Animal 17 (2023) 100730

Contents lists available at ScienceDirect

Animal

The international journal of animal biosciences

Improved cattle behaviour monitoring by combining Ultra-Wideband location and accelerometer data

S. Benaissa [a,b,*], F.A.M. Tuyttens [b,c], D. Plets [a], L. Martens [a], L. Vandaele [b], W. Joseph [a], B. Sonck [b,d]

[a] Department of Information Technology, Ghent University/imec, iGent-Technologiepark 126, 9052 Ghent, Belgium
[b] Flanders Research Institute for Agriculture, Fisheries and Food (ILVO), Scheldeweg 68, 9090 Melle, Belgium
[c] Department of Veterinary and Biosciences, Faculty of Veterinary Medicine, Heidestraat 19, B-9820 Merelbeke, Belgium
[d] Department of Animal Sciences and Aquatic Ecology, Faculty of Bioscience Engineering, Ghent University, Coupure Links 653, B-9000 Ghent, Belgium

ARTICLE INFO

Article history:
Received 22 June 2022
Revised 31 January 2023
Accepted 3 February 2023
Available online 11 February 2023

Keywords:
Behaviour monitoring
Dairy cows
Location system
Precision Livestock Farming
Sensors

ABSTRACT

Cattle behaviour is fundamentally linked to the cows' health, (re)production, and welfare. The aim of this study was to present an efficient method to incorporate Ultra-Wideband (**UWB**) indoor location and accelerometer data for improved cattle behaviour monitoring systems. In total, 30 dairy cows were fitted with UWB Pozyx wearable tracking tags (Pozyx, Ghent, Belgium) on the upper (dorsal) side of the cow's neck. In addition to the location data, the Pozyx tag reports accelerometer data as well. The combination of both sensor data was performed in two steps. In the first step, the actual time spent in the different barn areas was calculated using location data. In the second step, accelerometer data were used to classify cow behaviour using the location information of step 1 (e.g., a cow located in the cubicles cannot be classified as feeding, or drinking). A total of 156 hours of video recordings were used for the validation. For each hour of data, the total time each cow spent in each area and performing which behaviours (feeding, drinking, ruminating, resting, and eating concentrates) were computed using the sensors and compared against annotated video recordings. Bland-Altman plots for the correlation and difference between the sensors and the video recording were then computed for the performance analysis. The overall performance of locating the animals into the correct functional areas was very high. The R^2 was 0.99 ($P < 0.001$), and the root-mean-square error (**RMSE**) was 1.4 min (7.5% of the total time). The best performance was obtained for the feeding and lying areas ($R^2 = 0.99$, $P < 0.001$). Performance was lower in the drinking area ($R^2 = 0.90$, $P < 0.01$) and the concentrate feeder ($R^2 = 0.85$, $P < 0.05$). For the combined location + accelerometer data, high overall performance (all behaviours) was obtained with an R^2 of 0.99 ($P < 0.001$) and a RMSE of 1.6 min (12% of the total time). The combination of location and accelerometer data improved the RMSE of the feeding time and ruminating time compared to the accelerometer data alone (2.6–1.4 min). Moreover, the combination of location and accelerometer enabled accurate classification of additional behaviours that are difficult to detect using the accelerometer alone, such as eating concentrates and drinking (R^2 = 0.85 and 0.90, respectively). This study demonstrates the potential of combining accelerometer and UWB location data for the design of a robust monitoring system for dairy cattle.

Implications

Cattle behaviour is fundamentally linked to the cows' health, (re)production, and welfare. The current precision livestock farming systems focus on a limited number of behaviours. Moreover, the detection of behaviours that are less frequently expressed in animals or expressed in short duration, such as walking or drinking, remains a challenge. This study incorporates location and accelerometer data for improved cattle behaviour monitoring systems. The combination of both data improved the detection of feeding and ruminating behaviours and enabled accurate classification of additional behaviours that are difficult to detect using the accelerometer alone, such as drinking and eating concentrates.

Introduction

Cattle behaviour is fundamentally linked to the cows' health, (re)production, and welfare. Veterinarians, advisors, and farmers

* Corresponding author at: Department of Information Technology, Ghent University/imec, iGent-Technologiepark 126, 9052 Ghent, Belgium.
E-mail address: said.benaissa@ugent.be (S. Benaissa).

https://doi.org/10.1016/j.animal.2023.100730
1751-7311/

use cattle behavioural signs for purposes of disease diagnosis and livestock management. For example, real-time monitoring of feeding and ruminating behaviours helps in choosing a suitable feeding strategy for increased efficiency (Haskell et al., 2019; Krpalkova et al., 2021). Monitoring of feeding, drinking, or lying behaviour can also help to detect reproductive events such as oestrus and calving (Lanzoni et al., 2022; Szenci, 2022; Wang et al., 2022). In Soriani et al. (2012), it was reported that decreased ruminating time during the first few days of lactation was observed in cows with subclinical diseases or health disorders. Similarly, changes in lying time can alert for lameness or injuries in the animal. Pain, lameness, and infectious diseases indicate poor animal welfare, which can be detected via cattle behaviour (Hosseininoorbin et al., 2021).

Cattle behaviour has traditionally been monitored by direct observation, judgement, and experience of humans, providing information for a limited number of animals and for short time intervals. As the herd size increases, traditional inspection based on direct observation becomes a time-consuming and a labour-intensive task. By leveraging the advancements in smart sensor design, big data, and artificial intelligence, precision livestock farming (**PLF**) technologies have delivered reliable and feasible real-time data at the individual level to generate efficient digital monitoring and management systems for animal behaviour (Berckmans, 2017).

In literature, several sensor types have been adopted for cattle behaviour monitoring. For example, image analysis using a camera system was used in (McDonagh et al., 2021) to classify dairy cow behaviours, such as, standing, lying, and walking. An image analysis-based system was also proposed in (Achour et al., 2020) to monitor feeding behaviour and to identify individual cows. Sound analysis is another technique used for cattle behaviour monitoring. The potential of this method applied in dairy farms was investigated in (Meen et al., 2015). Other systems were developed based on radio-frequency identification tags, temperature, and pressure sensors (Ruuska et al., 2016). Although computer vision technology is recently widely investigated in PLF research (Saar et al., 2022; Lodkaew et al., 2023), nevertheless, wearable accelerometers remain currently the most common systems for automated real-time monitoring cattle behaviour in commercial herds (Riaboff et al., 2022). Extensive research was already conducted (Da Silva Santos et al., 2023) and several commercial systems are already available, such as the MooMonitor (Dairymaster, Tralee, Ireland), the IceTag (IceRobotics Ltd., Edinburgh, Scotland), the AfiAct Pedometer Plus (Afimilk, S.A.E. Afikim, Kibbutz Afikim, Israel) and the CowManager (Agis, Harmelen, the Netherlands). However, these systems focus on a limited number of behaviours, such as feeding and ruminating (neck collar sensors), or on lying and standing (leg sensors). Moreover, the detection accuracy of behaviours that are less frequently expressed in animals or expressed during a short duration, such as walking or drinking, remains a challenge. The changes in drinking behaviour are used as indicators of cow heat stress (Tsai et al., 2020). Similarly, the changes in walking behaviour are used for disease detection (Tsai et al., 2021). The use cases of the current PLF systems are still limited, and their detection accuracy needs to be improved. These limitations result in increased costs for the farmers (e.g., missed heat) as well as problems with animal welfare management (e.g., delayed detection of lameness). This justifies further development of new methods to monitor cattle behaviours from wearable sensors (Pavlovic et al., 2021).

Recently, the increasing availability of accurate and small-sized real-time location systems tags unlocked the potential of using location data for cattle behaviour monitoring and livestock management (Cabezas et al., 2022). In Riaboff et al. (2020), accelerometer data were combined with Global Positioning System (**GPS**) data to classify the main behaviours of dairy cows on pasture and to explore the interactions between cows and pasture characteristics, including the vegetation, trees, hedges, and soil moisture. Accelerometers and location data were combined also in recent study (Cabezas et al., 2022) to classify four cow's behaviours (grazing, ruminating, lying and steady standing), with best classification accuracy obtained for grazing (accuracy = 0.93). In practice, the incorporation of accurate location data for cattle monitoring would enhance the classification accuracy of the existing accelerometer-based systems, especially in wide areas (e.g., alleys, lying area). For example, detecting a cow in the lying area will reduce the number of possible behaviours to consider by the classification model (e.g., not feeding or drinking). Moreover, the adequate combination of the two data sources yields additional information on cow behaviour, such as the time spent in the feeding area while the cow is not feeding. Furthermore, in addition to the monitoring of the individual animal behaviour and locating the cows in the barn, the combination of both sensors could be used for tracking of the social interactions between the cows, which are fundamentally linked to their health and welfare (Jensen, 2018).

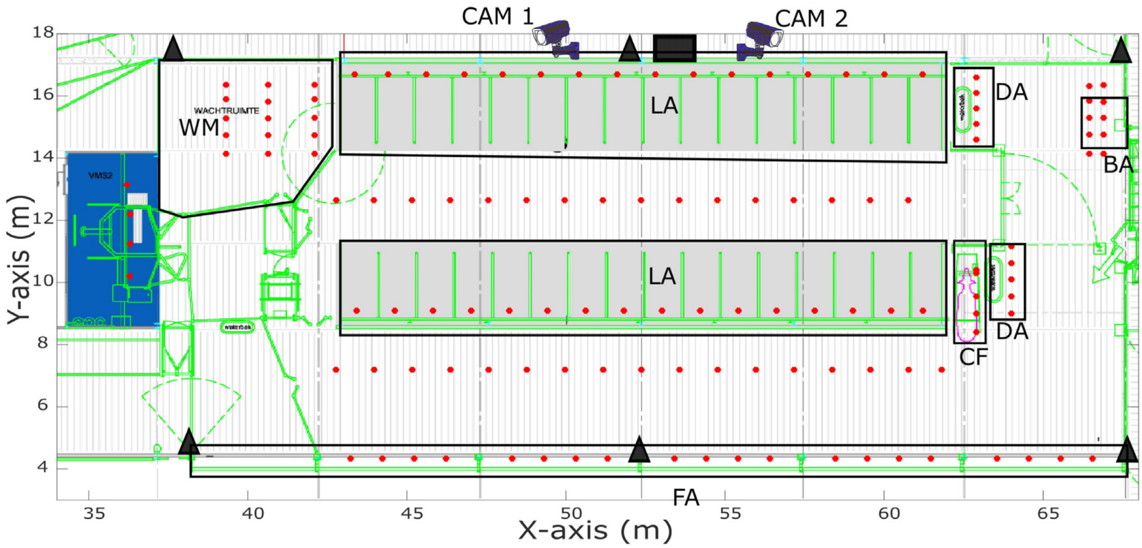
The aim of this study was to design a novel and efficient method to combine indoor location and accelerometer data for improved cattle behaviour monitoring. Classification algorithms developed in previous works consider all possible behaviours in each functional area, which makes it difficult to distinguish between behaviours with close patterns (eating concentrate vs drinking). Also, detecting behaviours that are less frequently expressed or expressed during a short duration is still challenging. The novelty of this paper is to restrict the number of behaviours considered by the accelerometer by considering the functional area the cow is located in (feeding, lying, drinking). This is an efficient method to (i) classify a wide range of behaviours, (ii) increase the accuracy of the algorithms when considering only a limited number of behaviours per area, and (iii) extract more relevant information such as time in the feeding area while not feeding (future work).

This study is structured as follows. A static validation of the Ultra-Wideband (**UWB**) location system is first executed to assess the accuracy and precision in stationary scenarios. Next, location and accelerometer data are combined to monitor the behaviour of cattle in barns. The combination of the acceleration and location data is performed in two steps. The first step consists of calculating the time spent in the different barn areas using the location data. In the second step, the accelerometer data are used to classify cow behaviour based on the location of the cow obtained in the first step (e.g., a cow located in the cubicles cannot be classified as feeding or drinking).

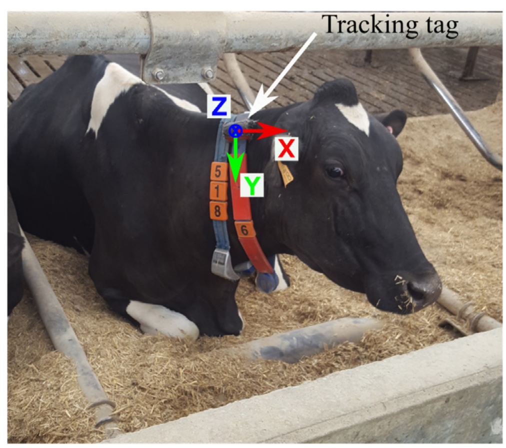
Material and methods

Animals and housing

In total, 30 Holstein cows (parity 1.8 ± 1.2) were used in this study. The cows were housed in an area of 40×15 m^2 in a free-stall barn of the Flanders Research Institute for Agriculture, Fisheries and Food, Melle, Belgium. The area contains individual cubicles and a concrete slatted floor (Fig. 1a). The cubicles (n = 32) were bedded with a lime-straw-water mixture. The cows were fed a roughage-concentrate mixture. The feed bunk is provided over the total length of the area (i.e., 30.5 m long) for 32 cows at maximal occupation. The bunk fence is made of two wooden beams with a total height of 20 cm and at a higher level an iron bar. The bunk has horizontal pillars every 5 meters. The bunk floor is 15 cm higher than the level of the slatted floor and coated with a polyester coating for a depth of 50 cm. The cows have free access to the feeding bunk. Additional concentrates were supplied by a



(a)



(b)

Fig. 1. (a) Layout of the barn used for the behaviour monitoring using UWB location and accelerometer data (Triangles: anchors; rectangle: gateway; FA: feeding area; DA: drinking area (1.5 × 2.5 m); LA: lying area (cubicles); CF: concentrate feeder (1.3 × 3.5 m); BA: brushing area; VMS: milking robot (blue rectangle); WM: waiting for milking area). The red marks are the positions used for the static validation (Experiment 1). (b) Position of the tracking tag on the cow's neck with the accelerometer sensor orientation. UWB = Ultra-Wideband.

computerised concentrate feeder. Drinking water (two deep water troughs) was available ad libitum. The cows were milked with a voluntary milking system (DeLaval, Sweden). The study (installation of the system, static validation, and data collection) was conducted between April and October 2021.

Tracking system

The Pozyx (Pozyx, Belgium) UWB location system was used in this study (enterprise Pozyx system). The system was installed in the barn as shown in Fig. 1a. It contains a gateway, six anchors, and 30 wearable tracking tags (dimensions (mm) 50 × 42 × 15, weight 21 g, Pozyx, 2022). The Pozyx system is based on the Time-Difference-of-Arrival location method, which uses a very precise measure of the time of arrival of a radio signal from a mobile transmitter tag to a set of time-synchronised receivers (Mazhar et al., 2017). This enables tagged objects/subjects to be accurately located relative to the anchor set (location accuracy of 15 cm, Pozyx, 2022). The sampling rate of the location system was set at 2 Hz. In the uplink packet transmission (Time-Difference-of-Arrival operation), the Pozyx tracking tag also reports the instantaneous acceleration data (i.e., three orthogonal accelerometer vectors), collected at a sampling rate of 12.5 Hz. Location and accelerometer data were available in real time. The orientation of the accelerometer is shown in Fig. 1b. This orientation was respected for all cows.

Experiment 1: Static validation of the Ultra-Wideband location system performance

For a first assessment of the merits of the location system, we assessed its positioning accuracy and precision via a set of (static) tests in the barn.

Data collection

Static validation experiments were performed prior to the data collection for behaviour monitoring. For the validation experiment, the cows were not present in the measurement area. A plastic tripod was used to mount the tag at a height of 1 m. During the experiment, the tripod was set at different positions in the barn

(Fig. 1a). At each static position, measurements were run for two consecutive minutes, which resulted in 240 position estimates (sampling rate of 2 Hz). The static measurements were carried out in eight different areas (Fig. 1a): feeding area (20 positions), drinking area (10 positions), lying area (cubicles, 32 positions), concentrate feeder (five positions), brushing area (10 positions), milking robot (four positions), waiting for milking area (15 positions), and alleys (33 positions). A laser meter (Bosch GLM 40, Germany, accuracy ±1.5 mm) was used to measure the real coordinates (ground truth) based on the barn ground plan.

Accuracy and precision

The goal of the UWB location system is to locate the animals with high accuracy and precision. These are the most important metrics that are critical for a location system. The 240 measurements taken at each test point were used to determine the location accuracy and precision at this position. The data processing was performed using MATLAB software (Release 2020b, The MathWorks, Inc., Natick, Massachusetts, United States).

Location accuracy is the measure of the correctness of the estimated location of the target by the system. The location accuracy is a straightforward metric measured as the mean Euclidian distance between the estimated position of an object and its real position (Qureshi et al., 2019). The accuracy is given by the following:

$$\text{Accuracy} = \frac{1}{N}\sum_{k=1}^{k=N}\sqrt{\left(\widehat{X_k} - X\right)^2 + \left(\widehat{Y_k} - Y\right)^2} \quad (1)$$

where N is the number of measurements, $\widehat{X_k}$ and $\widehat{Y_k}$ are the estimated coordinates by the UWB system, and X and Y are the real coordinates. Location accuracy describes a mean error, which lacks information regarding the consistency and robustness of the errors. For this reason, location precision is almost equally important. Location precision is often measured as the SD of the measured coordinates and is given by Qureshi et al. (2019):

$$\text{Precision} = \sqrt{\frac{1}{N}\sum_{k=1}^{k=N}\left(\widehat{X_k} - \bar{X}\right)^2 + \left(\widehat{Y_k} - \bar{Y}\right)^2} \quad (2)$$

where $\widehat{X_k}$ and $\widehat{Y_k}$ are the estimated coordinates by the UWB system, and $\bar{X}$ and $\bar{Y}$ are the mean values of the measured coordinates.

For each of the eight barn areas, the location accuracy and precision were calculated for each individual location axis (X and Y estimation) as well as for both axes (2D estimation).

Experiment 2: Behaviour monitoring

Data collection

Each cow was fitted with a Pozyx tracking tag as shown in Fig. 1b. The tag was attached on the upper (dorsal) side of the cow's neck for an optimal signal reception. The same orientation as experiment 1 was respected. However, the tag's orientation will somewhat change due to the movement of the collar. A counterweight (1 kg) was used to keep the tag upright on the highest point of the neck as much as possible. The collars containing the sensors were attached more than one week before starting the measurements to make the cows used to the tag's presence and not influence their behaviour during the actual monitoring period. For this experiment, sensor (location + accelerometer) and video recording data were collected for 5 days. However, due to the time and effort required for proper annotations that consider a wide range of behaviours, only 24 hours were randomly selected for the analysis. The clocks of the location system and the video recording were synchronised at the start of the measurement. The location and accelerometer data were stored in real-time on a laptop and used afterwards for processing. At the end of the experiment, video data were transferred as well to the laptop for annotation. Missing values were negligible (0.2%) since all data were saved in real time.

Video annotations

Video annotations were performed using ELAN software (The language archive, The Netherlands). The output of the recording system were video files with a duration of one hour including two views (two cameras, Fig. 1a). Since the behaviours were visually not clear at night, only data from 06 h00 until 19 h00 were considered. Recordings were omitted when the identification of the cows was uncertain or when the behaviours were ambiguous. Six of the 30 focal cows were omitted from the analyses as the total duration of annotated recordings did not amount to our minimal requirement of 1 h per cow. Consequently, data of 24 cows with a total of 156 hours (mean ± SD, 6.5 ± 1.3 hours per cow) of video recordings were used for the performance analysis. Table 1 lists the considered areas and behaviours in this study with their descriptive definitions. The annotation was performed for each cow and each one-hour file separately. The outputs of the ELAN software were.csv files containing the start, end, and duration of the considered areas and behaviours. One sample (a blue dot in Figs. 3 and 4) is considered as the time period between the instance when a cow starts to perform a certain behaviour (e.g., ruminating), until it stops the first behaviour and starts performing another behaviour

Table 1
Description of the barn's areas and cows' behaviours considered in this study.

Item	Definition
Areas	
Feeding area	The cow (most of the body) is located at the feeding zone with head through the feeding rail.
Lying area	The cow is located in one of the lying cubicles in a standing or lying position.
Waiting milking	The cow is located in the waiting for milking area.
Milking robot	The cow is located in the milking robot.
Drinking area	The cow is located in the drinking area close (less than 1 m) to the water trough.
Concentrate feeder	The cow is located inside the concentrate feeder.
Alleys	The cow is located in the alleys.
Behaviours	
Feeding	The cow is located at the feeding zone with head through the feeding rail while searching, masticating, or sorting the feed.
Drinking	The cow is drinking water from the water trough.
Ruminating	The cow is chewing and swallowing a ruminating bolus while moving her head and jaw with a circular motion.
Resting	The cow has a static position (inactivity), i.e., either standing or lying
Eating concentrates	The cow has her head in the concentrate feeder and is eating the concentrates.
Other activity	The cow is not performing any of the behaviours above.

(e.g., resting). The time spent performing that behaviour (ruminating in this case) is calculated using the sensor data and video annotations. Similar analysis was used for the time spent in barn areas. The output data were used then for performance analysis.

Combination of location and accelerometer data

The method to combine the location and accelerometer data consists of two steps. In the first step, the location data are used to determine in which of the considered areas a cow is located. The data were processed in 10-second intervals (Benaissa et al., 2019a). A time interval is considered spent in an area (e.g., feeding area) if the largest proportion of its location data belongs to that area. At the end, for each one-hour time interval, the total time spent in each area is calculated (sum of the 10-second intervals) and compared to the video annotations for performance analysis. We note that the brushing area was not considered in this section, since only a minority of the cows were frequently visiting it during the experiment (only six cows visited the brushing area with less than 2 min per cow).

In the second step, the accelerometer data are used to classify cow behaviours taking into consideration the obtained area of the first step as listed in Table 2. For example, if a cow is located in the feeding area in step 1, only feeding, resting, and other activities are considered in the classification by the accelerometer data in step 2. The accelerometer data were classified using a decision tree (**DT**) algorithm as presented in Benaissa et al. (2019a). The acceleration sum vector (A_{sum}) was calculated as follows:

$$A_{sum}\ (\mathrm{g}) = \sqrt{a_X{}^2 + a_Y{}^2 + a_Z{}^2} \quad (3)$$

where a_X is the acceleration along the X-axis, a_Y is the acceleration along the Y-axis, and a_Z is the acceleration along the Z-axis. Based on the A_{sum} values, the overall dynamic body acceleration was calculated as presented in Benaissa et al. (2019a). The thresholds of the DT were determined using the nested cross-validation technique as explained in Benaissa et al. (2019b). We note that although the location and accelerometer were collected in real time, the data were processed at the end of the experiment to compare with video recordings.

Table 2
The considered cows' behaviours by the decision tree algorithm (accelerometer) for each barn's area.

Areas (location)	Behaviours (accelerometer)
Alleys	Ruminating, resting, other activity
Drinking area	Drinking, resting, other activity
Wait for milking area	Ruminating, resting, other activity
Milking robot	Eating concentrate, other activity
Lying area	Ruminating, resting, other activity
Concentrate feeder	Eating concentrate, other activity
Feeding area	Feeding, resting, other activity

Table 3
Static accuracy and precision of the UWB location system used for cows' behaviours tracking for the considered barn's area.

Areas	Accuracy (mean ± SE, cm)			Precision (mean ± SE, cm)		
	X-axis	Y-axis	2D (XY)	X-axis	Y-axis	2D (XY)
Feeding	8.3 ± 1.4	17.3 ± 3.8	21.0 ± 3.6	5.0 ± 0.6	7.6 ± 1.1	9.1 ± 1.2
Lying cubicles	7.6 ± 1.2	15.3 ± 2.2	18.6 ± 2.1	4.8 ± 0.4	6.5 ± 0.7	8.2 ± 0.8
Alleys	6.0 ± 1.1	9.6 ± 1.3	12.6 ± 1.3	4.8 ± 0.7	6.0 ± 0.9	8.9 ± 1.1
Drinking area	15.5 ± 3.6	21.3 ± 6.0	29.6 ± 5.3	10.4 ± 1.8	11.0 ± 2.0	15.2 ± 2.6
Concentrate feed	14.3 ± 4.5	22.0 ± 9.0	28.8 ± 8.1	9.6 ± 1.3	12.6 ± 1.6	15.9 ± 2.0
Brushing area	4.0 ± 1.1	17.4 ± 2.8	18.2 ± 2.7	6.3 ± 0.5	6.1 ± 0.5	6.8 ± 0.7
Wait for milking	11.4 ± 2.2	8.37 ± 2.5	15.5 ± 2.8	7.4 ± 1.3	7.0 ± 1.5	10.3 ± 2.0
Milking robot	74.9 ± 19.7	34.9 ± 12.9	86.8 ± 17.8	34.9 ± 9.8	18.3 ± 3.0	39.6 ± 10.0
Average (Barn)	10.4 ± 1.3	16.0 ± 1.3	21.2 ± 1.6	6.8 ± 0.6	7.5 ± 0.5	10.4 ± 0.8

Abbreviations: UWB = Ultra-Wideband, 2D: two-dimensional (X and Y axes).

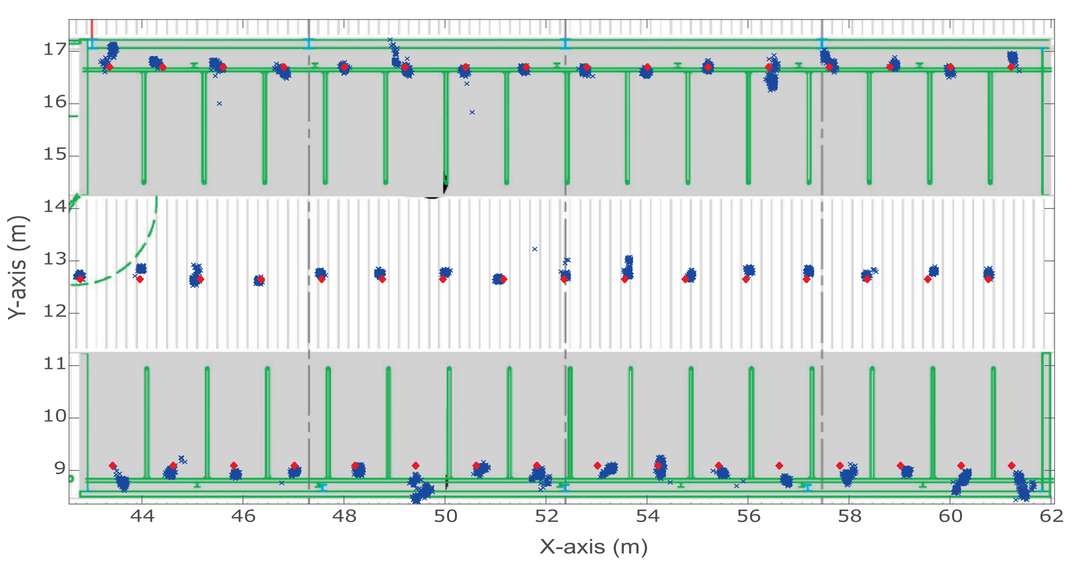


Fig. 2. Example of the UWB location system data (in blue) at 48 locations (ground truth in red). Data were collected for 2 min at each location with a sampling rate of 2 Hz. The tag was placed at 1 m height (average of cows' neck height). UWB = Ultra-Wideband.

A DT algorithm was used since the on-cow sensors used for behaviour monitoring have very small batteries with low processing and storage capabilities. This reduces the energy consumption and minimises both sensing and transmitting energies and consequently reduces the maintenance requirements associated with recharging of the batteries. Moreover, it was shown in Benaissa et al. (2019a) that the thresholds of the DT algorithm used for the classification of the cow behaviours have low cow variations. This is because the algorithm is based on only one feature (mean value of the overall dynamic body acceleration).

Performance analysis

Bland-Altman plots (Martin Bland and Altman, 1986) were used for performance analysis. This plot is commonly used to assess the degree of agreement between two quantitative methods of measurement (time spent in an area obtained by the sensor vs video in this case). For each one-hour time interval, the time spent in each area as well as the time spent in each behaviour were calculated using the sensors and the video recording. The output samples were then compared using the Bland-Altman plots. Bland-Altman plot is a scatter graph XY, in which the Y-axis shows the difference between the two measurements A–B (sensor-video in

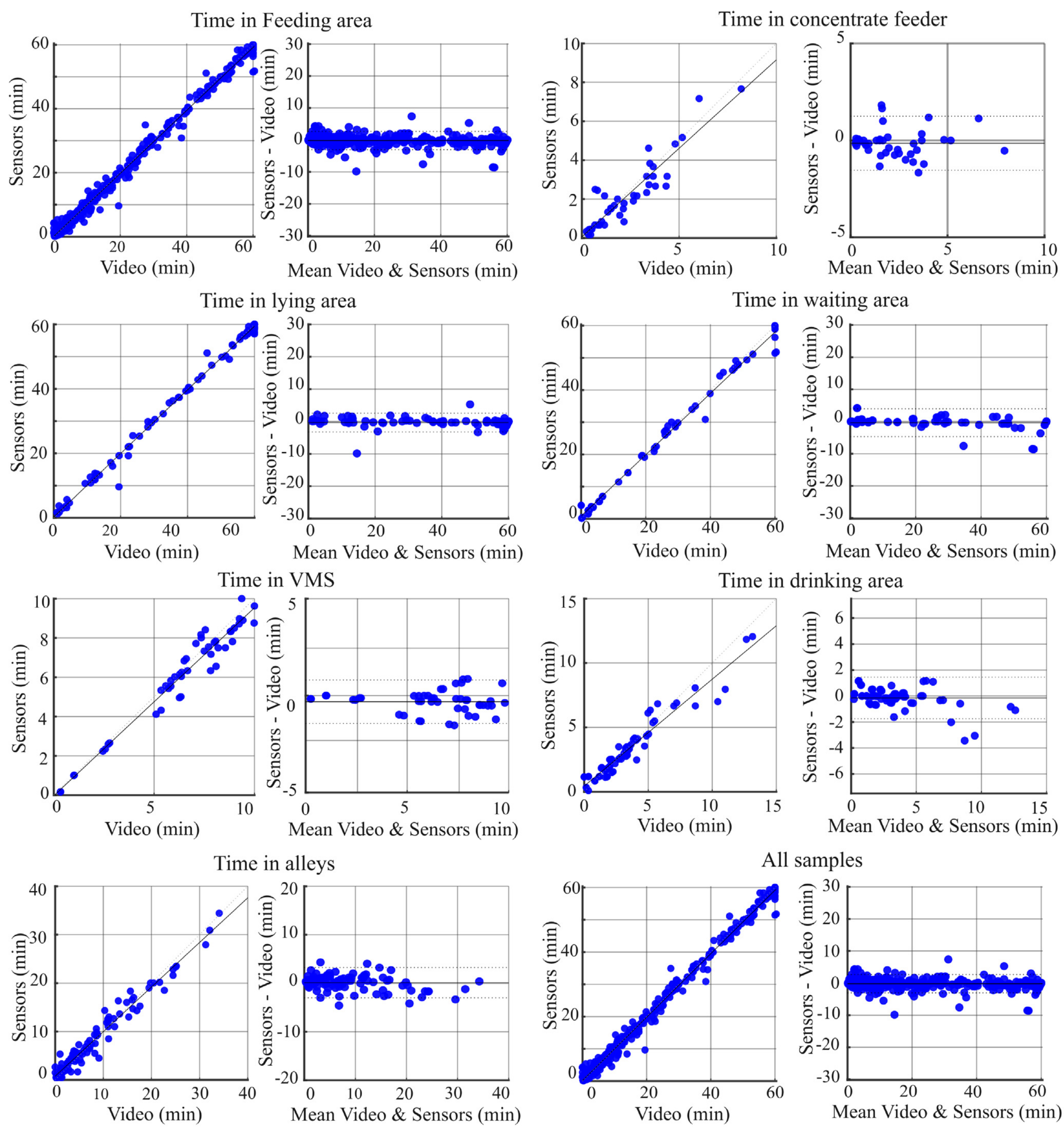


Fig. 3. Bland-Altman plots of the time spent in each area by the cows for the comparison between the sensors (location) and video annotations.

this case) and the X-axis represents the average of these measures ((A + B)/2). In other words, the difference in the two measurements is plotted against the mean of the two measurements (Giavarina, 2015).

In addition to Bland-Altman plot, scatterplots of the association between the sensor and video annotations were plotted. Based on these plots, the R^2, the RMSE, and the CV are calculated. While the R^2 assesses how strong the linear relationship is between two variables (e.g., values estimated by the sensors vs observed by the video recordings), the RMSE quantifies the differences between the two variables (Euser et al., 2008). The CV expresses the RMSE as a percentage of the samples' mean. This is useful in this study since the time spent in the barn areas or in a behaviour varies between a few minutes (e.g., drinking area, drinking time) to a couple of hours (e.g., lying area, ruminating time).

Results

Static performance of Ultra-Wideband location system

Table 3 lists the obtained results for the static validation. High overall performance of all eight areas of the barn (average) was obtained with an accuracy of 21.2 ± 1.6 cm (mean ± SE) and a precision of 10.4 ± 0.8 cm. The mean accuracy was highest for the alleys (12.6 ± 1.3 cm) and lowest for the milking robot area (86.8 ± 17.8 cm). Fig. 2 shows an example of the measured UWB location data (in blue) at 48 locations (in red).

Time spent in the barn areas

Fig. 3 shows Bland-Altman plots as well as scatterplots of the association between the sensor (location) and video annotations for time spent in the barn areas. The statistics of the plots are listed in Table 4. The overall performance of the location of the animals into the correct functional areas was very high. The R^2 was 0.99 ($P < 0.001$), and the RMSE was 1.4 min (CV = 7.5%). The correlation between the sensor and video recording was highest for the time spent in the feeding and lying areas (R^2 = 0.99, $P < 0.001$) and lowest for the time spent in the concentrate feeder area (R^2 = 0.85, $P < 0.05$) (Table 4). The lowest value of the RMSE was obtained for the time spent in the milking robot (0.5 min), and the highest value was obtained for the time spent in the waiting for milking area (2 min). The CV varied between 3.5% for the time spent in the feeding area and 33% for the time spent in the concentrate feeder.

Time spent in the behaviours

Fig. 4 shows Bland-Altman plots as well as scatterplots of the association between the sensor (location + accelerometer) and video annotations for time spent in the behaviours. The statistics of the plots are listed in Table 4. High overall performance (all behaviours) was obtained with an R^2 of 0.99 ($P < 0.001$) and a RMSE of 1.6 min (CV = 12%). The highest value of R^2 was obtained for feeding time and ruminating time (0.99, $P < 0.001$), and the lowest value of R^2 was obtained for other activity (0.83, $P < 0.01$). The RMSE varied between 0.7 min for drinking time and the time eating concentrates 1.8 min for ruminating time and resting time. For the CV, the highest value was obtained for other activity (30.0%) and the lowest value was obtained for feeding time (5.6%).

Discussion

In this study, the combination of UWB location and accelerometer data for cattle behaviour monitoring has been investigated. A static validation of the UWB system was first executed to assess its accuracy and precision in stationary scenarios. The accuracy was lower in the milking robot compared to the other areas presumably because the milking robot is covered with a concrete ceiling and suffers more from multipath effects. This leads to extra signal losses. The accuracy in Y-axis was lower than X-axis in all areas. This is probably due to the location of the anchors and the resulting lower geometric dilution of precision in the Y direction. In overall, the system presented a high accuracy of 21 cm compared to other location studies on cattle (see Table 5). A similar 0.2 m accuracy was reported by (Melzer et al., 2021) using a Ubisense UWB (Ubisense GmbH, Dusseldorf, Germany). The results from that study were nonetheless obtained within relatively the same area size as this study (46 × 22 m^2), but with a high number of anchors (14) and no obstacles between the tags and anchors. A better accuracy of 16 cm was obtained by (Meunier et al., 2018). This result can be explained by the greater number of anchors used in that study (i.e., 18) compared to only six in our study. Moreover, areas such as milking robot were not included in the accuracy measurements.

As listed in Table 5, different technologies have been used for locating cattle in barns. Techniques based on received signal

Table 4
Statistics (number of samples N, R^2, RMSE, and CV) of the difference in the time spent by the cows in each area obtained by the location data and time spent in each behaviour obtained by the location + accelerometer data and the video recordings. The MATLAB (release 2019b) function fitlm() was used to conduct a paired-sample *t*-test).

Data	Area/behaviour	Samples N	R^2 (–)	RMSE (min)	CV (%)
Location					
	Feed area	97	0.99***	1.5	5.3
	Lying area	98	0.99***	1.5	3.5
	Wait for milking	59	0.98**	2.0	8.6
	Milking robot (VMS)	48	0.95*	0.5	9.0
	Drinking area	67	0.93**	0.7	24.0
	Concentrate feeder	43	0.85*	0.7	33.0
	Alleys	98	0.96*	1.5	19.0
	All samples (Barn)	510	0.99***	1.4	7.5
Location + accelerometer					
	Feeding time	83	0.99***	1.4	5.6
	Drinking time	50	0.85**	0.7	25.0
	Ruminating time	86	0.99***	1.8	7.7
	Resting time	90	0.98**	1.8	13.0
	Eating concentrates	59	0.90*	0.7	18.0
	Other activity	83	0.83**	1.4	30.0
	All samples	454	0.99***	1.6	12.0

*$P < 0.05$, **$P < 0.01$, ***$P < 0.001$, no asterisks mean $P > 0.05$.

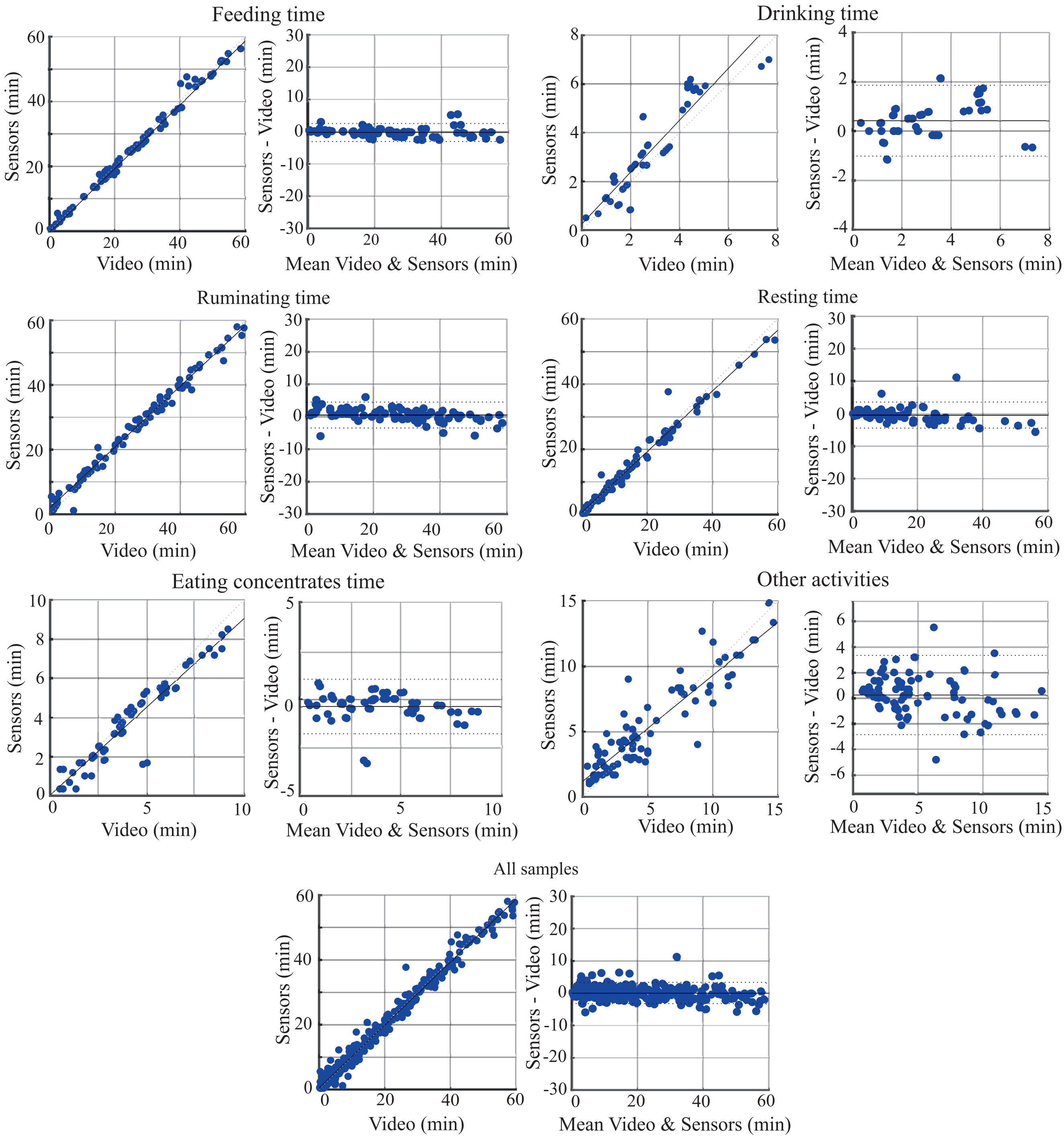


Fig. 4. Bland-Altman plots of the time spent in each cattle behaviour for the comparison between the sensors (location + accelerometer) and video annotations.

strength (**RSS**) have lower accuracy compared to UWB systems. However, they perform better in terms of network range (i.e., fewer anchors could cover larger location area). In addition to the location technique, extra processing is generally used to filter the raw location data (e.g., Jump, Kalman, median filters, Viterbi algorithm) of commercial systems (Melzer et al., 2021). Although the filtering improves the precision of the location system, it may require more computational power and could introduce extra delay in case of real-time monitoring.

After the static validation, location and accelerometer data were combined to monitor the behaviour of cattle in barns. For the time spent in the various barn areas, the best performance was obtained in the feeding and lying areas. However, the performance was lower in the concentrate feeder and drinking area (a CV of 33 and 24%, respectively). These two areas are very small compared to the other area (e.g., lying area, alleys), and they are close to each other, which make the location samples frequently crossing the neighbouring areas. Installing more anchors at strategic positions could be a solution to increase the location accuracy in small areas. However, this solution introduces additional costs to the farmer. Similar results were obtained in (Melzer et al., 2021). In that study, it was reported that the time spent in an area is relevant for the smallest areas, where visit durations usually range from seconds to several minutes (Chizzotti et al., 2015).

Table 5
Accuracy of location systems used for cattle tracking in barns. Different filtering techniques are used to enhance the accuracy of the location system.

Study	Location System	Filtering	Accuracy (m)
Gygax et al., 2007	LPM® Radar	–	0.5
Huhtala et al., 2007	AeroScout (RSS)	–	1.0–3.0
Tøgersen et al., 2010	Bluetooth (RSS)	Kalman filter	0.6
Wolfger et al., 2017	Smartbow® (RSS)	Wavelet filtering	1.5
Bloch and Pastell, 2020	Bluetooth Low-Energy (RSS)	Viterbi algorithm	3.3
Frondelius et al., 2014	Ubisense (UWB)	–	0.5
Porto et al., 2014	Ubisense (UWB)	–	0.5
Meunier et al., 2018	CowView (UWB)	Image processing	0.16
Melzer et al., 2021	Ubisense (UWB)	Jump, Kalman, median filters	0.2
This study	Pozyx (UWB)	–	0.2

Abbreviations: UWB = Ultra-Wideband, RSS = Received signal strength.

The use of location data to detect cows in distinct areas within a barn was investigated in other studies. In (Chapa et al., 2021), the ability of the Smartbow (Smartbow GmbH) location system to measure the time cows spent in relevant areas of the barn was addressed. An overall accuracy of 87.6% was obtained in that study. However, only three areas were included (alleys, feed bunk, and cubicles). In another study (Melzer et al., 2021), location data were used to assign the cows to specific areas (i.e., lying stalls, walking alley, brush area, feed, and water bins) and compare them with the video-based zone assignments. In addition, different filtering and smoothing methods (i.e., Kalman, jump, and median filters) were applied to raw location data. The obtained results were similar to this study with the best performance obtained in the cubicles and alleys (sensitivity and precision >0.86).

For the time spent performing different behaviours, the highest performance was obtained in the present study for feeding time and ruminating time, while other activities and eating concentrates presented the lowest performance. The combination of location and accelerometer data improved the RMSE of the feeding time from 2.6 min in the previous study (Benaissa et al., 2019a) to 1.4 min in this study. Moreover, it enabled the classification of additional behaviours, such as eating concentrates and drinking. These behaviours, which occur less frequently and have short durations, are the most difficult to detect using only accelerometer sensors (Riaboff et al., 2022). The changes in these behaviours are used as indicators of cow heat stress, which is a sign of a poor welfare (Tsai et al., 2020).

The combination of accelerometer and location data was investigated in previous studies. (Riaboff et al., 2020) investigated the relationship between behaviours of outdoor dairy cows and pasture characteristics using a combination of accelerometer and GPS data. The accelerometer and GPS data were not adequately combined since each data were processed separately. Similar methods were presented in (Cabezas et al., 2022), where accelerometer data were used for cattle behaviour classification (i.e., grazing, ruminating, lying and steady standing) and GPS data were used to estimate the spatial scattering of herds. In another study (Wang et al., 2018), location and accelerometer data were combined to classify seven cow behaviours (feeding, lying, standing, lying down, standing up, normal walking, and active walking). The location data were used to improve the poor results of feeding (sensitivity 52%, precision 55%) versus standing (sensitivity 46%, precision 58%), which were difficult to differentiate using a leg-mounted sensor (Wang et al., 2018). Similarly, the individual cow behaviours were estimated in (Riaboff et al., 2021) from accelerometer and GPS and used for lameness detection on pastures. Feeding behaviour was estimated first based on accelerometer data and then combined with the GPS position to determine feeding bout length and number of feeding bouts. The accuracy and precision of the sensor-recorded position in that study were greater than 2.8 m. Therefore, it was not possible to specify if the non-feeding behaviours were occurring in a free-stall or in other areas of the barn. In another study, (Barker et al., 2018) tested and validated a neck-mounted mobile sensor system that combines location and accelerometer to classify three categories of behaviour (i.e., feeding, not feeding, and out of pen for milking) based on a decision tree algorithm. The feeding behaviour (number of bouts, mean bout duration, total duration across all bouts) was then used for lameness detection in dairy cattle.

In addition to behaviour monitoring, the adequate combination of the two data sources would considerably reduce the power consumption of the monitoring system. For example, when detecting the cow in the lying area, the location sensor could be turned-off until detecting the cow is standing up with the accelerometer. This could save more than 50% of the energy of the monitoring system, since cows spend 12–14 hours per day lying down (Gomez and Cook, 2010). The combination of the two sensors can also be used to track the social interactions between the cows, which are fundamentally linked to the health and welfare of dairy cattle (Gibbons et al., 2010). For example, Proudfoot et al. (2014) reported that sick dairy cows isolate themselves and avoid contacts with herd mates by using the corner of the pen. Proximity loggers have been used to monitor the social behaviour of cattle based on social network analysis (Boyland et al., 2016). Although the proximity loggers could estimate the nearest neighbours of a cow, they cannot classify which behaviour the two cows are performing. By using a combination of location and accelerometer, the location data give information on the contacts between cows and the accelerometer data could classify which behaviour the cows are performing (e.g., licking, mounting, head-to-head pushing, sniffing, etc.).

The cost of the UWB location system is one of the main challenges in using location data for cattle monitoring. As stated earlier, the range of UWB systems is limited compared to RSS-based location systems. Deploying a UWB system in large barns requires installing many anchors to ensure a good accuracy, which consequently increases the cost of the UWB system. The lifetime of the sensor is also a challenge in using UWB sensors in barns. In this study, the lifetime of the sensors was estimated to 4–6 months. The lifetime of the sensor could be extended by decreasing the sampling rate (e.g., from 2 to 0.5 Hz) and turning-off the sensor when a cow is resting (based on accelerometer). In this scenario, the lifetime of the sensor may reach 5 years (Pozyx, 2022).

Conclusions

In this study, a novel and efficient method to combine UWB indoor location and accelerometer data for improved cattle behaviour monitoring was presented. The time spent in each of the eight barn areas was first calculated using the location data. When a cow is located in an area, its behaviour was classified by the accelerometer data taking into consideration only those behaviours a cow can perform in that area. The overall performance of the location of the animals into the correct functional areas was very high. The best performance was obtained for the feeding and lying areas. Performance was lower in the drinking area and the concentrate feeder. For the combined location + accelerometer data, high overall performance (all behaviours) was obtained. The combination of location and accelerometer data improved the RMSE of the feeding time and ruminating time compared to the accelerometer data alone. Moreover, the combination of location and accelerometer enabled accurate classification of additional behaviours that are difficult to detect using the accelerometer alone, such as drinking and eating. This study demonstrates the potential of combining accelerometer and UWB location data for the design of a robust monitoring system for dairy cattle. In addition to the monitoring of the individual animal behaviour and locating the cows in barn, future work will include the tracking of social interactions between the cows, which are fundamentally linked to the health and welfare of dairy cattle. This study is an important step in combining data from multiple sources (e.g., on-cow sensors, camera, milking robot, etc.) to develop advanced PLF solutions for an increased production efficiency and more focus on animal welfare and sustainability.

Ethics approval

Not applicable.

Data and model availability statement

The data/models were not deposited in an official repository. Data are available upon request.

Author ORCIDs

Said Benaissa: https://orcid.org/0000-0001-7962-6900
Frank Tuyttens: https://orcid.org/0000-0002-1348-218X
David Plets: https://orcid.org/0000-0002-8879-5076
Luc Martens: https://orcid.org/0000-0001-9948-9157
Leen Vandaele: https://orcid.org/0000-0002-4563-6796
Wout Joseph: https://orcid.org/0000-0002-8807-0673
Bart Sonck: https://orcid.org/0000-0002-0546-5304

Author contributions

SB, **FT**, **DP**, **WJ**, and **BS** contributed to conception of the paper. **SB** conducted the data collection experiments, processed the data, and wrote the first draft of the manuscript. **LV** assisted the data collection experiments. All authors contributed to manuscript revision, read, and approved the submitted version.

Declaration of interest

All authors declare that they have no conflicts of interest.

Acknowledgments

The authors would like to thank Stefan Meirlaen and Björn Inghelbrecht for their help during the measurements. Said Benaissa is a Post-Doctoral Fellow of the FWO-V (Research Foundation Flanders, Belgium).

Financial support statement

This work was supported by the Research Foundation Flanders (FWO-V), Belgium (grant number 1274321N).

References

Achour, B., Belkadi, M., Filali, I., Laghrouche, M., Lahdir, M., 2020. Image analysis for individual identification and feeding behaviour monitoring of dairy cows based on Convolutional Neural Networks (CNN). Biosystems Engineering 198, 31–49.
Barker, Z.E., Vázquez Diosdado, J.A., Codling, E.A., Bell, N.J., Hodges, H.R., Croft, D.P., Amory, J.R., 2018. Use of novel sensors combining local positioning and acceleration to measure feeding behavior differences associated with lameness in dairy cattle. Journal of Dairy Science 101, 6310–6321.
Benaissa, S., Tuyttens, F.A.M., Plets, D., Cattrysse, H., Martens, L., Vandaele, L., Joseph, W., Sonck, B., 2019a. Classification of ingestive-related cow behaviours using RumiWatch halter and neck-mounted accelerometers. Applied Animal Behaviour Science 211, 9–16.
Benaissa, S., Tuyttens, F.A.M., Plets, D., de Pessemier, T., Trogh, J., Tanghe, E., Martens, L., Vandaele, L., Van Nuffel, A., Joseph, W., Sonck, B., 2019b. On the use of on-cow accelerometers for the classification of behaviours in dairy barns. Research in Veterinary Science 125, 425–433.
Berckmans, D., 2017. General introduction to precision livestock farming. Animal Frontiers 7, 6–11.
Bloch, V., Pastell, M., 2020. Monitoring of Cow Location in a Barn by an Open-Source, Low-Cost. Low-Energy Bluetooth Tag System. Sensors 20, 3841.
Boyland, N.K., Mlynski, D.T., James, R., Brent, L.J.N., Croft, D.P., 2016. The social network structure of a dynamic group of dairy cows: From individual to group level patterns. Applied Animal Behaviour Science 174, 1–10.
Cabezas, J., Yubero, R., Visitación, B., Navarro-García, J., Algar, M.J., Cano, E.L., Ortega, F., 2022. Analysis of Accelerometer and GPS Data for Cattle Behaviour Identification and Anomalous Events Detection. Entropy 24, 336.
Chapa, J.M., Lidauer, L., Steininger, A., Öhlschuster, M., Potrusil, T., Sigler, M., Auer, W., Azizzadeh, M., Drillich, M., Iwersen, M., 2021. Use of a real-time location system to detect cows in distinct functional areas within a barn. JDS Communications 2, 217–222.
Chizzotti, M.L., Machado, F.S., Valente, E.E.L., Pereira, L.G.R., Campos, M.M., Tomich, T.R., Coelho, S.G., Ribas, M.N., 2015. Technical note: Validation of a system for monitoring individual feeding behavior and individual feed intake in dairy cattle. Journal of Dairy Science 98, 3438–3442.
Da Silva, S.A., de Medeiros, V.W.C., Gonçalves, G.E., 2023. Monitoring and classification of cattle behavior: a survey. Smart Agricultural Technology 3, 100091.
Euser, A.M., Dekker, F.W., le Cessie, S., 2008. A practical approach to Bland-Altman plots and variation coefficients for log transformed variables. Journal of Clinical Epidemiology 61, 978–982.
Frondelius, L., Pastell, M., Mononen, J., 2014. Validation of the TrackLab positioning system in a cow barn environment. Proceedings of Measuring Behavior 2014, 27–29.
Giavarina, D., 2015. Understanding Bland Altman analysis. Biochemia Medica 25, 141–151.
Gibbons, J.M., Lawrence, A.B., Haskell, M.J., 2010. Measuring sociability in dairy cows. Applied Animal Behaviour Science 122, 84–91.
Gomez, A., Cook, N.B., 2010. Time budgets of lactating dairy cattle in commercial freestall herds. Journal of Dairy Science 93, 5772–5781.
Gygax, L., Neisen, G., Bollhalder, H., 2007. Accuracy and validation of a radar-based automatic local position measurement system for tracking dairy cows in free-stall barns. Computers and Electronics in Agriculture 56, 23–33.
Haskell, M.J., Rooke, J.A., Roehe, R., Turner, S.P., Hyslop, J.J., Waterhouse, A., Duthie, C.-A., 2019. Relationships between feeding behaviour, activity, dominance and feed efficiency in finishing beef steers. Applied Animal Behaviour Science 210, 9–15.
Hosseininoorbin, S., Layeghy, S., Kusy, B., Jurdak, R., Bishop-Hurley, G.J., Greenwood, P.L., Portmann, M., 2021. Deep learning-based cattle behaviour classification using joint time-frequency data representation. Computers and Electronics in Agriculture 187, 106241.
Huhtala, A., Suhonen, K., Mäkelä, P., Hakojärvi, M., Ahokas, J., 2007. Evaluation of Instrumentation for Cow Positioning and Tracking Indoors. Biosystems Engineering 96, 399–405.
Jensen, M.B., 2018. The role of social behavior in cattle welfare. In: Tucker, C. (Ed.), Advances in cattle welfare. Woodhead Publishing, Duxford, UK, pp. 123–155.
Krpalkova, L., O'Mahony, N., Carvalho, A., Campbell, S., Corkery, G., Broderick, E., Riordan, D., Walsh, J., 2021. Association of Feed Efficiency, Feeding Rate, and Behaviour with the Milk Performance of Dairy Cows. Dairy 2, 684–694.
Lanzoni, L., Chincarini, M., Giammarco, M., Fusaro, I., Iannotta, M., Podaliri, M., Contri, A., Gloria, A., Vignola, G., 2022. Changes in the behaviour before normal calving to predict its onset in Mediterranean buffaloes heifers. Applied Animal Behaviour Science 254, 105721.
Lodkaew, T., Pasupa, K., Loo, C.K., 2023. CowXNet: An automated cow estrus detection system. Expert Systems with Applications 211, 118550.
Martin Bland, J., Altman, D., 1986. Statistical methods for assessing agreement between two methods of clinical measurement. The Lancet 327, 307–310.

Mazhar, F., Khan, M.G., Sällberg, B., 2017. Precise Indoor Positioning Using UWB: A Review of Methods, Algorithms and Implementations. Wireless Personal Communications 97, 4467–4491.
McDonagh, J., Tzimiropoulos, G., Slinger, K.R., Huggett, Z.J., Down, P.M., Bell, M.J., 2021. Detecting Dairy Cow Behavior Using Vision Technology. Agriculture 11, 675.
Meen, G.H., Schellekens, M.A., Slegers, M.H.M., Leenders, N.L.G., van Erp-van der Kooij, E., Noldus, L.P.J.J., 2015. Sound analysis in dairy cattle vocalisation as a potential welfare monitor. Computers and Electronics in Agriculture 118, 111–115.
Melzer, N., Foris, B., Langbein, J., 2021. Validation of a real-time location system for zone assignment and neighbor detection in dairy cow groups. Computers and Electronics in Agriculture 187, 106280.
Meunier, B., Pradel, P., Sloth, K.H., Cirié, C., Delval, E., Mialon, M.M., Veissier, I., 2018. Image analysis to refine measurements of dairy cow behaviour from a real-time location system. Biosystems Engineering 173, 32–44.
Pavlovic, D., Davison, C., Hamilton, A., Marko, O., Atkinson, R., Michie, C., Crnojević, V., Andonovic, I., Bellekens, X., Tachtatzis, C., 2021. Classification of Cattle Behaviours Using Neck-Mounted Accelerometer-Equipped Collars and Convolutional Neural Networks. Sensors 21, 4050.
Porto, S.M.C., Arcidiacono, C., Giummarra, A., Anguzza, U., Cascone, G., 2014. Localisation and identification performances of a real-time location system based on ultra wide band technology for monitoring and tracking dairy cow behaviour in a semi-open free-stall barn. Computers and Electronics in Agriculture 108, 221–229.
Pozyx, 2022. Datasheet: Wearable Tracking Tag. Retrieved on 15 November 2022, from https://www.pozyx.io/products/hardware/tags/wearable-tracking-tag.
Proudfoot, K.L., Jensen, M.B., Weary, D.M., von Keyserlingk, M.A.G., 2014. Dairy cows seek isolation at calving and when ill. Journal of Dairy Science 97, 2731–2739.
Qureshi, U.M., Umair, Z., Hancke, G.P., 2019. Evaluating the Implications of Varying Bluetooth Low Energy (BLE) Transmission Power Levels on Wireless Indoor Localization Accuracy and Precision. Sensors 19, 3282.
Riaboff, L., Couvreur, S., Madouasse, A., Roig-Pons, M., Aubin, S., Massabie, P., Chauvin, A., Bédère, N., Plantier, G., 2020. Use of Predicted Behavior from Accelerometer Data Combined with GPS Data to Explore the Relationship between Dairy Cow Behavior and Pasture Characteristics. Sensors 20, 4741.
Riaboff, L., Relun, A., Petiot, C.-E., Feuilloy, M., Couvreur, S., Madouasse, A., 2021. Identification of discriminating behavioural and movement variables in lameness scores of dairy cows at pasture from accelerometer and GPS sensors using a Partial Least Squares Discriminant Analysis. Preventive Veterinary Medicine 193, 105383.
Riaboff, L., Shalloo, L., Smeaton, A.F., Couvreur, S., Madouasse, A., Keane, M.T., 2022. Predicting livestock behaviour using accelerometers: A systematic review of processing techniques for ruminant behaviour prediction from raw accelerometer data. Computers and Electronics in Agriculture 192, 106610.
Ruuska, S., Kajava, S., Mughal, M., Zehner, N., Mononen, J., 2016. Validation of a pressure sensor-based system for measuring eating, rumination and drinking behaviour of dairy cattle. Applied Animal Behaviour Science 174, 19–23.
Saar, M., Edan, Y., Godo, A., Lepar, J., Parmet, Y., Halachmi, I., 2022. A machine vision system to predict individual cow feed intake of different feeds in a cowshed. Animal 16, 100432.
Soriani, N., Trevisi, E., Calamari, L., 2012. Relationships between rumination time, metabolic conditions, and health status in dairy cows during the transition period1. Journal of Animal Science 90, 4544–4554.
Szenci, O., 2022. Accuracy to Predict the Onset of Calving in Dairy Farms by Using Different Precision Livestock Farming Devices. Animals 12, 2006.
Tøgersen, F.A., Skjøth, F., Munksgaard, L., Højsgaard, S., 2010. Wireless indoor tracking network based on Kalman filters with an application to monitoring dairy cows. Computers and Electronics in Agriculture 72, 119–126.
Tsai, Y.-C., Hsu, J.-T., Ding, S.-T., Rustia, D.J.A., Lin, T.-T., 2020. Assessment of dairy cow heat stress by monitoring drinking behaviour using an embedded imaging system. Biosystems Engineering 199, 97–108.
Tsai, I.C., Mayo, L.M., Jones, B.W., Stone, A.E., Janse, S.A., Bewley, J.M., 2021. Precision dairy monitoring technologies use in disease detection: Differences in behavioral and physiological variables measured with precision dairy monitoring technologies between cows with or without metritis, hyperketonemia, and hypocalcemia. Livestock Science 244, 104334.
Wang, R., Gao, Z., Li, Q., Zhao, C., Gao, R., Zhang, H., Li, S., Feng, L., 2022. Detection Method of Cow Estrus Behavior in Natural Scenes Based on Improved YOLOv5. Agriculture 12, 1339.
Wang, J., He, Z., Zheng, G., Gao, S., Zhao, K., 2018. Development and validation of an ensemble classifier for real-time recognition of cow behavior patterns from accelerometer data and location data. PLOS ONE 13, e0203546.
Wolfger, B., Jones, B.W., Orsel, K., Bewley, J.M., 2017. Technical note: Evaluation of an ear-attached real-time location monitoring system. Journal of Dairy Science 100, 2219–2224.