J. Dairy Sci. 100:1–11
https://doi.org/10.3168/jds.2016-11526

Machine-learning-based calving prediction from activity, lying, and ruminating behaviors in dairy cattle

M. R. Borchers,* Y. M. Chang,† K. L. Proudfoot,‡ B. A. Wadsworth,* A. E. Stone,* and J. M. Bewley*[1]
*Department of Animal and Food Sciences, University of Kentucky, Lexington 40546
†Research Support Office, Royal Veterinary College, University of London, NW1 0TU, United Kingdom
‡Department of Veterinary Preventive Medicine, The Ohio State University, Columbus 43210

ABSTRACT

The objective of this study was to use automated activity, lying, and rumination monitors to characterize prepartum behavior and predict calving in dairy cattle. Data were collected from 20 primiparous and 33 multiparous Holstein dairy cattle from September 2011 to May 2013 at the University of Kentucky Coldstream Dairy. The HR Tag (SCR Engineers Ltd., Netanya, Israel) automatically collected neck activity and rumination data in 2-h increments. The IceQube (IceRobotics Ltd., South Queensferry, United Kingdom) automatically collected number of steps, lying time, standing time, number of transitions from standing to lying (lying bouts), and total motion, summed in 15-min increments. IceQube data were summed in 2-h increments to match HR Tag data. All behavioral data were collected for 14 d before the predicted calving date. Retrospective data analysis was performed using mixed linear models to examine behavioral changes by day in the 14 d before calving. Bihourly behavioral differences from baseline values over the 14 d before calving were also evaluated using mixed linear models. Changes in daily rumination time, total motion, lying time, and lying bouts occurred in the 14 d before calving. In the bihourly analysis, extreme values for all behaviors occurred in the final 24 h, indicating that the monitored behaviors may be useful in calving prediction. To determine whether technologies were useful at predicting calving, random forest, linear discriminant analysis, and neural network machine-learning techniques were constructed and implemented using R version 3.1.0 (R Foundation for Statistical Computing, Vienna, Austria). These methods were used on variables from each technology and all combined variables from both technologies. A neural network analysis that combined variables from both technologies at the daily level yielded 100.0% sensitivity and 86.8% specificity. A neural network analysis that combined variables from both technologies in bihourly increments was used to identify 2-h periods in the 8 h before calving with 82.8% sensitivity and 80.4% specificity. Changes in behavior and machine-learning alerts indicate that commercially marketed behavioral monitors may have calving prediction potential.
Key words: calving prediction, precision dairy monitoring technology, machine learning

INTRODUCTION

Parturition is an important period for both cows and their calves. Dystocia and calf mortality in this period can negatively affect farm economics and animal welfare (Mee, 2004). In the United States, 19% of primiparous and 11% of multiparous cows experience mild to severe dystocia at calving (USDA, 2010). Cows that labor more than 70 min past the appearance of the amniotic sac outside the vulva are at increased risk for dystocia (Schuenemann et al., 2011). Providing timely calving assistance may reduce the risk of dystocia, reduce the pain associated with assisted labor (Mainau and Manteca, 2011), and improve reproductive performance in the subsequent lactation (Bellows et al., 1988). Identifying laboring cattle allows managers to assist in cases of dystocia. Dairy producers currently use a combination of breeding records and visual cues to estimate calving time; however, even experienced personnel may not accurately detect all calvings, because perceptible behavioral and physiological changes do not occur for every cow or at a consistent time across calvings (Hofmann et al., 2006; Sendag et al., 2008).

Precision dairy monitoring technologies provide alternatives to the subjective observation and assessment of calving behaviors, and they represent an alternative approach for predicting calving time. To date, the application of precision technologies in calving detection has consisted primarily of maternal body-temperature monitors. Maternal body temperature has been shown

Received May 29, 2016.
Accepted March 26, 2017.
[1]Corresponding author: jbewley@uky.edu

to decrease approximately 48 h before calving (Lammoglia et al., 1997; Burfeind et al., 2011). Commercially marketed temperature monitors measure dairy cattle reticulorumen temperature, skin temperature, and vaginal temperature, but none have been validated for calving prediction. Monitors inserted in the vagina and expelled at the beginning of the second stage of labor also exist (Palombi et al., 2013), but these tools have also not been validated. As well, these technologies are costly, and to our knowledge, no economic research establishing their feasibility on dairy farms has been completed.

Validated measures of activity (Champion et al., 1997; Robert et al., 2009; Bikker et al., 2014), lying behavior (McGowan et al., 2007; Ledgerwood et al., 2010; Mattachini et al., 2013a; Borchers et al., 2016), and rumination (Schirmann et al., 2009; Bikker et al., 2014; Borchers et al., 2016) exist and may offer other options for calving prediction. As well, many of these technologies and the variables they monitor are already commonly used on dairy farms (Borchers and Bewley, 2015). Furthermore, dairy cows change feeding, rumination (Huzzey et al., 2005; Schirmann et al., 2013; Pahl et al., 2014), and lying behavior (Huzzey et al., 2005; Miedema et al., 2011; Jensen, 2012) as calving approaches, making technologies that measure these behaviors potentially useful tools for calving prediction. Some research has endeavored to predict calving events using these measures. Clark et al. (2015) used the SCR HR Tag (SCR Engineers, Ltd., Netanya, Israel) to monitor rumination behavior and predict calving events, achieving 70% sensitivity and 70% specificity in predicting the day of calving. Similarly, Ouellet et al. (2016) evaluated systems that monitored rumination time, vaginal temperature, and lying behaviors for their accuracy in calving prediction and found that a combination of these variables had a greater level of prediction accuracy than considering any of them alone (77% sensitivity, 77% specificity).

Most algorithm development and usage implements elements of statistical process control (MacGregor and Kourti, 1995), requiring the use of trial and error and development of deviations from baseline values. A newer approach in event prediction is machine-learning event prediction. Most machine-learning research in the dairy sciences has been applied to mastitis and estrus detection (Firk et al., 2003; Cavero et al., 2008; Sun et al., 2010); no research has addressed its use in calving prediction. Additionally, to our knowledge, no commercial precision dairy monitoring technologies use machine-learning techniques to create alerts.

Before these technologies can be useful in calving prediction, research is needed to determine whether the behaviors measured (e.g., activity, rumination, and lying behavior) are highly sensitive and specific in detecting imminent calving. The objectives of this study were 2-fold: (1) to quantify activity, rumination, and lying behaviors before calving using 2 commercially available technologies and compare these behaviors to previous literature and (2) to determine the calving prediction efficacy of these technologies, both individually and in combination, using machine-learning prediction techniques. Cow-specific data commonly available from herd management software were also included in the prediction methods. We hypothesized that activity, rumination, and lying behaviors on the day of calving would differ from typical values. In the calving prediction analysis, we hypothesized that a combination of variables from both technologies would generate greater prediction accuracy with machine-learning methods than variables from either technology alone.

MATERIALS AND METHODS

Data were collected using 20 primiparous and 33 multiparous prepartum Holstein dairy cattle (mean ± SD; gestation length 277.6 ± 4.9 d; parity 2.3 ± 1.5) from September 2011 through May 2013 at the University of Kentucky Coldstream Dairy Facility (IACUC Protocol Number: 2010-0776). Beginning 30 d before the expected calving date, cows were moved to dry cow facilities and housed in a 9.15- × 21.34-m sawdust-bedded pack with constant access to 3.64 ha of pasture. A TMR was delivered to the pen once per day.

Two technologies were fitted to each cow by 28 d before the predicted calving. After calving, data were reduced to include only the 2 wk before calving from each cow. The HR Tag (SCR Engineers Ltd., Netanya, Israel) was placed on the left side of the neck and automatically collected neck activity and rumination data in 2-h periods using a 3-axis accelerometer and a microphone with a microprocessor, respectively. The IceQube (IceRobotics Ltd., South Queensferry, United Kingdom) was attached to the left rear leg and automatically collected number of steps, time spent lying, time spent standing (inverse of time spent lying), number of transitions from standing to lying (lying bouts), and a proprietary total motion variable in 15 min periods using a 3-axis accelerometer. Third-party technology variable validations have been completed for the HR Tag (Schirmann et al., 2009) and the IceQube (McGowan et al., 2007; Mattachini et al., 2013b; Borchers et al., 2016), and both technologies have been found to accurately monitor their respective variables.

Cows in the dry pen were monitored for signs of calving every 3 h. Individual cows were monitored every