk quotas. Briefing Document: EPRS_BRI(2015)564599.

Exadaktylos, V., M. Silva, S. Ferrari, M. Guarino, C.J. Taylor, J.-M. Aerts, and D. Berckmans. 2008. Time-series analysis for online recognition and localization of sick cow (Sus scrofa) cough images. J. Acoust. Soc. Am. 124(6):3803–3809. doi:10.1121/1.2998780

Flower, F.C., and D.M. Weary. 2009. Gait assessment in dairy cattle. Animal 3(1):87–95. doi:10.1017/S1751731108003194

Ismayilova, G., M. Oczak, A. Costa, L.T. Sonoda, S. Viazzi, M. Fels, E. Franken, J. Hartung, C. Bahr, D. Berckmans, and M. Guarino. 2013. How do pigs behave before starting an aggressive interaction? Identification of typical body positions in the early stage of aggression using video labelling techniques. Berl. Munch. Tierarztl. Wochenschr. 126:3–4, 113–120.

Kashiha, M., A. Pluk, C. Bahr, E. Franken, and D. Berckmans. 2013. Development of an early warning system for a broiler house using computer vision. Biosystems Eng. 116(1):36–45. doi:10.1016/jbiosystemseng.2013.06.004

Quanten, S., E. de Valck, R. Cluydt, J.M. Aerts, and D. Berckmans. 2006. Individualized and time-variant model for the functional link between thermoregulation and sleep onset. J. Sleep Res. 15(2):183–198. doi:10.1111/j.1365-2869.2006.00519.x

Rutten, C.J., A.G. Vethuis, W. Steeneveld, and H. Hogeveen. 2013. Invited review: Sensors to support health management on dairy farms. J. Dairy Sci. 96(4):1928–1952. doi:10.3168/jds.2012-6107

Van Hertem, T., S. Viazzi, M. Steensels, E. Maltz, A. Antler, V. Alchanatis, A. Schlageter-Tello, K. Lokhorst, E.C.B. Romanini, C. Bahr, D. Berckmans, and I. Halachmi. 2014. Automatic lameness detection based on consecutive 3D-video recordings. Biosystems Eng. 119:108–116. doi:10.1016/jbiosystemseng.2014.01.009

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