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Research Paper

A software tool for the automatic and real-time analysis of cow velocity data in free-stall barns: The case study of oestrus detection from Ultra-Wide-Band data

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The increase in the design and utilisation of real-time location systems has produced a huge amount of data to be handled in real time. As a consequence, challenges still exist in improving the analysis process of data streams by designing new tools. In this context, a software tool for automatic and real-time analysis of cow velocity data acquired by an ultra-wide band real-time location system (UWB RTLS) in a free-stall barn was designed and developed. A functionality implemented in this software determined the instant velocity of each cow over time, which was represented through an interactive graph (CowVelocityGraph). Feasibility of the software tools for the visualisation and analysis of UWB data was assessed. A use case of this software tool was carried out to verify its suitability to acquire useful information related to the occurrence of cow's oestrus, which is the case study of this research. The results showed that a pattern, related to the behaviour of the cow analysed, could be identified in CowVelocityGraph when the state of oestrus occurred, allowing for visualisation and analysis of UWB data.

The software developed in this study provides the user with the ability to work in real time by acquiring the RTLS data updated at short time intervals, greatly exploiting the UWB RTLS potentialities. Further tests need to be repeated in different farming conditions, on a significant number of cows. On a broader perspective, this study addressed the lack of analysis tools for data streams acquired in livestock houses.

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1. Introduction

In buildings for intensive livestock farming, a large number of animals are raised in highly controlled environmental conditions. In this context, the development of automated monitoring systems has enhanced animal housing by introducing technological innovations capable of improving animal welfare and, therefore, guarantee a improved food safety for consumers (Tullo, Fontana, & Guarino, 2013).

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Different real-time monitoring systems for animal localisation and the detection of cow behavioural activities have been tested, such as wireless network-based systems (Huhtala, Suhonen, Mäkelä, Hakojärvi, & Ahokas, 2007; Kumar & Hancke, 2015; Tullo, Fontana, Gottardo, Sloth, & Guarino, 2016; Wietrzyk & Radenkovic, 2008), Bluetooth technology-based systems (Tøgersen, Skjøth, Munksgaard, & Højsgaard, 2010), radar technology (Gygax, Neisen, & Bollhalder, 2007), UHF technology-based systems (Ipema, Van De Ven, & Hogewerf, 2013; Porto et al., 2012), real-time pedometers (Brehme, Stollberg, Holz, & Schleusener, 2008; Chanvallon et al., 2014; Jónsson, Blanke, Poulsen, Caponetti, & Højsgaard, 2011), accelerometers (Arcidiacono, Porto, Mancino, & Cascone, 2017a, 2017b; Maselyne et al., 2017; Nielsen, Pedersen, Herskin, & Munksgaard, 2010; Oudshoorn et al., 2013; Pastell, Tiusanen, Hakojärvi, & Hänninen, 2009), and motion and image analysis-based methods (Porto, Arcidiacono, Anguzza, & Cascone, 2015; Tsai & Huang, 2014; Van Hertem et al., 2014; Van Hertem et al., 2016; Viazzi et al., 2014). As a consequence of the use of these systems, a huge amount of data has to be handled, also in real time. Therefore, challenges still exist with data analysis and interpretation.

It is recognised that there is a need both to improve the analysis process of data streams and to design new tools for analysis and pattern identification, management analysis, indexing, querying and visualisation of information (Gao, Campbell, Bidder, & Hunter, 2013). These new tools could support farmers in herd management and researchers in analysing animal behaviour by using real-time monitoring systems and information-based technologies.

With regard to intensive dairy cow farming, efficient data management is the key to improve breeding, e.g., to control cow's oestrus and reduce calving intervals, to carry out early detection of diseases, and to verify welfare status of cows.

In previous research studies (Porto, Arcidiacono, Anguzza, Giummarra, & Cascone, 2013; Porto, Arcidiacono, Giummarra, Anguzza, & Cascone, 2014), the localisation and identification performance of a real-time location system (RTLS) based on Ultra Wide Band (UWB) technology (Ubisense, UK) within a free-stall barn were evaluated. Localisation and identification performance of the RTLS was assessed by applying an outlier data cleaning technique to tag localisation errors and using precision and sensitivity indices. The results showed that, in the environmental conditions of the barn, the RTLS produced errors which were comparable to those declared by the RTLS producer for the fixed reference tag whereas localisation errors relating to tags applied to the body of the cows were higher, yet less than 1 m. RTLS performance in this environment proved to be generally independent of cow behaviour, as has been observed for other systems, indicating that RTLS should be suitable to determine the occupancy level of the different functional areas of the barn, compute cow behavioural indices, and track each animal in the herd. Possible applications of this UWB-based RTLS were indicated, such as real-time data analysis aimed at the early detection of a specific physiological status (e.g., cow's oestrus) or disease (e.g., lameness).

In the Ubisense UWB system, data management tools for the analysis of real-time data were very limited and unsuitable to analyse the data acquired by the system in the specific environment of dairy houses. Therefore, specific data analysis tools need to be designed and implemented, and the suitability of data to be utilised for early detection of a specific status of the cow should be assessed.

On this basis, the main objective of this study was to contribute to filling the gap of the lack of visualisation and analysis tools for data streams coming from a Ubisense UWB system. A software tool (CowVelocityGraph) was developed for the automatic and real-time analysis of cow location and velocity data, which were obtained from an Ubisense UWB system installed in a free-stall barn. A specific use case of this software tool was designed and then implemented to acquire and obtain useful information relating to the occurrence of cow's oestrus, which is the case study of this research. Other specific use cases could be performed for other purposes (e.g., diseases and behavioural activities). The collection of oestrus data in real time is of considerable importance to avoid delayed cow inseminations, which could reduce cow fertilisation rate, increase calving intervals, decrease milk production, and, as a consequence, have negative economic impacts on farm budget and costs.

2. Materials and methods

The experiment was performed in a dairy house, located in the province of Ragusa (Sicily, Italy), which had a rectangular plan with three sides completely open. The area of interest was composed of the resting area with 16 head-to-head cubicles, the feeding alley, the service alley, and two side passages (Fig. 1).

The commercial RTLS based on UWB technology (Ubisense, UK) was installed in the selected area of the barn to detect the position of eight dairy cows. The RTLS was composed of four sensors IP30 Series 7000 and eight Compact Tags IP65. The system was wired and connected to a Power-over-Ethernet (PoE) switch, which in turn was connected to a personal computer. The four sensors were fixed at the corner pillars of the area of interest, at a height of 3.78 m above the floor. The RTLS acquired information on the position of the eight cows at 1-second intervals. Please refer to our previous work (Porto et al., 2014) for further details on the configuration of the RTLS and its localisation and identification performance when installed in a free-stall barn.

In this paper, a specific software was developed by using Microsoft® Visual C# Express (framework.NET) to allow visualisation of cow velocity data acquired by the UWB RTLS. In Fig. 2 the flow-chart of the algorithm implemented in this software is shown.

2.1. *Data selection*

As described in our previous work (Porto et al., 2014), a database was populated in the acquisition phase of the data produced by the UWB-based RTLS. The software proposed in that paper was designed to access the database and extract the information required for the analysis. When performing data elaboration, the user had the possibility to filter data by a SQL query, which worked on the data table containing all the

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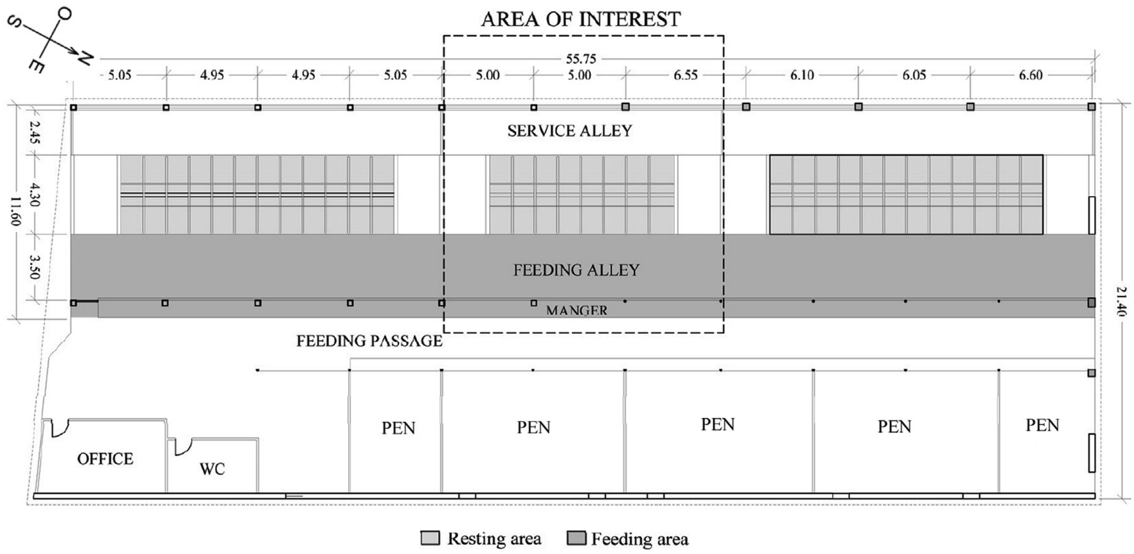

Fig. 1 – Plan of the free-stall barn with the area of interest for the experiment.

information acquired by the UWB-based RTLS and filtered the rows by taking into account the tag ID and the time interval.

2.2. *'CowVelocityGraph' implementation*

The 'CowVelocityGraph' tool was implemented to allow visualisation and real-time usage of cow velocity data. It showed the trend over time of the velocity of each individual cow, computed at time intervals selected by the user (observation period).

The implementation of CowVelocityGraph was done using two separate modules, i.e., the server side and the client side (Fig. 2). In the server side module, a class was implemented to store the positions of the cows recorded at 1-s time intervals, i.e., the Cartesian coordinates x and y, the date and the ID of the tag. Next, another class was implemented to contain the velocity module computed from the average positions of the cows in a sampling time interval.

In detail, to draw the CowVelocityGraph, the whole observation time was subdivided into 5-seconds time intervals. For each time interval ΔT_i the average values of the position data ($\bar{x}$, $\bar{y}$) of the considered cow and the velocity v_i (m s^{-1}) in the x–y plane were computed:

$$v_i = \sqrt{\left(\frac{\bar{x}_i - \bar{x}_{i-1}}{\Delta T_i}\right)^2 + \left(\frac{\bar{y}_i - \bar{y}_{i-1}}{\Delta T_i}\right)^2} \quad (1)$$

After this computation an outlier data filtering technique was adopted (Peck, Olsen, & Devore, 2011). This filter was implemented in the module 'Cow's velocity calculation' of Fig. 2. The v_i values together with the related time stamp were stored in an XML file, produced by a specifically developed XML Parser, in order to plot the cow velocity data.

The open source charting library *dygraph-combined.js* (Dygraph, 2013) provided the Web browser with the functions suitable for plotting the XML file data. Dygraph is a fast and flexible library suitable for charting huge datasets. Moreover, in the CowVelocityGraph the chart is interactive as it is possible to hover the mouse to highlight individual values on the chart, click and drag to zoom, double-clicking to execute a zoom (back) out, and shift-drag to pan.

2.3. *A use case of the software tool: cow's oestrus detection from CowVelocityGraph data*

A use case of the software tool for the automatic and real-time analysis of cow location and velocity data was carried out to assess the performance of the implemented features and to verify the adequacy of the results, obtained from the application of the tool, to find useful information related to the occurrence of cow's oestrus.

The data analysed in this experiment was acquired by the UWB-based RTLS during August 2013. In this use case, an observation period is the time interval between two events of oestrus and elaborations are shown for seven days straddling the event of oestrus of the cow with identification number ID020. As was visually observed by the farmer, this cow manifested the state of oestrus on the 3rd day of the considered time interval at around 9:30 a.m.

For each of the seven days considered, a CowVelocityGraph was built and analysed for the cow equipped with the ID020 tag.

In this study, the objective of performing the real time recognition of the cow's oestrus status was carried out by controlling whether a velocity threshold was exceeded and, when exceeded, by assessing the increase of velocity over time from UWB data in order to avoid false positives.

To compute the velocity threshold, the maximum values of velocity were computed at 1-min time intervals, and then they were averaged for each day of the week considered, excluding the day when oestrus occurred. The daily averages (M_{Di}) of the maximum values, the related confidence intervals (*CI*), and the interval plot for differences in means were computed by using ANOVA with Tukey's test and a 95% confidence level. M_{Di} and *CI* were used to define a threshold S_{cow} of cow velocity for oestrus detection by using the following relation:

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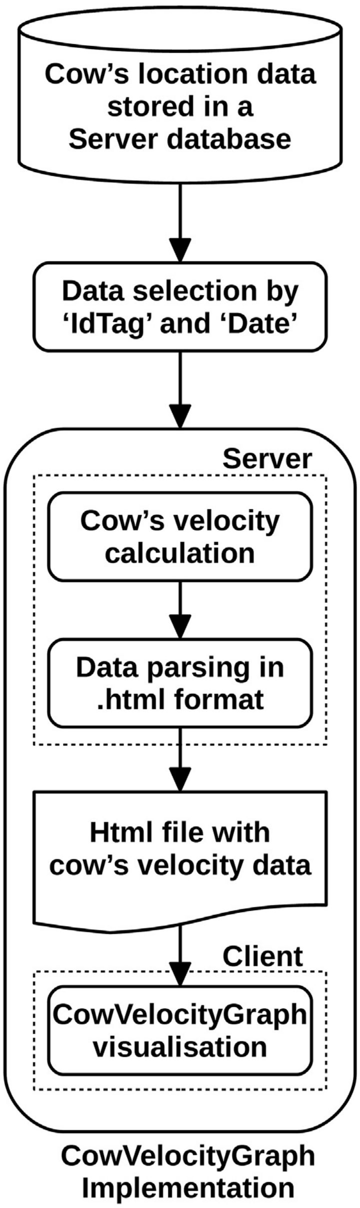

Fig. 2 – Data flow process of the system implemented in the software tool for the visual analysis of the cow velocity data.

$$S_{cow} = Max\left\{M_{Di} + \left[\frac{CI_{sup}(M_{Di}) - M_{Di}}{2}\right]\right\} \tag{2}$$

where $CI_{sup}(M_{Di})$ was defined as follows:

$$CI_{sup}(M_{Di}) = M_{Di} + t_\alpha \frac{\sigma_{pooled}}{\sqrt{n}} \tag{3}$$

in which t_α equals 1.96 for $\alpha = 0.05$, i.e. for a 95% Confidence Interval, σ_{pooled} is the pooled standard deviation, and n is the number of observations. The pooled standard deviation is defined as:

$$\sigma_{pooled} = \sqrt{\frac{(n_1-1)\sigma_1^2 + (n_2-1)\sigma_2^2 + \cdots + (n_k-1)\sigma_k^2}{n_1 + n_2 + \cdots + n_k - k}} \tag{4}$$

where n_1, n_2, …, n_k are the number of observations in the k days considered.

Therefore, the use case of cow's oestrus detection in real time required the following steps:

– computation of the 15-min means of the maximum values, named $\overline{v}_{max\_15min_j}$ hereafter, obtained from the maximum values at 1-min time intervals, where j indicates the 15-min time interval considered within the observation period.
– computation of the cumulative mean values C_h of the $\overline{v}_{max\_15min_j}$ values in 24 h by using the following relation:

$$C_h = \frac{\sum_{j=h-96}^{h} \overline{v}_{max\_15min_j}}{96} \tag{5}$$

where 96 is the number of 15-min time intervals within a day, $j = h - 96$ indicates the first 15-min time interval, and $j = h$ refers to the current 15-min time interval in the observation period.

– comparison between C_h and S_{cow}, for each ith 15-min time interval.
– sending an alert to the farmer when C_h exceeded S_{cow}.

3. Results

The CowVelocityGraph proved to be a valuable tool for the analysis of UWB-based RTLS data. The use case of the software tool carried out in this work showed that a pattern related to the cow behaviour analysed, i.e., when the state of oestrus occurred, could be identified in the CowVelocityGraph.

The comparisons between the day when oestrus occurred and the other days of the considered period can be obtained from Figs. 3 and 4 where the CowVelocityGraphs relative to the tag with ID020 are reported for the day of oestrus (Fig. 3) and the first day after the oestrus event (Fig. 4). These figures clearly show that in the day of oestrus (Fig. 3) the instantaneous velocity reached higher values compared to those recorded in the other day (Fig. 4), especially in the time interval ranging from 8:00 a.m. to 12:00 a.m., when oestrus occurred.

Analogous considerations could be derived from the comparison between the instantaneous velocities obtained on the other days and those relative to the time interval when the cow was in oestrus (data not reported).

To control whether the cow velocity threshold S_{cow} was exceeded, the average velocities $\overline{v}_{max\_15min_j}$ for each day of the considered period were computed (Fig. 5).

By applying a statistical comparison procedure based on Tukey's test, the daily means of velocity data were obtained for each day of the period considered. Outliers were discarded for each day by building a function in Microsoft Excel. Table 1 shows the results of the procedure that confirm the significant difference of the daily mean recorded on the third day of the week when the event of oestrus occurred. Furthermore, Fig. 6 and Table 1 show that the confidence intervals in each of the

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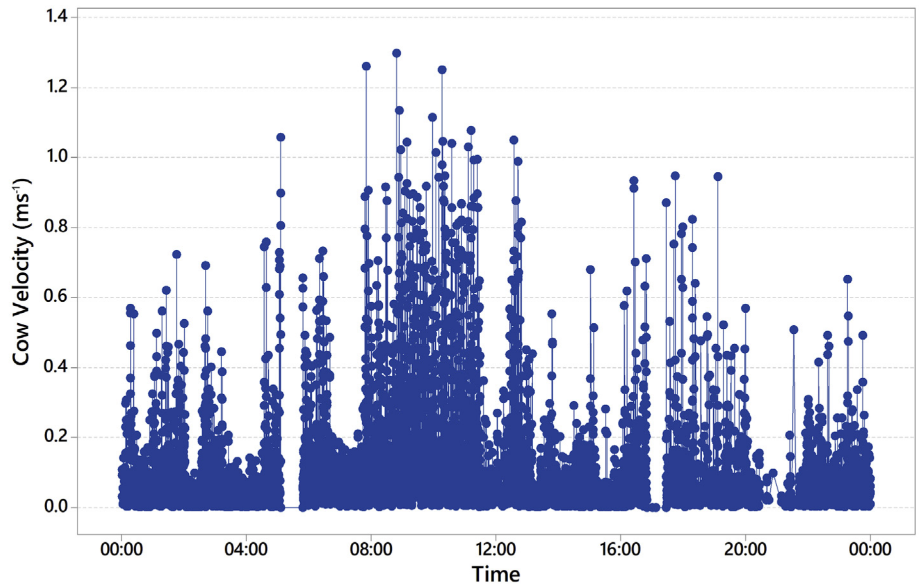

Fig. 3 – CowVelocityGraph of the tag with ID 020 relative to the day when oestrus occurred.

days considered have the same amplitude of about 0.04 m s^{-1}. This result highlighted that for each day of the period the data values of cow velocity acquired by the UWB RTLS system had the same average distance from the daily mean. Therefore, the velocity threshold S_{cow} computed by Equation (2) is suitable to set an alarm for oestrus detection because it provides the greatest cow velocity value recorded in a day other than that of the oestrus event.

In this experiment, a threshold equal to 0.1771 m s^{-1} was obtained. For a more general definition of S_{cow} threshold, a set of oestrus detections for the same cow should be acquired and the search for a common threshold for a group of cows could be further investigated, however these analyses are out of the scope of this research. The increase in velocity over time, and the exceedance of the threshold, were verified by computing the cumulative mean values C_h of the $\overline{v}_{\max\_15min_j}$ by using Equation (5). In Fig. 7 the graph of the computed values of C_h is reported. It highlights the sudden change in cow velocity during the morning hours of the day when oestrus manifested.

4. Discussion

The software tools, specifically developed for the visual analysis of cow velocity obtained from UWB RTLS data

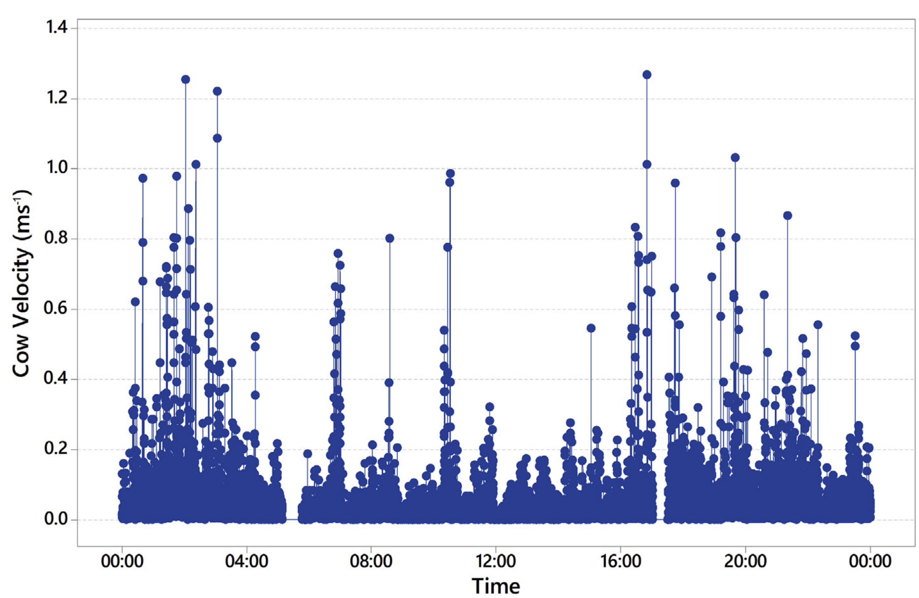

Fig. 4 – CowVelocityGraph of the tag with ID 020 relative to the first day after oestrus event.

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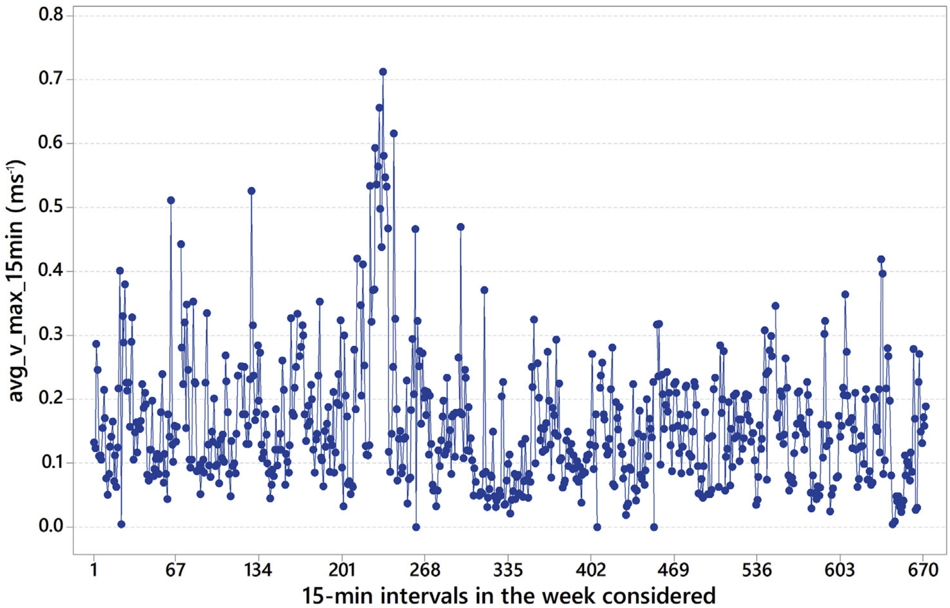

Fig. 5 – 15-min means of the maximum values of the 1-min time intervals of the velocity ($\overline{v}_{max\_15min_j}$) related to the cow tagged with ID 020 for all the days of the considered week.

Table 1 – Statistical measures obtained using Anova with Tukey's test and a 95% confidence interval, related to $\overline{v}_{max\ 15min_j}$.

Day number in the week of observations	Number of 15-min means	Mean (m s^{-1})	Grouping	95% CI (m s^{-1})
3rd (day of oestrus)	94	0.2266	A	(0.2067; 0.2465)
1st (two days before oestrus)	94	0.1672	B	(0.1473; 0.1871)
2nd (one day before oestrus)	93	0.1667	B	(0.1467; 0.1867)
6th (three days after oestrus)	91	0.1533	B	(0.1331; 0.1736)
5th (two days after oestrus)	94	0.1402	B	(0.1203; 0.1601)
7th (four days after oestrus)	93	0.1354	B	(0.1154; 0.1554)
4th (one day after oestrus)	92	0.1250	B	(0.1049; 0.1451)

Pooled StDev = 0.0982 m s^{-1}; mean of CI ranges = 0.04 m s^{-1}.

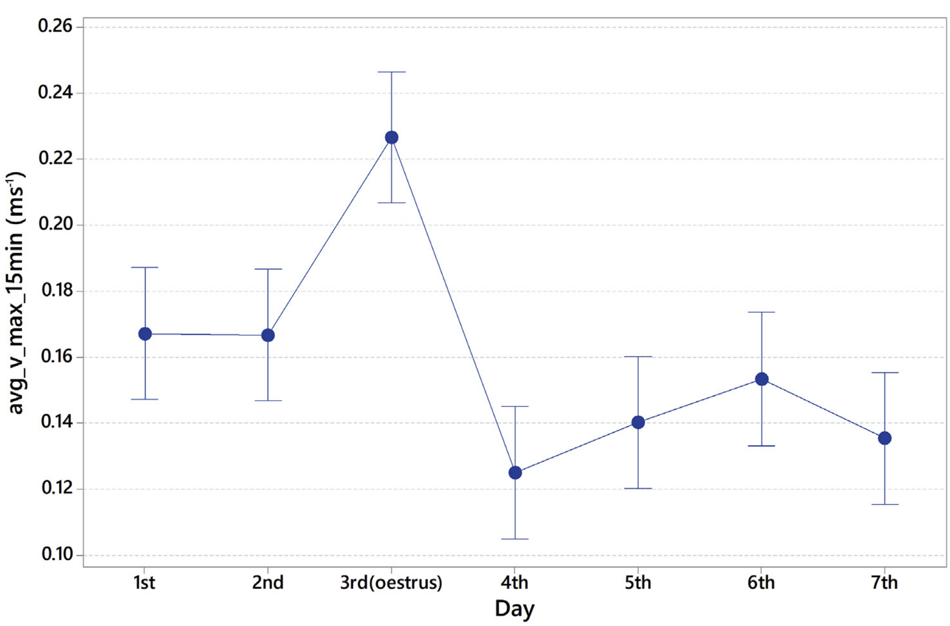

Fig. 6 – Daily averages of velocity computed for each day of the time interval considered and related confidence intervals.

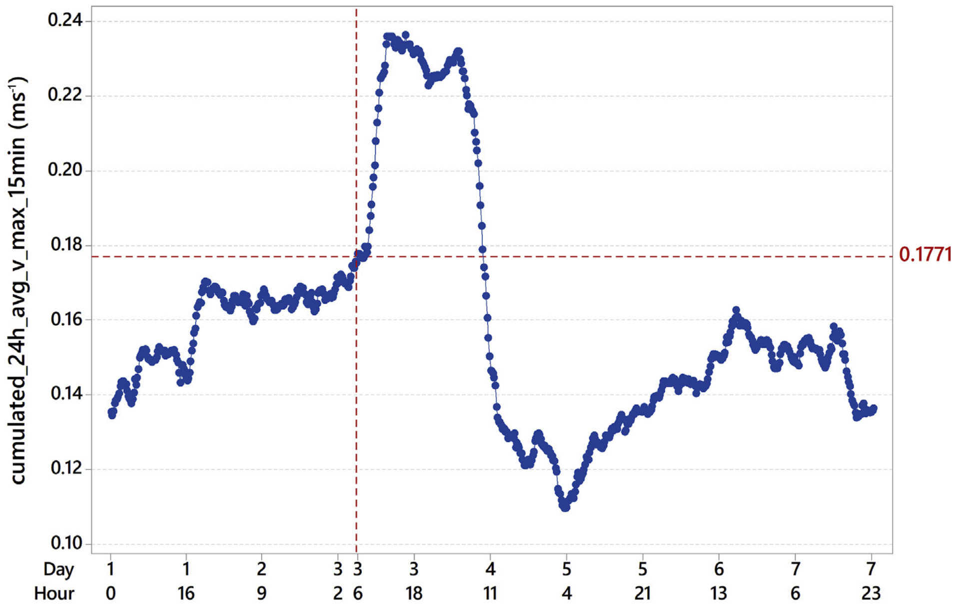

Fig. 7 – Values of the 24-h cumulative mean C_h of the 15-min averaged maximum values ($\overline{v}_{max\_15min_j}$) in the time interval of seven days.

acquired in a free-stall barn, produced good results with regard to both the performance of the implemented features and its use for the purpose of automatic oestrus detection in real-time.

An important feature of these software tools is the capability of performing the analysis for each cow independently according to one of the PLF principles. This is of relevant importance when the behaviour of an animal needs to be analysed individually, i.e., not in relation to the group to which it belongs (Martinez-Ortiz, Everson, & Mottram, 2013).

Saumande (2002) assessed a commercially available electronic oestrus detection device that alerts the farmer by flashing at different intervals when oestrus occurs. This kind of system, specially designed for cow's oestrus detection, requires visual observation of the herd or needs to be coupled with a real-time image analysis system in order to provide automatic alerts to the farmer. Since the herd size has progressively increased in farms all over Europe, the detection of oestrus by visual observation has become unsuitable, whereas the need for two detection systems would have a higher cost for the farmer.

The software developed in the present study offers the ability to work in real time by monitoring the RTLS data updated at short time intervals. In fact, it can be launched during the execution of both the location platform and the tools for data recording in the database, and automatically takes constantly updated records from the database as input.

A further improvement of the features offered by the software could regard the implementation of functions useful to perform statistical operations. Furthermore, by adding new control modules, this system would also be capable of notifying any problem through alert messages, as a result of changes in dairy cow behaviour.

5. Conclusions

In this work the objective of designing and developing a software tool for the automatic and real-time visualisation and analysis of cow location data acquired by an UWB RTLS was achieved. This software uses the RTLS potentiality to provide the user with a useful tool to perform specific analyses, such as oestrus detection. Good results with regard to both the performance of the implemented features and their use were obtained in a use case, where useful information related to the occurrence of the physiological state of oestrus was automatically achieved.

This software was designed to have the features necessary to be integrated into the world of Internet of Things (IoT), by providing the user with the ability to handle RTLS data in real time. Further improvement of the software tool could regard the implementation of new control modules to notify any problem occurring to the herd (e.g., reduction of locomotion activity, competition for food or cubicles, and lameness). By means of alert messages as a result of changes in dairy cow behaviour, it would possible to alert the farmer in real time.

The full benefits of the UWB RTLS remain to be verified on a greater number of cows, in different farming systems and for other specific objectives of the farmers.

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