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Behavioral and physiological changes around estrus events identified using multiple automated monitoring technologies

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ABSTRACT

This study included 2 objectives. The first objective was to describe estrus-related changes in parameters automatically recorded by the CowManager SensOor (Agis Automatisering, Harmelen, the Netherlands), DVM bolus (DVM Systems LLC, Greeley, CO), HR Tag (SCR Engineers Ltd., Netanya, Israel), IceQube (IceRobotics Ltd., Edinburgh, UK), and Track a Cow (Animart Inc., Beaver Dam, WI). This objective was accomplished using 35 cows in 3 groups between January and June 2013 at the University of Kentucky Coldstream Dairy. We used a modified Ovsynch with G7G protocol to partially synchronize ovulation, ending after the last $PGF_{2\alpha}$ injection (d 0) to allow estrus expression. Visual observation for standing estrus was conducted for four 30-min periods at 0330, 1000, 1430, and 2200 h on d 2, 3, 4, and 5. Eighteen of the 35 cows stood to be mounted at least once during the observation period. These cows were used to compare differences between the 6 h before and after the first standing event (estrus) and the 2 wk preceding that period (nonestrus) for all technology parameters. Differences between estrus and nonestrus were observed for CowManager SensOor minutes feeding per hour, minutes of high ear activity per hour, and minutes ruminating per hour; twice daily DVM bolus reticulorumen temperature; HR Tag neck activity per 2 h and minutes ruminating per 2 h; IceQube lying bouts per hour, minutes lying per hour, and number of steps per hour; and Track a Cow leg activity per hour and minutes lying per hour. No difference between estrus and nonestrus was observed for CowManager SensOor ear surface temperature per hour. The second objective of this study was to explore the estrus detection potential of machine-learning techniques using automatically collected data. 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%. When we compared visual observation with progesterone profiles of all 32 cows, we found 65.6% accuracy. Based on these results, machine-learning techniques have potential to be applied to automatically collected technology data for estrus detection.
Key words: precision dairy farming technology, estrus detection, automated estrus detection, technology, machine learning

INTRODUCTION

Detecting a high percentage of cows in estrus is essential to maintain reproductive performance in dairy herds using AI. The most common form of estrus detection is visual observation, used by 93% of US dairy operations (USDA, 2007). The Dairy Records Management Systems reported mean yearly estrus detection rate on US Holstein herds (including all reproductive management strategies) as 44.9% in 2015 (DRMS, 2015). This low estrus-detection rate may be a result of the extreme decline in Holstein cattle estrus duration (from 18 to less than 8 h) over the last 50 yr (Reames et al., 2011). Increasing age, milk production, and environmental factors (greater ambient temperature, uncomfortable housing, and so on) can also negatively affect length and intensity of estrus expression (Vailes and Britt, 1990; López-Gatius et al., 2005; Palmer et al., 2010).

Automated estrus detection (**AED**) technologies are an available alternative to supplement or replace visual estrus detection. Parameters with potential for AED include mounting events, activity level, lying time, rumination events, blood or milk progesterone (**P4**) levels, feeding time, body temperature, and more (Senger, 1994; Saint-Dizier and Chastant-Maillard, 2012; Fricke et al., 2014). Estrus-related changes in some of

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these parameters (mounting events, activity level, lying time, rumination events, and P4) have been quantified repeatedly. However, a lack of consistent data exists surrounding estrus-related changes in feeding time and body temperature. Additionally, not all of these parameters have been measured on the same cows during the same estrus periods.

To determine the accuracy of a specific AED technology, estrus events identified by the technology algorithm (a set of criteria used to determine "estrus") are compared with a gold standard such as visual observation, ultrasonography, blood or milk P4 levels, or a combination of these. Correctly identified estrus events are considered true positives (**TP**), nonalerted estrus events are false negatives (**FN**), nonalerted nonestrus events are true negatives (**TN**), and alerted nonestrus events are false positives (**FP**; Firk et al., 2002). Detecting estrus events is a balance of sensitivity and specificity. Sensitivity, the probability that an event is alerted, is equal to $TP/(TP + FN) \times 100$ (Hogeveen et al., 2010). Specificity, the probability that when an event does not occur no alert is generated, is equal to $TN/(TN + FP) \times 100$. Because neither sensitivity nor specificity account for the prevalence of the event, other comparative measurements are also useful, including accuracy: $[(TP + TN)/(TP + TN + FP + FN) \times 100]$.

The estrus-detection accuracy of a technology depends on 3 factors: (1) how strongly and closely the measured parameters are associated with estrus, (2) how accurately the technology is measuring those parameters, and (3) if the technology manufacturer algorithm is accurately processing the data to create useful estrus alerts. Most technology manufacturer algorithms are proprietary, making it difficult to identify how well each of the 3 factors described above are performing. Machine-learning techniques can replace the manufacturer alert algorithms and evaluate technologies based solely on parameter data collected. Mitchell et al. (1996) and Krieter (2005) previously described the use of machine-learning techniques for estrus detection; however, both studies focused on identifying the day of estrus rather than a more specific period. Additionally, no commercially available AED technologies were evaluated in those analyses.

Our study included 2 objectives. The first objective was to describe estrus-related changes in neck activity, ear activity, leg activity, step count, lying bouts, lying time, rumination, feeding time, reticulorumen temperature, and ear surface temperature as measured using 5 AED technologies on the same cows. The second objective of our study was to explore the estrus-detection potential of machine-learning techniques using parameters collected by AED technologies.

MATERIALS AND METHODS

This study was conducted at the University of Kentucky Coldstream Dairy under Institutional Animal Care and Use Committee protocol number 2013–1069. All lactating cows (n = 82) were housed in 2 groups, separated by a shared, raised feedbunk. Both groups maintained open access to freestalls, one group with sawdust-covered rubber-filled mattresses (PastureMat; Promat, Ontario, Canada) and the other group with sawdust-covered Dual Chamber Cow Waterbeds (Advanced Comfort Technology Inc., Reedburg, WI). Cows received access to a grass-seeded exercise lot for 1 h/d at 1000 h, weather permitting. All other surfaces accessible to cows (freestall area, feed bunk, holding pen, and alleys) contained grooved concrete. Delivery of a TMR ration containing corn silage, alfalfa silage, whole cottonseed, and grain mix occurred twice daily at 0530 and 1330 h. Milking occurred twice daily at 0430 and 1530 h.

Our study enrolled 32 Holstein cows not bred in their current lactation. Parity, DIM at the beginning of the study protocol, and summit milk production from the current lactation of these cows were (mean ± SD) 2.0 ± 1.2, 77.8 ± 20.5 d, and 39.8 ± 8.8 kg, respectively. Cow ovulations were synchronized in 3 groups of 14, 10, and 8 cows, starting on January 24, March 19, and May 14, respectively. The synchronization protocol (Figure 1) was a modification of the standard Ovsynch (Pursley et al., 1995), preceded by G7G (Bello et al., 2006). In contrast to the standard Ovsynch, the last injection of GnRH (gonadorelin diacetate tetrahydrate, Cystorelin; Merial Limited, Duluth, GA; 100 μg i.m.) was not administered to stimulate estrus expression. Additionally, to stimulate corpus luteum regression, 2 $PGF_{2\alpha}$ injections (dinoprost tromethamine, Lutalyse; Zoetis, Florham Park, NJ; 25 mg i.m.) were given on the last day of the protocol (7 d after the first GnRH injection), 6 h apart (0800 and 1400 h). Day 0 was designated as the last day of the synchronization protocol in each group (Figure 1).

Estrus Confirmation

Visual observation of cows for four 30-min periods at 0330, 1000, 1430, and 2200 h occurred on d 2, 3, 4, and 5 (Figure 1). Two observers were present at each shift, with one assigned to each side of the separated housing area. Study cows were clearly identified using spray paint. Observers recorded the time of each standing estrus event.

Blood samples (10 mL) were collected from cow coccygeal veins on d −2, −1, 0, 1, 2, 7, 9, and 11 (Figure