Technical note: Calving prediction in dairy cattle based on continuous measurements of ventral tail base skin temperature using supervised machine learning

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ABSTRACT

In this study, we developed a calving prediction model based on continuous measurements of ventral tail base skin temperature (ST) with supervised machine learning and evaluated the predictive ability of the model in 2 dairy farms with distinct cattle management practices. The ST data were collected at 2- or 10-min intervals from 105 and 33 pregnant cattle (mean $\pm$ standard deviation: 2.2 ± 1.8 parities) reared in farms A (freestall barn, in a temperate climate) and B (tiestall barn, in a subarctic climate), respectively. After extracting maximum hourly ST, the change in values was expressed as residual ST (rST = actual hourly ST – mean ST for the same hour on the previous 3 d) and analyzed. In both farms, rST decreased in a biphasic manner before calving. Briefly, an ambient temperature-independent gradual decrease occurred from around 36 to 16 h before calving, and an ambient temperature-dependent sharp decrease occurred from around 6 h before until calving. To make a universal calving prediction model, training data were prepared from pregnant cattle under different ambient temperatures (10 data sets were randomly selected from each of the 3 ambient temperature groups: $<15^\circ\text{C}$, $\geq 15^\circ\text{C}$ to $<25^\circ\text{C}$, and $\geq 25^\circ\text{C}$ in farm A). An hourly calving prediction model was then constructed with the training data by support vector machine based on 15 features

extracted from sensing data (indicative of pre-calving rST changes) and 1 feature from non-sensor-based data (days to expected calving date). When the prediction model was applied to the data that were not part of the training process, calving within the next 24 h was predicted with sensitivities and precisions of 85.3% and 71.9% in farm A ($n = 75$), and 81.8% and 67.5% in farm B ($n = 33$), respectively. No differences were observed in means and variances of intervals from the calving alerts to actual calving between farms (12.7 ± 5.8 and 13.0 ± 5.6 h in farms A and B, respectively). Above all, a calving prediction model based on continuous measurement of ST with supervised machine learning has the potential to achieve effective calving prediction, irrespective of the rearing condition in dairy cattle.

Key words: body surface temperature, parturition prediction, precision dairy farming, wearable sensor

Technical Note

In a recent study, monitoring the ventral tail base skin temperature (ST) was proposed as a less invasive approach for calving prediction by detecting the decrease in body temperature during the precalving period with the empirically calculated cut-off values of ST (Koyama et al., 2018). In this study, we developed a calving prediction model based on continuous measurements of ST using supervised machine learning. We also evaluated the predictive ability of the model for calving prediction within the next 24 h in 2 dairy farms with distinct cattle management practices. We hypothesized that sensitivities and precisions of the developed model on unknown data from the 2 farms would be comparable to each other. The predictive ability of the model would also be similar to or higher than that of the previous

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studies using a simple thresholding method based on body temperature sensing.

The experiment was conducted in 2 dairy farms. Average ambient temperatures from February 2018 to August 2019 were 17.1°C on farm A in a temperate climate and 5.6°C on farm B in a subarctic climate (Japan Meteorological Agency, 2019). In farm A, approximately 1,900 dairy cattle were housed in a sawdust-bedded freestall barn. In farm B, approximately 80 dairy cattle were housed year-round in a sawdust-bedded tiestall barn. In both farms, pregnant cattle were moved to an individual maternity pen (3 m × 3 to 6 m) when they showed the premonitory signs of calving (i.e., restlessness, pelvic ligament relaxation, and teat filling). Calving assistance was provided to cattle when farm staff detected abnormalities in the progress of labor. All animal procedures were approved by the Institutional Animal Care and Use Committee of the National Agriculture and Food Research Organization (#17-087) and the Hokkaido Research Organization (#20170324-3 and #20180312-3).

A total of 138 pregnant dairy cattle (17 heifers and 121 cows with average parities of 2.2 ± 1.8 ; 93 Holsteins and 12 Brown Swiss in farm A, and 33 Holsteins in farm B) were enrolled in this study. Pregnancy was confirmed via transrectal ultrasonography at approximately 30 and 60 d postinsemination and before dry up. The expected calving date was calculated from the breeding records of AI or embryo transfer, and estimated based on the fetal crown-rump length measurements (White et al., 1985) for natural bred animals, assuming to be 280, 290, 290, and 285 d for Holstein, Brown Swiss, Japanese Black, and Holstein-Japanese Black crossbred fetuses, respectively (Andersen and Plum, 1965; Isogai et al., 1994).

The ST was measured using a tail-attached sensor as described previously (Miura et al., 2017) with slight modifications. As shown in Figure 1, the sensor was put into a silicone rubber belt and sealed with urethane gel to prevent skin damage. The silicone rubber belt with the sensor was then attached to the ventral tail base using double-sided adhesive tape (KZ-12, Nitomus, Tokyo, Japan), and its position was stabilized by an outer belt with an adjustable hook-and-loop fastener strap. The sensor was suspended from the back of the animal by a rubber loop attached with hook-and-loop fasteners and wrapped with elastic medical bandages (SRPH75 and SRPH50, Nichiban, Tokyo, Japan).

The sensor was attached to the pregnant cattle at 9 to 35 d before the expected calving date (15.5 ± 4.8 d) and measured ST every 2 or 10 min until at least 24 h after calving. The sensor wirelessly transmitted the ST measurement data to the receiver connected to the gateway nodes secured on a beam near the tested

cattle and the data were uploaded on the cloud server. Calving time, defined as the time when the fetus was expelled from the vulva, was determined through visual observation or video recording. During the experiment, ambient temperature was measured every minute using a digital thermometer (TR-72nw-S, T & D Corp., Tokyo, Japan) and stored on the cloud server via the gateway node.

In data preprocessing phase, the maximum hourly ST was extracted to minimize the effects of rapid momentary decreases of ST in raw data. After cleaning the data for missing values by forward-filling (i.e., taking the last known value and using this to fill), ST changes were expressed as residual ST ($rST = \text{actual hourly ST} - \text{mean ST for the same hour on the previous 3 d}$) to exclude the influence of the circadian rhythm (Miura et al., 2017). To build a calving prediction model, a total of 16 features (15 features from the sensing data and 1 feature from the non-sensor-based data) were prepared (Table 1).

For data analysis, the 3 ambient temperature groups ($<15^\circ\text{C}$, $\geq 15^\circ\text{C}$ to $<25^\circ\text{C}$, and $\geq 25^\circ\text{C}$) were designated, because it has been reported that the thermoregulatory mechanism was not required at ambient temperatures between 0°C and 15°C , activated at around 15°C and beginning to fail at around 25°C in European cattle (Brody, 1956). The data obtained from farm A were split into 2 complementary subsets; 10 data sets were randomly selected from each of the 3 ambient temperature groups classified based on the average ambient temperature for 24 h before actual calving (30 data sets in total) and used as “training data.” The remaining 75 data sets were used as part of the “test data” as described below. The training data during the last 12 h before calving were labeled as positive instances and the remaining data were labeled as negative instances; then the data were used to generate a calving prediction model by support vector machine using the package e1071 (Meyer et al., 2019) of R version 3.4.0 for Windows. The hyperparameter cost and gamma were empirically set to 0.01 and 0.05, respectively, with a positive class weight of 10. All features were scaled to zero mean and unit variance.

Following the development of the prediction model, unlabeled data (test data) from farms A (75 data sets) and B (33 data sets) were applied to the model and classified into “near calving” or “not near calving” every hour. At least 3 consecutive hours of “near calving” predictions were regarded as a calving alert to minimize excessive alerts. If intermittent alerts were presented within 12 h, they were assumed to be related and counted as a single alert. When the calving alert has been given within 24 h before the calving, the alert was regarded as a true-positive predictor to take into

Figure 1. Structure and usage of the wearable wireless tail skin temperature (ST) sensor. (A) ST sensor (20.0 mm × 26.0 mm × 10.0 mm, weighed 5.5 g) designed for fitting to the ventral tail base of a heifer. (B) ST sensor in an attachment unit. (C) Position of the ST sensor. (D) Sensor attachment unit fixed on the surface of the ventral tail base. (E) Sensor attachment unit suspended from the back of the animal. (F) Sensor attachment unit wrapped with elastic medical bandages.

account individual differences in the timing of pre-calving ST drop. Nonalerted calving events and alerted noncalving events were regarded as false-negative and false-positive predictors, respectively. Sensitivity (true-positive rate) and precision (positive predictive value) were calculated as $[\text{true-positive}/(\text{true-positive} + \text{false-negative})]$ and $[\text{true-positive}/(\text{true-positive} + \text{false-positive})]$, respectively.

For analyzing changes in rST around calving, data obtained between −120 h to 12 h from calving were divided into 3 groups classified based on the average am-

bient temperature for 24 h before actual calving. Within the same ambient temperature groups, hourly rST values during −72 h to 12 h of calving were compared with the mean values during the control noncalving period (−120 h to −73 h from calving) by the nonparametric Steel test. At each time point, the nonparametric Kruskal–Wallis test was used to detect differences in rST among the ambient temperature groups. Sensitivities and precisions of the model were compared by the 2-tailed Fisher's exact test. Variances and means of the time intervals from the true-positive calving alert to ac-

Table 1. Description of the 16 features used to build the calving prediction model by supervised machine learning

Features derived from sensing data

$y(t)$: maximum hourly tail skin temperature (ST) at time t
 $q_{SD}(t) = p(t)^1 / SD[y(s): s = t - 24, \dots, t - 72]$
 $q_{max}(t) = p(t) - \max[p(s): s = t, \dots, t - i], i = 6, 12, 24$
 $q_{min}(t) = p(t) - \min[p(s): s = t, \dots, t - i], i = 6, 12, 24$
 $q_{SD}(t') = p(t') / SD[y(s): s = t' - 24, \dots, t' - 72], t' = t - 6$
 $q_{max}(t') = p(t') - \max[p(s): s = t', \dots, t' - i], t' = t - 6, i = 6, 12, 24$
 $q_{min}(t') = p(t') - \min[p(s): s = t', \dots, t' - i], t' = t - 6, i = 6, 12, 24$
 Feature derived from non-sensor-based data
 Days to expected calving date

¹The exponentially weighted moving average (EWMA) was applied to the residual ST data $\{u(t) = y(t) - \text{mean}[y(s): s = t - 24, t - 2 \times 24, t - 3 \times 24]\}$ for removing short-term (within a few hours) inconsequential ups and downs. The EWMA was calculated as follows: $p(0) = u(0)$, $t = 0$. $p(t) = \alpha u(t) + (1 - \alpha)p(t - 1)$, $\alpha = 0.1$, $t > 0$. min = minimum; max = maximum. The characters y , q , p , and u indicate functions, and s , t' , and i are time variables.

tual calving were compared by the F -test and one-way ANOVA followed by Bonferroni's multiple comparison tests, respectively, after confirming the normality of the data distribution by the Shapiro–Wilk test. Statistical analyses were performed among different ambient temperature groups on the respective farms and between farms. Statistical analyses were performed using R, and differences were considered significant at $P < 0.05$.

As shown in Figure 2, rST started to decrease from approximately 36 h before calving, and a significant reduction in rST was observed from around 24 h before calving in cattle kept at both farms, regardless of the ambient temperature. Mean rST became constant around 16 h before calving and then sharply decreased again from approximately 6 h before calving, whereas the amplitude of the drop tended to be more pronounced

Figure 2. Residual tail skin temperature (rST) changes around calving. (A) rST changes in farm A ($n = 32, 31$, and 42 at $<15^{\circ}\text{C}$, $\geq 15^{\circ}\text{C}$ to $<25^{\circ}\text{C}$, and $\geq 25^{\circ}\text{C}$ ambient temperature, respectively). (B) rST changes in farm B ($n = 25$ and 8 at $<15^{\circ}\text{C}$ and $\geq 15^{\circ}\text{C}$ to $<25^{\circ}\text{C}$ ambient temperature, respectively). Data were standardized to calving (0 h). Black, gray, and white horizontal bars indicate the periods with differences between rST at the indicated time point and the average rST (from 120 to 73 h before calving) at $<15^{\circ}\text{C}$, $\geq 15^{\circ}\text{C}$ to $<25^{\circ}\text{C}$, and $\geq 25^{\circ}\text{C}$, respectively ($P < 0.05$). Asterisks (*) indicate the time points with significant difference in mean rST at different ambient temperatures. Values presented as mean $\pm$ SD.

Table 2. Performance of the calving prediction model based on continuous measurements of ventral tail base skin temperature with supervised machine learning for calving prediction within 24 h before parturition

Farm	Average ambient temperature	Number of calving	True positive	False negative	False positive	Sensitivity (%)	Precision (%)	Average time interval ¹ (h)
A	<15°C	22	16	6	15	72.7	51.6 ^a	14.0 ± 5.1
	≥15°C to <25°C	21	19	2	6	90.5	76.0 ^{ab}	13.8 ± 7.0
	≥25°C	32	29	3	4	90.6	87.9 ^b	11.3 ± 5.2
	Subtotal	75	64	11	25	85.3	71.9	12.7 ± 5.8
B	<15°C	25	21	4	9	84.0	70.0	12.8 ± 5.4
	≥15°C to <25°C	8	6	2	4	75.0	60.0	13.8 ± 6.6
	Subtotal	33	27	6	13	81.8	67.5	13.0 ± 5.6
A + B	<15°C	47	37	10	24	78.7	60.7 ^a	13.3 ± 5.3
	≥15°C to <25°C	29	25	4	10	86.2	71.4 ^{ab}	13.8 ± 6.8
	≥25°C	32	29	3	4	90.6	87.9 ^b	11.3 ± 5.2
	Total	108	91	17	38	84.3	70.5	12.8 ± 5.8

^{a,b}Values with different superscripts within a column for the same farm are significantly different ($P < 0.05$).

¹Average time intervals from the true-positive calving alerts to the actual calving. Values presented as mean ± SD.

with lowering ambient temperature. Supervised machine learning is the search for algorithms that reason from externally supplied instances (training data) to produce general hypotheses (models). Therefore, we prepared the training data from 3 ambient temperature groups to make a calving prediction model work under wide range of ambient temperatures. We extracted the 15 features that could reflect calving-associated temperature changes, as listed in Table 1, because only a given numerical value for ST or rST seemed to not necessarily be indicative of calving without monitoring its sequential changes. Moreover, a non-sensor-based variable (days to expected calving date) was also included in the prediction model, since most of the calvings occurred around the expected calving date with means of 0.5 ± 5.6 d ($n = 105$) and 0.6 ± 3.9 d ($n = 33$) in farms A and B, respectively.

As shown in Table 2, the present calving prediction model showed no statistically different sensitivities and precisions on test data (i.e., unknown data) from the 2 farms, though the precision tended to be lower at lower ambient temperature in farm A. Moreover, there were no differences in means and variances of intervals from the calving alerts to actual calving between farms, indicating that the present calving prediction model should be robust to farm variations. The present result was also comparable to that in the previous studies using the simple thresholding method based on vaginal (Burfeind et al., 2011; Ouellet et al., 2016; Ricci et al., 2018), reticulo-ruminal (Costa et al., 2016), and tail skin temperatures (Koyama et al., 2018): sensitivity of 62% to 89% and precision of 49% to 80% in predicting the 24-h period before calving. Moreover, the present model could help to predict not only eutocic but also dystocic calving, because dystocic calving (assisted or

cesarean) does not influence the change in vaginal temperature before calving (Ricci et al., 2018). However, it should be stressed that the present calving prediction model was developed based only on 30 training data sets. Variation in the precisions across ambient temperature groups might imply that the present training data did not cover all possible situations. In particular, relatively low performance of the model at <15°C in farm A suggests that the training data may be insufficient for generalization and limits the practical use of the model in its present form. Although there is currently a lack of consensus on how to consider sample size for machine learning models (Faes et al., 2020), a follow-up study with a larger sample size is needed to definitively characterize ST changes around calving for improving the calving prediction model.

In conclusion, we developed a calving prediction model (sensitivity of 84.3% and precision of 70.5% in predicting calving within the next 24 h with an average of 12.8 ± 5.8 h before actual calving) using supervised machine learning with sequential ST data obtained by a tail-attached sensor we developed. To our knowledge, this is the first report of applying a machine learning method to body temperature sensing data for calving prediction. Results of the current study indicate that a model based on continuous measurement of ST with supervised machine learning has the potential to achieve effective calving prediction, irrespective of the rearing condition in dairy cattle.

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