The evolving world of precision dairy technology – Part I

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Abstract

Precision dairy farming involves the use of technologies to measure physiological, behavioral, and production indicators on individual animals. Examples include wearable sensors (neck, ear, legs, or tail), rumen boluses, subcutaneous implants, inline or online milk sensors, cow-side tests, video analysis, and facial recognition. These technologies can help improve performance and welfare of dairy herds. This review focuses on technologies used to monitor the individual cow on the farm, and more specifically wearable sensors. Sensors should be validated to establish whether they measure the behavior they are supposed to measure (e.g. rumination, lying, standing, feeding, or activity). In addition, research needs to be conducted to investigate whether the sensor data can accurately detect the animal condition that it is supposed to detect, such as estrus or metabolic disease. Studies have shown promise on using rumination, activity, feeding or standing behavior for early detection of transition cow disorders, such as ketosis, metritis or retained placenta. On the farm, the data collected by the sensors should result in action taking place with that animal to improve performance and health of the herd in an economically sustainable manner.

Key words: individual cow monitoring, cow health, dairy technology

Résumé

L'agriculture de précision à la ferme laitière requière l'utilisation de technologies qui mesurent des indices physiologiques, comportementaux et de production auprès d'individus. Parmi celles-ci, on retrouve des capteurs portables (au niveau du cou, des pattes ou de la queue), des bolus dans la panse, des implants sous-cutanés, des indicateurs en ligne pour le lait, des tests auprès de la vache, des analyses vidéos et la reconnaissance faciale. Ces technologies peuvent aider à améliorer la performance et le bien-être dans les troupeaux laitiers. Cette synthèse se penche sur les technologies qui permettent de surveiller individuellement des vaches à la ferme et plus particulièrement sur les capteurs portables. Les capteurs devraient être validés afin d'établir s'ils permettent de bien mesurer le comportement qu'ils sont supposés mesurer (e.g. rumination, décubitus, position debout, alimentation ou activité). De plus, il faut faire des travaux pour déterminer si les données du capteur peuvent détecter correctement une condition animale particulière comme l'œstrus ou la maladie métabolique. Des études prometteuses ont utilisé la rumination, l'activité, l'alimentation ou la position debout comme indices précoces de désordre chez la vache en transition comme l'acétonémie ou la rétention placentaire. Les données amassées à la ferme par les capteurs devraient permettre la mise en place d'interventions ciblant une vache particulière afin d'améliorer la performance et la santé du troupeau dans une perspective de viabilité économique.

Introduction

A suggested definition of precision livestock farming[6] is "the coordinated use of sensors to measure behavioral, physiological, and production parameters in animals and the characteristics of the farm environment (temperature, hygrometry, ventilation), and of information and communication technologies to exchange, store, transform, and restore this information to farmers to support decision-making in conjunction with their own observations." It has been suggested[2] that precision livestock farming can create a herd management system based on continuous automatic real-time monitoring and control of production, reproduction, animal health, and welfare.

This review paper focuses on technologies used to monitor the individual cow in dairy herds. Sensors that can measure various parameters in dairy cows have been developed since the 1970s and initially included pedometers, milk conductivity, and cow identification.[15] The number of technologies available in the market today is almost overwhelming, from wearable sensors (neck, ear, legs, tail) to rumen boluses and subcutaneous implants, to inline or online milk sensors, to cow-side tests, to video analysis, and facial recognition.

The application of technology to biological processes has become increasingly more feasible in recent years. For example, wireless data transmission is less expensive and reliable, sensor and sensing (e.g. camera, microphone) technologies needed to develop precision dairy products are small and can withstand the harsh environment of a farm, the cost of devices such as mobile phones has decreased and some mobile phone technologies (e.g. gyroscope, accelerometer) can be used for on-farm applications.[2] The use of cloud-based connectivity to integrate and network sensors for data collection and analysis is becoming more commonplace today. The world of precision dairy farming is certainly evolving!

General Considerations About Sensors

One can describe the development of sensor systems in 4 levels:[15] measurement of something about the cow (e.g.

rumination time); interpretation of changes in the sensor data (e.g. a reduction in rumination time associated with calving); integration of information from multiple sources; and decision-making by the farmer. More research and development has been conducted on the levels of measurement and interpretation than on the levels of integration and decision making.

To evaluate a sensor, we compare the alerts given by the sensor with the occurrence of an event (gold standard).[7] From these experiments we can classify the observation as true positives (observations where the event occurs with an alert); false negatives (observations where the event occurs without an alert); false positives (observations where the event does not occur with an alert); and true negatives (observations where the event does not occur without an alert). We can then evaluate the performance of a sensor by calculating sensitivity and specificity: Sensitivity (%) = 100 * True Positive Count/(True Positive Count + False Negative Count); Specificity (%) = 100 * True Negative Count/(False Positive Count + True Negative Count). It is important to keep in mind that sensitivity and specificity are interdependent. When we increase the threshold of a test, the number of positive outcomes and therefore the sensitivity will decrease, whereas the specificity will increase. Thresholds need to be set so that the performance of a sensor in terms of sensitivity and specificity is optimized.[7]

The prevalence of an event will influence sensitivity and specificity, so it has been suggested instead that a success rate and a false-alert rate be used on the farm.[7] In addition, the gold standards, algorithms, and sample size in experiments can all influence sensor performance results. The detection performance under 2 different gold standards for different algorithms most likely will not be comparable.[15] Sensor systems for mastitis (discussed in Part II) and estrus detection have been more extensively studied, although there might still be a need to improve detection performance; however, more work is needed for detection of metabolic problems or lameness.[14]

Another very important consideration about sensors is that they should be validated by third-party research in order to establish whether the sensor measures the behavior it is supposed to measure (e.g. rumination, lying, standing, feeding, activity, steps). Various validation studies have been conducted and 2 examples are presented. Visually recorded feeding behaviors in cows housed in freestalls were moderately correlated with an ear-tag accelerometer (r = 0.88, concordance correlation coefficient (CCC) = 0.82) and a leg-mounted sensor (r = 0.93, CCC = 0.79).[3] Visually recorded rumination behaviors were strongly correlated with one brand of ear-tag accelerometer (r = 0.97, CCC = 0.96), but weakly correlated with another ear-tag brand (r = 0.69, CCC = 0.59).[3] Visually recorded lying behaviors were strongly correlated with 3 brands of leg-mounted pedometers or accerelometers (r >0.99, CCC >0.99).[3] Visual observations for 4 behaviors were highly to weakly correlated (eating: r = 0.88, CCC = 0.88; rumination: r = 0.72, CCC = 0.71; not active: r = 0.65, CCC = 0.52; and active: r = 0.20, CCC = 0.19) to data collected by an ear-tag accelerometer in grazing dairy cows.[12]

Detection of Estrus and Calving Time

A recent review of the literature[16] summarized the performance of various technologies for estrus and calving-time detection. Automatic activity sensors for estrus detection included pedometers, neck-collar mounted activity meters, and 3D-accelerometers attached to the leg or the neck. The sensitivity of these sensors ranged from 59 to 94%, their specificity from 90 to 100%, and their positive predictive value from 36 to 92% when using milk or blood progesterone concentrations as gold standard for estrus identification. When compared with visual observation (2 to 6 times a day, 10 to 30 minutes per observation) of estrus, sensors had equivalent or higher sensitivity, with fewer false positives.

Many factors can affect performance of wearable pedometers and accelerometers for estrus detection, including methodological, technical or biological factors. The threshold used in the algorithm to define an increase in activity as an indicator of estrus can affect the performance of the sensor. Lowering the activity threshold can increase the efficacy of estrus detection but will result in more false positives, therefore lower specificity. It is also important to point out that the definition of true estrus (the gold standard) can lead to different results. Using visual observation of behavioral signs of estrus on the day of insemination to define a true estrus episode vs serial milk or blood progesterone can underestimate silent ovulations and create fewer false alarms.

Estrus detection rates were 96% and 93 to 100% for natural and synchronized estrus, respectively, when using a vaginal temperature sensor.[16] These sensors have been marketed for disease detection but could likely be used to improve estrus detection. However, more research is needed to investigate the performance of these sensors across different seasons and ambient temperatures and when cows have a fever. The performance of a system that automatically collects milk samples at parlors or robotic milking stations to test for progesterone, lactate dehydrogenase, and betahydroxybutyrate to detect estrus, tissue damage and metabolic disorders, respectively, was also evaluated in a few studies.[16] This system detected 99% of confirmed estrus (for which an AI resulted in a pregnancy) and 93% of estrus defined by a progesterone profile matching that of confirmed estrus, with a specificity of 94%. Another study in commercial herds reported an average heat detection rate of 95%.

Combination of several parameters and application of machine-learning techniques to data collected by various sensors will most likely improve estrus detection. A pilot study[5] showed that the best performance for estrus detection was obtained with either 4 continuously recorded behaviors (activity, resting time, rumination, and feeding time) or the combined number of steps, lying bouts, and lying time collected with accelerometers. Three machine-learning techniques (random forest, linear discriminant analysis, and neural network) were applied to automatically collected parameter data from the 18 cows observed in standing estrus. Machine learning accuracy for all technologies ranged from 91.0 to 100.0%.

A review of the research investigating the feasibility of using activity sensors for evaluation of pre-calving behaviors in dairy cattle was conducted.[16] A study showed that monitoring of lying bouts and lying time, alone or combined, predicted calving time within the next 6 to 24 h but with high rates of false negatives and false positives – sensitivity of 58% and specificity of 61%. In another study, an activity index combining the number of steps, lying bouts, and standing time predicted the calving time of Holstein dairy cows and heifers on average 6 hours before its occurrence (from 2 hours to 14 hours; more than 4 hours in 76% of cows). When using the same device and applying 3 different machine-learning techniques to the numbers of steps, lying bouts, lying and standing times during the 21 days prepartum, the actual day of calving could be predicted with high accuracy in Holstein dairy cows (78 to 89% sensitivity, 94 to 98% specificity, 42 to 73% positive predictive value and 99% negative predictive value).

Other technologies that might be useful for prediction of calving time are rumination sensors and image analysis. In addition, combination of measurements could improve accuracy. A study[16] combining rumination time, activity, lying and standing behaviors (lying bouts, lying time, number of steps, and standing time) and analyzed using the machine learning neural network analysis resulted in a sensitivity of 100%, a specificity of 97%, positive predictive value of 60%, and negative predictive value of 100% when compared with each set of data used alone. However, the use of multiple sensors on animals is not very cost-effective.

Monitoring Transition Cows

The periparturient (or transition) period is considered one of the most critical periods of a dairy cow's life. It has been estimated that approximately 50% of cows have 1 or more adverse health events during the transition into early lactation, with the largest number of health disorders happening the first 10 days-in-milk (DIM).[8] A reduction in morbidity of transition cows can improve animal welfare and farm profitability by reducing treatment costs, improving milk yield and reproductive performance, and minimizing premature culling or death.

Rumination behavior can be a good indicator of health in dairy cows, so it is a measurement that could potentially be used to help manage health of transition cows. There are validated[13,17] rumination sensors in the market that make collection of these data feasible in commercial farms. A study in Israel[18] using rumination sensors on periparturient cows showed that cows without health disorders or only mild health disorders after calving had greater average rumination time (over 520 minutes per day) during the first 10 DIM than cows with subclinical diseases or health disorders (450 minutes per day). Cows diagnosed with metritis and cows that delivered twins had reduced postpartum daily rumination time than cows not diagnosed with metritis and cows that delivered singletons, respectively, in a study conducted with 296 cows fitted with rumination sensors and housed in a conventional freestall barn.[12] Another study[10] indicated that rumination time could help identify multiparous cows with subclinical ketosis.

A more intensive study with 23 cows fitted with rumination sensors[4] assessed markers of inflammation and some enzyme activities along with biochemical indicators of energy, protein, and mineral metabolism. Blood samples were collected from 30 days before calving to 42 DIM. A liver functionality index was used to evaluate the severity of inflammation around calving. Cows were categorized according to rumination time between 3 and 6 DIM into those with the lowest (L) and highest (H) rumination time. Rumination time reached a minimum value at calving (30% less than before calving) and was nearly stable after 15 DIM. There was a lower average value of liver functionality index in L (−6.97) than H (−1.91) cows. Additional results suggested that severe inflammation around parturition was associated with a slower increase in rumination time after calving. More than 90% of the cows in the L group had clinical diseases in early lactation compared with 42% of the H cows. These results suggested that it would be beneficial to monitor rumination time around calving, and in particular during the first week of lactation, as a way to more timely identify cows at a greater risk of developing a disease in early lactation.

In addition to rumination, activity and lying behavior of transition cows could potentially be used as a predictor of disease. Cows later diagnosed with clinical ketosis had 20% greater standing time during the week before calving (14.3 ± 0.6 vs 12.0 ± 0.7 hours per day) and 35% greater on the day of calving (17.2 ± 0.9 vs 12.7 ± 0.9 hours per day) than cows without ketosis, but no differences were observed post-partum.[9] Cows with clinical ketosis also had fewer standing bouts (14.6 ± 1.9 vs 20.9 ± 1.8 bouts per day) and stood for longer time per bout (71.3 minutes per bout vs 35.8 minutes per bout) than cows without clinical ketosis on the day of calving.[9] In another study with 296 cows housed in a freestall barn and fitted with rumination-activity neck sensors,[11] retained placenta tended to and was associated with reduced prepartum (444.3 ± 11.0 vs 466.5 ± 4.3 arbitrary unit) and postpartum (488.2 ± 14.5 vs 538.8 ± 5.7 arbitrary unit) activity, respectively. In addition, cows diagnosed with metritis (512.5 ± 11.5 vs 539.2 ± 6.0 arbitrary unit) and subclinical ketosis (502.20 ± 16.5 vs 536.6 ± 6.2 arbitrary unit) had reduced activity postpartum.

A series of studies at Cornell University[19,20,21] showed that an automated health monitoring system that combines rumination time and activity could be useful to identify transition cows with metabolic and digestive disorders, severe cases of metritis, and clinical cases of coliform mastitis.

Lying or standing time might also be a behavior measurement that helps detect disease in early lactation. A study[14] investigating resting behavior from -30 to 3 days post-calving showed the strongest correlation was obtained between standing time at 3 days prepartum and blood betahydroxybutyrate at 3 days postpartum. ($P < 0.01$; $r = -0.84$). It was a negative correlation indicating that cows that were the most susceptible to subclinical ketosis postpartum remained standing for a shorter time in the prepartum period. A model that included standing time, body weight, body condition score, and dry matter intake at 6 days prepartum accounted for most of the variation ($P < 0.01$; R2 = 0.90) in the betahydroxybutyrate data at 3 days postpartum. These preliminary data suggest that standing time could be a useful tool to build prediction models for early detection of subclinical ketosis post-partum.

Lameness Detection

Lameness remains an important concern in the dairy industry, as it has economic and animal welfare implications. Early and automated detection of lameness can be highly beneficial for dairy producers. Several techniques have been used for automated gait analysis, including force platforms, accelerometer, electromyography, and kinematics modelling.[22] These technologies have high cost or have not been able to accurately detect lameness. The image processing technique can provide a less expensive and non-invasive method to obtain visual information.[22] Some recent studies focused on vision technology, but most of them focused on the spine arc and head bobbing, which have been estimated to only cover 33.6% of possible lameness information. It has been suggested[22] that to improve the practicality of vision technology for lameness detection, other measurements such as symmetry, speed, tracking, and tenderness should be included.

A study[22] using a 621-video dataset investigated the use of a novel approach to detect lameness with high accuracy and more practicality. The goal was to quantify the gait pattern of cows and demonstrate the possibility of classifying lameness using the features extracted from movement analysis. The motion curve was analyzed to generate 6 features referring to the gait asymmetry, speed, tracking up, stance time, stride length, and tenderness. A Decision Tree classifier was applied to the dataset, and 2-, 3-, and 10-fold cross validation was used to verify the performance of the algorithm. The accuracy of the classification was 90.18%, and the averages of sensitivity and specificity were 90.25% and 94.74%, respectively.

In another study[1] a novel proxy for lameness using 3-dimensional depth video data to analyze a cow's gait asymmetry was tested. This dynamic proxy was derived from the height variations in the hip joint during walking. Cows were automatically recorded using an overhead 3-dimensional depth camera as they walked freely in single file after milking. Using a linear Support Vector Machine binary classification model, the threshold achieved an accuracy of 95.7% with a 100% sensitivity (detecting lame cows) and 75% specificity (detecting non-lame cows). These studies demonstrate that the use of video technology might be the most practical for the detection of lameness on dairy farms, but more development and field testing is needed.

Conclusions

Individual cow monitoring technologies can be a tool for detecting health problems and estrus in dairy cattle, although improved accuracy of detection might still be needed. Some examples of peer-reviewed studies were presented and they indicate that precision dairy technologies can help improve dairy cattle welfare and health. However, producers need to be able to use the data in a practical manner that leads to action on the farm. The integration of technologies and interpretation of data is critical to make improvements happen. Third-party validation of technologies available in the market is also important.

References

1. Abdul Jabbar K, Hansen MF, Smith ML, Smith LN. Early and non-intrusive lameness detection in dairy cows using 3-dimensional video. *Biosyst Eng* 2017; 153:63-69.
2. Berckmans D. Precision livestock farming technologies for welfare management in intensive livestock systems. *Rev Sci Tech Off Int Epiz* 2014; 33:189-196.
3. Borchers MR, Chang YM, Tsai IC, Wadsworth BA, Bewley JM. A validation of technologies monitoring dairy cow feeding, ruminating, and lying behaviors. *J Dairy Sci* 2016; 99:7458-7466.
4. Calamari L, Soriani N, Panella G, Petrera F, Minuti A, Trevisi E. Rumination time around calving: An early signal to detect cows at greater risk of disease. *J Dairy Sci* 2014; 97:3635-3647.
5. Dolecheck KA, Silvia WJ, Heersche G Jr, Chang YM, Ray DL, Stone AE, Wadsworth BA, Bewley JM. Behavioral and physiological changes around estrus events identified using multiple automated monitoring technologies. *J Dairy Sci* 2015; 98:8723-8731.
6. Hostiou N, Fagon J, Chauvat S, Turlot A, Kling-Eveillard F, Boivin X, Allain C. Impact of precision livestock farming on work and human-animal interactions on dairy farms. A review. *Biotechnol Agron Soc Environ* 2017; 21:268-275.
7. Hogeveen H, Kamphuis C, Steeneveld W, Mollenhorst H. Sensors and clinical mastitis—The quest for the perfect alert. *Sensors* 2010; 10:7991-8009.
8. Ingvartsen KL, Dewhurst RJ, Friggens NC. On the relationship between lactational performance and health: Is it yield or metabolic imbalance that cause production diseases in dairy cattle? A position paper. *Livest Prod Sci* 2003; 83:277-308.
9. Itle AJ, Huzzey JM, Weary DM, von Keyserlingk MAG. Clinical ketosis and standing behavior in transition cows. *J Dairy Sci* 2015; 98:128-134.
10. Kaufman, EI, LeBlanc SJ, McBride BW, Duffield TF, DeVries TJ. Association of rumination time with subclinical ketosis in transition dairy cows. *J Dairy Sci* 2016; 99:5504-5618.
11. Liboreiro, DN, Machado KS, Silva PRB, Maturana MM, Nishimura TK, Brandão AP, Endres MI, Chebel RC. Characterization of peripartum rumination and activity of cows diagnosed with metabolic and uterine diseases. *J Dairy Sci* 2015; 98:6812-6827.
12. Pereira GM, Heins BJ, Endres MI. Technical note: Validation of an ear-tag accelerometer sensor to determine rumination, eating, and activity behaviors of grazing dairy cattle. *J Dairy Sci* 2018; 101:2492-2495.

13. Reiter S, Sattlecker G, Lidauer L, Kickinger F, Öhlschuster M, Auer W, Schweinzer V, Klein-Jöbstl D, Drillich M, Iwersen M. Evaluation of an ear-tag-based accelerometer for monitoring rumination in dairy cows. *J Dairy Sci* 2018; 101:3398-3411.
14. Rodriguez-Jimenez S, Haerr KJ, Trevisi E, Loor JJ, Cardoso FC, Osorio JS. Prepartal standing behavior as a parameter for early detection of postpartal subclinical ketosis associated with inflammation and liver function biomarkers in peripartal dairy cows *J Dairy Sci* 2018; 101:8224-8235.
15. Rutten CJ, Velthuis AGJ, Steeneveld W, Hogeveen H. Invited review: Sensors to support health management on dairy farms. *J Dairy Sci* 2013; 96:1928-1952.
16. Saint-Dizier M, Chastant-Maillard S. Potential of connected devices to optimize cattle reproduction. *Therio* 2018; 112:53-62.
17. Schirmann K, von Keyserlingk MA, Weary DM, Veira DM, Heuwieser W. Technical note: Validation of a system for monitoring rumination in dairy cows. *J Dairy Sci* 2009; 92:6052-6055.
18. Soriani, N, Trevisi E, Calamari L. Relationships between rumination time, metabolic conditions and health status in dairy cows during the transition period. *J Anim Sci* 2012; 90:4544-4554.
19. Stangaferro ML, Wijma R, Caixeta LS, Al-Abri MA, Giordano JO. Use of rumination and activity monitoring for the identification of dairy cows with health disorders: Part I. Metabolic and digestive disorders. *J Dairy Sci* 2016; 99:7395-7410.
20. Stangaferro ML, Wijma R, Caixeta LS, Al-Abri MA, Giordano JO. Use of rumination and activity monitoring for the identification of dairy cows with health disorders: Part II. Mastitis. *J Dairy Sci* 2016; 99:7411-7421.
21. Stangaferro ML, Wijma R, Caixeta LS, Al-Abri MA, Giordano JO. Use of rumination and activity monitoring for the identification of dairy cows with health disorders: Part III. Metritis. *J Dairy Sci* 2016; 99:7422-7433.
22. Zhaoa K, Bewley JM, Hea D, Jin X. Automatic lameness detection in dairy cattle based on leg swing analysis with an image processing technique. *Computers and Electron Agric* 2018; 148:226-236.