Localization and accelerometer sensors for the detection of oestrus in dairy cattle

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Abstract

The aim of this work was to combine ultra-wide band (UWB) localization tracking, a neck-mounted accelerometer and a leg-mounted accelerometer for the detection of oestrus in dairy cows. Twelve Holstein cows with successful artificial insemination (AI) were used in this study. The sensors were attached two weeks before the expected day of oestrus and removed after AI. Different cow variables (e.g., lying time, number of steps, ruminating time, travelled distance) were extracted from the raw sensor data and used to build and test the detection models. Logistic regression models were developed for each individual sensor as well as for each combination of sensors (two or three). The performances were similar when one sensor was used only as when combining the neck- and leg-mounted accelerometer (sensitivity (Se) =75-78%, area under curve (AUC) =93-94%). The performance increased when localisation was combined with either the neck- or leg-mounted accelerometer, especially for the sensitivity (80 % for leg accelerometer + localisation and 88 % for neck accelerometer + localisation). The AUC were nearly the same (97 %). The best performance was obtained with the combination of all three sensors (Se=90%, AUC= 99%). Future work will consist of expanding this research to other herds with larger sample size as well as considering cows' anomalies (e.g., mastitis, lameness) and other sensors (e.g., bolus or eartag to measure the temperature).

Keywords: Accelerometer, UWB localization system, dairy cows, machine learning, K-mean, support vector machine, behaviours classification, oestrus, internet-of-animals

Introduction

The profitability of dairy farms depends greatly on the breeding efficiency of dairy cows and the timely detection of oestrus (De Vries, 2010). Without accurate detection of oestrus in artificial insemination (AI) breeding programs, mistakes can be made and costs can be elevated due to wasted straws of semen, technician costs and time. In addition, numerous studies have documented that additional days in which cows are not pregnant beyond the optimal time post-calving are costly (Groenendaal et al., 2010; Meadows et al., 2010). Ultimately, accurate oestrus detection should be used to successfully breed cattle with AI. However, visual detection of oestrus becomes difficult in large sized herds, as the cows may not show visual signs of oestrus (e.g., restlessness, standing to be mounted) during the time visual observation is being performed due to the impact of stress and other diseases (e.g., lameness).

To manage oestrus detection in high density livestock farms, farmers increasingly rely on automated systems using sensors for the collection and the interpretation of animal data. Several studies have investigated a variety of sensors (pressure, activity meters, video cameras, recordings of vocalization, measurements of body temperature and milk progesterone concentration) for oestrus detection (Reith and Hoy, 2018; Roelofs et al., 2010; Stevenson, 2001). On the basis of their review, Reith and Hoy (2018) recommended to give highest priority to the detection based on sensor-supported activity monitoring (e.g., accelerometers) as being most successful tools for automated oestrus detection. Meanwhile, the increasing availability of positioning systems based on small devices unlock the potential of using real-time animal location data for the benefit of cow and farmer. Although recent studies (Homer et al., 2013; Porto et al., 2014; Tullo et al., 2016) started to involve positioning data for the monitoring of dairy cows, localisation sensors were never combined with neck- and leg-mounted accelerometers for oestrus detection up to now. This will likely increase the detection accuracy by expanding the range of predictor variable and allow automated alerting the farmer to a wider range of issues (not only oestrus) that require his action or attention as compared to systems based on one sensor

In the present study, ten cow variables were extracted from three sensors (i.e., neck- and leg-mounted accelerometers and localisation sensor). Three variables were extracted from each accelerometer (e.g., ruminating time, feeding time, and resting time from the neck-mounted accelerometer, and lying time, lying bouts, and number of steps from the leg-mounted accelerometer), and four variables were extracted from the localisation data (i.e., travelled distance, time in cubicles, time in feeding zone, time in drinking zone). These variables were reported previously as good predictor for oestrus detection (Pahl et al., 2015a; Reith et al., 2014). This work is the first to investigate combining a neck-mounted accelerometer, a leg-mounted accelerometer, and a localisation sensor for the detection of oestrus in dairy cattle.

The use of a combination of sensors is likely increase the detection accuracy by expanding the range of predictor variable and allow automated alerting the farmer to a wider range of issues in addition to oestrus (e.g., lameness, calving) that require his action or attention as compared to systems based on one sensor. Moreover, smart communication between multiple sensors may considerably reduce the power consumption as compared to each sensor operating independently of one another. For example, when detecting a cow in lying down position by the leg-mounted accelerometer, the localisation sensor could be turned-off until detecting the cow is changing position. This could save more than 50 % of the energy of the position monitoring, since cows spend 12 to 14 hours per day lying down (Gomez and Cook, 2010).

Material and methods

Animals and housing

In total, 12 cows (parity 2.8 ± 1.3) with successful insemination were used for the detection of oestrus events. The cows were housed with other cows (31 in total) in a free-stall barn of the Flanders Research Institute for Agriculture, Fisheries and Food (ILVO), Melle, Belgium. The barn contains four areas of 30 m long and 13 m wide each, with individual cubicles and a concrete slatted floor. The cubicles (n = 32, width 115 cm, length from curb to front rail 178 cm, front rail height 70 cm, neck rail height 109 cm, neck rail distance from curb 168 cm) were bedded with a lime-straw-water mixture. The cows were fed roughage ad libitum. The concentrates were supplied by computerized concentrate feeders. Drinking water was available ad libitum (two drinking troughs). This study was conducted between September 2017 and April 2018.

Sensors

Each cow was fitted with three sensors: a localization node, a leg-mounted accelerometer (right hind leg), and a collar-mounted accelerometer (Figure 1). For the localization data, an OpenRTLS ultra-wide band (UWB) localization system (DecaWave, Ireland) was installed in the barn using 7 anchors (including the master anchor). The sampling rate of the localization system was set to 2 Hz to enable a logging interval of about 4 weeks. Accuracy measurements were performed beforehand. A localization node was put in 46 different locations in the cubicles and the alley. Then, a comparison was made between the actual locations and locations estimated by the localisation system. The mean and median accuracy were 38 and 34 centimetres. The acceleration data (i.e., 3 orthogonal accelerometer vectors) were logged with a sampling rate of 10 Hz (10 samples each second) using Axivity AX3 loggers (Axivity Ltd, Newcastle, UK). The clocks of the localization system and the accelerometers were synchronized at the start of the experiments.

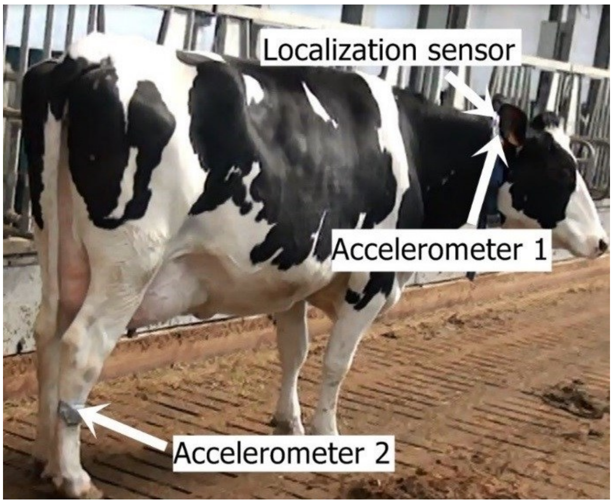

Figure 1: A cow wearing the three sensors.

Data collection procedure

The sensors were attached 2 weeks before the expected day of oestrus and removed after the AI. Decisions about timing of insemination were made by the ILVO stockpeople. Not all inseminations were associated with real estruses as insemination might be performed on the basis of a false alert or erroneous interpretation of a cow's behaviour. Therefore, to ensure that the data-set was based on true cases of oestrus, only data from periods around inseminations that led to confirmed pregnancy were used in this study. From 15 cows, 12 cows with successful insemination were used to create the dataset.

Processing of sensors data

The data processing was performed using MATLAB software (Release 2018b, The MathWorks, Inc., Natick, Massachusetts, United States).

In total, three variables were extracted from each accelerometer (i.e., hourly ruminating time, feeding time, and resting time from the neck-mounted accelerometer, and hourly lying time, lying bouts, and number of steps from the leg-mounted accelerometer).

As presented in (Benaissa et al., 2018), the data of the neck-mounted accelerometer were used to obtain ruminating, feeding, and resting times. We note here that resting behaviour is when the cow has a static position (inactivity), i.e., either standing or lying. Lying bouts and lying time were extracted from the leg-mounted accelerometer as presented in (Ito et al., 2009). Finally, a simple k-Nearest Neighbours (kNN) algorithm was developed and validated (accuracy of 97 % compared to direct observations) to count the number of steps based on the data of the leg-mounted accelerometer.

In total, four variables were extracted from the localisation data for each one-hour time interval (i.e., travelled distance, time in cubicles, time in feeding zone, time in drinking zone). The travelled distance is the sum of all distances that are labelled as walking, along the trajectory. A distance between two location updates is labelled as such if the travelled distance exceeds a threshold within a certain interval. When a cow is located within the lying zone, e.g. the cubicles, a first timer is started. When this timer exceeds a hold-off time (i.e., 1 minute), the real lying timer starts. The purpose of the first timer is to remove false positives (e.g., when a cow is falsely located in the boxes for a short time). The timer stops when the cow is located outside the boxes for the same hold-off time. The time at drinking zone and feeding zone were calculated with the same procedure as time in lying cubicles but with another zone label. These zones are rectangles (or more generally polygons) that have to be specified once and can be drawn on the floor plan or defined in a text document.

Detection models

Since the aim was to build a model for binary classification (e.g., a cow is in oestrus or not), logistic regression was chosen. Also, logistic regression is widely adopted when interested in the impact of various variables (variables from different sensors in this case) on a response variable (Sperandei, 2014). All variables (feeding time, number of steps, lying time, etc.,) were summarized in 1-h intervals. The 1-h intervals were adjusted relative to the time of the actual AI (0 is the time of AI). Only 1 week before AI was used for the detection models, as the first week was considered as a habituation period. A 24-h moving average was applied to smooth the data as performed in (Borchers et al., 2017). To estimate the changes over time of the cow variables, each value of the calculated hourly variables was subtracted from the mean value of the past 24 values of the same cow (i.e., 24 hours) as presented in (Rutten et al., 2017). Any alerts during hours -1 to -24 were treated as true positives. Finally, to measure the performances of the detection models, the leave one out cross validation strategy was used (Arlot and Celisse, 2010) to calculate the precision, the sensitivity, the specificity, the overall accuracy, and the area under curve (AUC). The data of one cow were used as testing set and the data of the remaining cows were used as training set. This was repeated for all cows in the data set and the average the precision, the sensitivity, the specificity, and the overall accuracy were considered.

Results and Discussion

For the neck-mounted accelerometer, ruminating time decreased by 26% ($P<0.01$) between the reference period (i.e., 6 days before the day of oestrus) and the day of AI. Similarly, resting time decreased by 23% ($P<0.01$). However, feeding time did not show a significant change ($P>0.05$). For the leg-mounted accelerometer, the lying time decreased 38% ($P<0.01$) and the number of steps increased by 95% ($P<0.01$), while lying bouts did not change significantly ($P>0.05$). Finally, for the localisation sensor, the travelled distance increased by 92% ($P<0.01$) and the time in cubicles decreased by 32% ($P<0.05$). The change was not significant ($P>0.05$) for both the time in drinking zone and in feeding zone. In comparison to other studies, Dolecheck et al. (2015) found that lying time decreased during the oestrus period by 58%. Time spent lying and resting time decrease around oestrus because of increased activity and restlessness (Jónsson et al., 2011). This explains also the decrease of resting time. Ruminating time in our study decreased during oestrus by 37%. Reith and Hoy (2012) evaluated 265 oestrus events, finding that ruminating time on the day of oestrus decreased by 17% (74 min), but with large variation between herds (14 to 24%). In a follow-up study that looked at 453 oestrous cycles, ruminating time decreased by 20% (83 min) on the day of oestrus (Reith et al., 2014). Pahl et al. (2015) also found a decrease in ruminating time (19.3%) on the day of AI. The decreases in ruminating time around oestrus found in the current study (26%) is comparable to previous studies, although a small number of cows was considered. The change is feeding time was not significant, similar to the conclusions reported by De Silva et al. (1981), who found no change in feed intake during the 3-d period around oestrus.

Table 1: Mean values and standard error (SE) of the cow variables obtained by the three sensors, [-24, 0] is the 24 hours before the AI. (*$P<0.05$, **$P<0.01$, no asterisks means $P>0.05$)

Sensors	Variables	[-168,-24]	[-24,0]	Difference	
Neck accelerometer	Ruminating time [hours]	8.4±0.6	6.2±0.7	-2.2**	-26%
	Feeding time [hours]	4.5±0.5	5.1±0.3	0.6	13%

	Resting time [hours]	7.3±0.7	5.6±0.5	-1.7**	-23%
Leg accelerometer	Lying bouts [-]	6.8±1.2	6.1±0.8	-0.7	-10%
	Lying time [hours]	12.0±0.9	7.4±1.1	-4.6**	-38%
	Number of steps [-]	2470±210	4824±302	2354**	95%
Localisation	Travelled distance [m]	2161±165	4146±285	1985**	92%
	Time in cubicles [hours]	10.5±0.8	7.1±1.0	-3.4*	-32%
	Time in feeding zone [hours]	4.8±0.5	4.9±0.4	0.1	2%
	Time in drinking zone [min]	14.4±10.6	19.1±13.2	4.7	32%

Detection performance for oestrus is listed in Table 2. Similar results were obtained when using one sensor as compared to combining a neck- and a leg-mounted accelerometers (Se=75-78%, AUC=93-94%). In both cases, the overall accuracy was around 95%. The performance increased when localisation with either neck- or leg-mounted accelerometer was combined, especially for the sensitivity (80 % for leg accelerometer + localisation and 88 % for neck accelerometer + localisation). The AUC were nearly the same (97 %). The use of one sensor limits the number of cow variables that can be accurately detected by the monitoring system. Although some studies (Mattachini et al., 2013; Resheff et al., 2014) suggest that one accelerometer could detect several cow variables, not all variables are detected with the same accuracy. As presented in (Benaissa et al., 2017), neck-mounted accelerometer is better for monitoring ruminating and feeding behaviours, while leg-mounted accelerometer is better for lying behaviour monitoring (e.g., lying time, bouts). On the other hand, not all variables changed during oestrus. For example, the lying bouts and the time in feeding zone did not change significantly during the oestrus period. With all three sensors combined, the precision increased to 93 % and the sensitivity increased to 90 %. The use of different sensors increases the number of cow variables that could change during oestrus. These results show clearly an improved performance, enhancing the number of successful alerts and significantly reducing the number of false alarms.

Table 2: The precision (Pr), sensitivity (Se), specificity (Sp), overall accuracy, and AUC using one sensor, a combination of two sensors, and a combination of the three sensors.

Model based on	Pr [%]	Se [%]	Sp [%]	Accuracy [%]	AUC [%]
Neck Acc	91±1.8	77±1.1	93±0.3	95±0.2	93±0.6
Leg Acc	92±2.4	77±1.2	92±0.5	95±0.3	94±0.4
Localisation	89±2.0	75±0.7	92±0.6	94±0.5	93±0.4
Neck + Leg Acc	89±2.9	78±0.7	98±0.6	95±0.5	93±0.6
Neck Acc + Localisation	86±3.2	88±1.9	97±0.5	97±0.8	97±0.5
Leg Acc+ Localisation	88±1.3	79±2.4	98±0.2	96±0.4	96±0.7
All sensors	93±1.4	90±1.3	99±0.2	98±0.3	99±0.1

Conclusions

In the present study, the combination of accelerometers (neck- and leg-mounted) and a localisation sensor was investigated for the detection of oestrus in dairy cattle. The performance at detecting oestrus was similar for each sensor separately (Se=75-78%, AUC=93-94%). The performance (and the sensitivity in particular) increased when localisation was combined with either a neck- or a leg-mounted accelerometer, especially for the sensitivity (AUC≈ 97 %). The best performance was obtained with the combination of all three sensors (Se=90%, AUC= 99%). This study demonstrates the potential of combining different sensors to increase the detection performance of oestrus monitoring systems for dairy cattle. Future work will consist of expanding this research to other herds with larger sample size as well as considering cows' anomalies (e.g., mastitis, lameness) and other sensors (e.g., bolus or eartag to measure the temperature).

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