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Image analysis to refine measurements of dairy cow behaviour from a real-time location system

Bruno Meunier [a,*], Philippe Pradel [b], Karen H. Sloth [c], Carole Cirié [b], Eric Delval [a], Marie M. Mialon [a], Isabelle Veissier [a]

[a] Université Clermont Auvergne, INRA, VetAgro Sup, UMR Herbivores, 63122 Saint-Genès-Champanelle, France
[b] UE1414 Herbipôle, INRA, 63122 Saint-Genès-Champanelle, France
[c] GEA Farm Technologies GmbH, Nørskovvej 1B, 8660 Skanderborg, Denmark

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Long-term monitoring of animal activity can yield key information for both researchers in ethology and engineers in charge of developing precision livestock farming tools. First, a barn is segmented into delimited areas (e.g. cubicles) with which an activity can be associated (e.g. resting), then a real-time location system (RTLS) can be used to automatically convert cow position into behaviour. Working within the EU-PLF project, we tested a system already able to determine basic activities (resting, moving, eating...) and logged a "big data" set of billions of data points (123 days × 190 cows × 1 location-per-second readings). We then focused on integrating image analysis techniques to help visualise and analyse the dataset, first to validate the data and then to enrich the information extracted. The algorithm developed using freely available tools quickly confirmed the ability of the system to determine cows' main activities (except drinking behaviour), even with 11% of positions missing. The good localisation precision (16 cm) made it possible to enrich the time-budget with new activities such as using brushes and licking mineral blocks. For both activities, using visual observations as gold standard, activity profiles with excellent sensitivity (nearly 80%) were extracted. This validation procedure is both necessary and generalisable to other situations. The improvement of biological information contained in such data holds promise for people designing alarm devices and health and welfare indicators for farmers and/or vets.

1. Introduction

Time spent by cows on various activities over the course of a day can be indicative of their welfare and health status. For instance, uncomfortable resting areas may prompt cows to spend less time lying (Veissier, Capdeville, & Delval, 2004) while sickness may prompt a cow to spend less time eating (Gomez & Cook, 2010; Uzal & Ugurlu, 2010). Monitoring livestock time-budgets manually, round the clock (24/7) is simply unrealistic in commercial farm conditions. Monitoring using animal-attached sensors such as accelerometers potentially included in commercial systems (e.g. IceTags-3D© IceRobotics, Scotland) is still in its infancy, and further research is needed

* Corresponding author.
E-mail address: bruno.meunier@inra.fr (B. Meunier).
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Nomenclature

24/7	round-the-clock
ACC	accuracy
CEP-R95	circular error probability at the 95% level
CSV	comma-separated value
CV	coefficient of variation
FN	false-negative
FNR	false-negative rate
FP	false-positive
FPR	false-positive rate
GIS	geographic information system
GNSS	global navigation satellite system
GPS	global positioning system
MV	missing values
NTP	network time protocol
PLF	precision livestock farming
PPP	precise point positioning
PV−	negative predictive value
PV+	positive predictive value
ROI	region-of-interest
RTLS	real-time location systems
TN	true-negative
TNR	true-negative rate
TP	true-positive
TPR	true-positive rate
UWB	ultra-wideband
VBA	visual basic for applications

on data mining or data validation (Arcidiacono, Porto, Mancino, & Cascone, 2017; Martiskainen et al., 2009; Nielsen, 2013). Research on wild animals outdoors is already identifying basic behaviours such as foraging, resting and moving, and is expected to identify many more behaviours in the near future (Wilmers et al., 2015). Indoors, location monitoring using computer vision can automatically quantify major behaviours such as lying (Porto, Arcidiacono, Anguzza, & Cascone, 2013) or drinking (Benvenutti et al., 2015). However, optical approaches are unsuitable for use in dusty environments, when a large area needs to be covered, and when large numbers of animals need to be individually monitored for long periods. In such conditions, the radar approach is generally the only way forward, as it facilitates efforts to both identify and track animals, both key information inputs for studying animal time-budgets, i.e. how much time animals spend on each identified activity during a day. Positioning data is thought to have the potential to give access to 15 out of 40 maintenance (e.g. rubbing against objects) or social behaviours (e.g. horn-to-horn contact) (Kilgour, 2012) as soon as the trajectory of each individual can be modelled. Several positioning technologies have already been identified and evaluated, first at pasture by mobilising a global positioning system (GPS) mounted on the animal with a collar (Anderson, Estell, & Cibils, 2013). With data filtration methods or even Precise Point Positioning (PPP) correction, the spatiotemporal resolution of this kind of sensor can reach 1 m in the plan with a data rate of 1 s, making it possible to correlate large animal track (>1 m) with relatively fine map information (10 m^2) to quantify time spent grazing and resting (Barbari et al., 2006), walking (Williams, Mac Parthalain, Brewer, James, & Rose, 2016), and at the watering point or in a specific patch (Handcock et al., 2009).

In closed environments and when the global navigation satellite system (GNSS) loses coverage, real-time location systems (RTLS) using ultra-wideband (UWB) frequency are one of the most reliable and accurate technologies available (Alarifi et al., 2016). Based on a network of fixed antennas (sensors), UWB–RTLS enables 3D tracking of thousands of mobiles, each equipped with an emitting tag smaller than a credit card, with high precision (<10 cm) and fast sampling rate (>10 Hz). This technology is already deployed in industries and hospitals to monitor both devices and people (Deak, Curran, & Condell, 2012; Judah, Huberts, Drassal, & Aunger, 2017; Maalek & Sadeghpour, 2016). In a barn – which is a known, fixed and segmented environment – this technology gives the opportunity not only to localise each animal in real-time but also to classify its behaviour—for instance, a cow may be identified as resting as soon as it is precisely localised in a resting area. All these features raise prospects for proposing precision livestock farming (PLF) tools, on condition that the technology solution is (i) biologically valid, i.e. capable of precisely measuring the behaviours of interest, (ii) reliable long-term, i.e. 24/7, and (iii) non-invasive, i.e. without risk of injury or disturbance to the animal. Gygax, Neisen, and Bollhalder (2007) demonstrated that it is possible to get less than 13% missing values (MV) and better than 0.5 m spatial precision with an UWB–RTLS (Abatec, Regau, Austria) mounted on a 2.5 kg collar. Porto, Arcidiacono, Giummarra, Anguzza, and Cascone (2014) evaluated UWB ear-tags (Ubisense, UK) on 8 dairy cows and obtained a mean accuracy of 0.51 m with 2% MV. The authors did not observe any sensor-related disturbance of cows' behaviour and the cow detection readings were validated with visual recognition of behaviours (feeding and lying) in the video-recordings. Recently, Shane, White, Larson, Amrine, and Kramer (2016) detected presence of calves in the drinking and eating area using the same Ubisense technology. They validated positive detections with video analysis and obtained a percentage of accurate classification varying from 42% to 88% according to target activity. These results, although promising, were obtained on a small dataset, with a specific commercial solution that was lightweight enough (<100 g) to assume it had little impact on animal behaviour, but too short on autonomy (2 months) to make it compatible with long-term analyses unless data acquisition rate is reduced enough to substantially increase battery life.

Here, we evaluate, in commercial farming conditions, the performance and possibilities given by another UWB–RTLS (Zebra, USA) already packaged and sold under the brandname CowView (GEA Farm Technologies, Bönen, Germany) as a PLF tool for dairy farmers, and protected under an international patent (Sloth, & Frederiksen, 2014). This system determines the main activities of cows based on their movements and their position in zones that have been predefined in the barn setting. The time-budget information based on these main activities (at feeding table, walking and standing in alleys, resting in cubicles) has been validated (accuracy > 95%) by Tullo, Fontana, Gottardo, Sloth, and Guarino (2016) in one

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specific barn configuration using video analysis, but this strategy is time-consuming and exposed to criticism over the observer effect (Shane et al., 2016). Our objective is to propose a generalisable methodology based on a static image analysis technique to quickly gauge the potential extractability of behavioural patterns from positioning data. Here we propose to map and segment the animal environment not *a priori* but *a posteriori*, using an empirical approach. We then validate the use of this mapping in a dynamic setting to detect a new set of cows' activities and consequently refine the time-budget information.

2. Material and methods

2.1. Facilities, animals and sensors

The study was conducted at the INRA's 'Herbipole' experimental facility (Marcenat, France, alt. 1100 m.a.s.l.) in a freestall barn (Fig. 1) equipped with several recent PLF solutions such as weighing troughs, automatic feeders, automatic weighing of animals, and electronic gates. This 41×117 m^2 barn is partitioned into services area (corridors, milking parlour, waiting area, offices) and 6 similar rearing pens, each accommodating 28 cows (maximum 168 dairy cows). The cows are indoors from November to April and at pasture for the rest of the year. The CowView UWB–RTLS was installed by GEA in February 2015. The study was carried out from November 2015 to March 2016. Measurements and rearing conditions were all part of on-farm routine and our study did not require any intervention on animals or their environment.

The barn housed an average 160 dairy cows inside at any given time, all equipped with a counter-weighted collar (565 g) on which an active tag ($6 \times 5 \times 4$ cm^3 – 146 g) was mounted above the neck so as to be visible to a wired network of 18 sensors fixed on the ceiling at a height of 5 m. This constellation provides coverage of all 6 pens plus the waiting area in front of the milking parlour (total covered area, 41 m $\times$ 82 m). A further 12 fixed performance tags equally distributed in the barn (Fig. 2) and positioned 1.5 m above the floor (i.e. at the mean height of cow necks) are used for 24/7 surveillance of system performance. Each tag is set to emit a unique identifier twice per second for 3–4 years without any maintenance. The 18 antennas are wired (Power over Ethernet) to a central processing unit handling the localisation and identification of the basic activities (at feeding table, at drinker, walking in alleys, standing in alleys, resting in cubicles) of each individual cow in real-time. The device is connected to Ethernet to ensure perfect clock synchronisation using the Network Time Protocol (NTP), dating in the epoch time system, and data transmission to the external GEA database.

2.2. Real-time location system dataset

2.2.1. Raw data description and logging

To construct the time-budget from the five basic activities, the raw X and Y coordinates of a tag are pre-processed with filters (Sloth, & Frederiksen, 2014) and aggregated in a single point if successive raw positions did not move by more than several cm. This procedure produces clustered positions (CP-data) characterised by a position (*x*, *y* in the GEA system) with cm resolution and start and end timestamps, both with ms time resolution (Fig. 3). If successive raw positions moved by more than 15 cm, the start and end timestamps of the CP-data are equal. These CP-data are then compared to a virtual map of the barn that has been drawn *a priori* (Fig. 2). According to that map, the animal is detected in one of the basic activities as in cubicle, at feeding table, at drinker, in alleys, and during a certain period of time (stop timestamps of the last point minus start timestamps of the first point entering the area) if one or more CP-data are successively detected inside a polygon corresponding to the cubicles, the feeding table, the drinker and the alleys (Figs. 1–3). In the alleys area, the cow is detected moving and a daily travelled distance is processed if

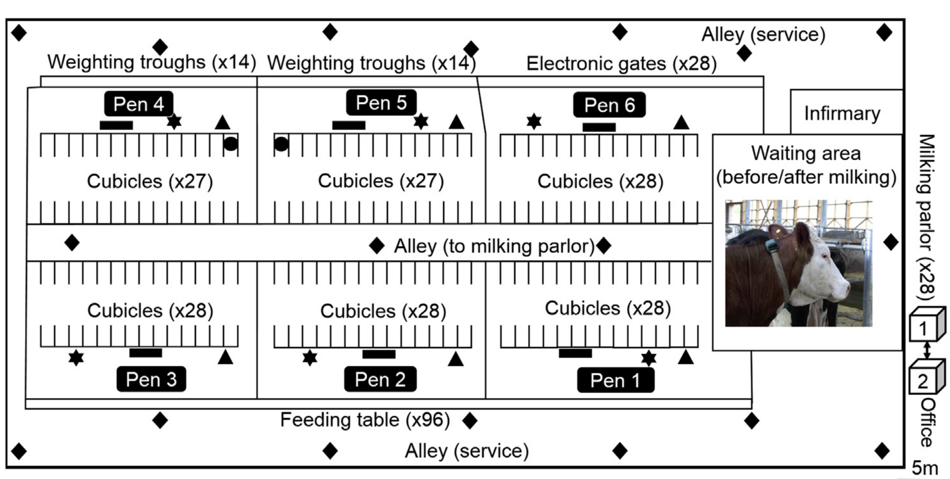

Fig. 1 – Floorplan of the barn equipped with the CowView system (1) connected to the logger PC (2) by Ethernet and to each of 18 antennas (diamond symbol) by Power over Ethernet (PoE). Each pen (1–6) is equipped with an automatic brush (star symbol), a drinker (rectangular symbol) and a mineral lick (triangular symbol). Two cubicles are occupied by automatic feeders (circular symbol). The picture shows a dairy cow equipped with a counter-weighted collar on which the active tag was mounted atop the neck.

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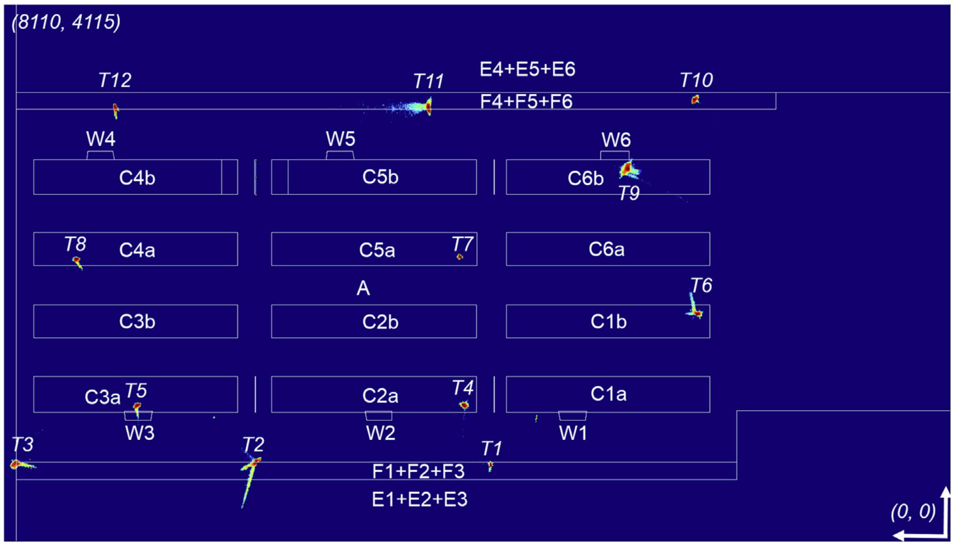

Fig. 2 – Virtual map of the barn drawn *a priori*. Lower right point is origin (0, 0) and upper left point is dimension in cm (8110, 4115). Each polygon is associated with an activity. C1a to C6b: cubicle a of pen 1 to cubicle b of pen 6; W1 to W6: drinker of pen 1 to pen 6; F1 and F2: feeding table of pen 1 to 3 and 4 to 6; E1 and E2: extended feeding table of pen 1 to 3 and 4 to 6; A: alleys. Additional information (not used by CowView) is given in italics. The accumulated CP-data of the 12 fixed performance tags T1 to T12 (DSFIX dataset) are represented in false-colour density and characterised by their CEP-R95 (in brackets), T1 (11), T2 (17), T3 (19), T4 (17.5), T5 (19), T6 (16), T7 (11), T8 (15), T9 (21.5), T10 (14), T11 (15.5) and T12 (17). The white arrows are 5 m.

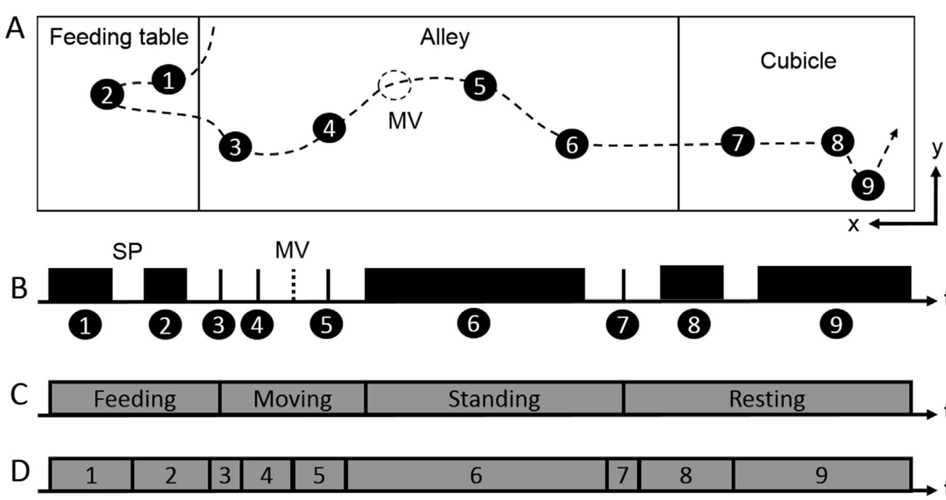

Fig. 3 – Representation of several seconds of one cow's life described via its successive CP-data (dots 1–9) from a spatial (A), temporal (B) and behavioural (C) point of view. Some points have null duration (e.g. dot 3, start date = stop date), some have non-null duration (e.g. dot 1, start date < stop date), and some are missing values (MV). Time between two successive points is called sampling period (SP). Corrected duration of each dot is processed by adding SP to each original duration. The rate of MV (%MV) may then be processed as the ratio of the sum of corrected durations to total duration of logging. Temporal representation (D) of the normalised CP-data in which no points have null duration (start and stop dates are corrected) and missing period due to missing point (MV) is distributed to each neighbour (e.g. dots 4 and 5) such that daily duration (sum of individual durations for a 24 h window) is 24 h. This procedure is an imputation.

several successive CP-data each have a null duration (stop timestamps equal to start timestamps); otherwise, the cow is declared standing. If the tag is inactive or masked for more than 60 s, the cow is considered to be in its last recorded position.

The CP-data were collected locally in real-time and then saved daily in comma-separated value (CSV) files using version 2 (2015) of the datalogger software EUPLFlogger.exe (GEA Farm Technologies) developed for the needs of this experiment. This software was running on a personal computer (PC) connected via Ethernet to the CowView system (Fig. 1). These CSV files were gathered to produce a single raw dataset covering the period P1 counting the 123 consecutive days from 28th November 2015 until 29th March 2016.

2.2.2. *Data quality, imputation and filtering methods (temporal, individual, spatial)*

A daily time-budget can only be viably processed if the device is reliable, i.e. technically capable of acquiring, processing and logging all data from all tags during the entire time period. In general, over-95% availability is considered the standard (Alarifi et al., 2016). The performance study has been done on the 12 fixed performance tags as they have been positioned in the most favourable visibility situation for the antennas (Fig. 2). For the entire period of P1 recording time, daily duration was processed from the daily-recovered CP-data to estimate the rate of MV. As some CP-data may have had null duration and consequently a null weight in the calculation of the raw duration, we calculated a corrected duration adding the individual sampling period to each CP-data. Thus, a number P2 of non-consecutive days were declared technically usable with less than 5% MV, i.e. less than 1.2 h per day. As the delay between two successive CP-data could be greater than the sampling period due to misdetection, we calculated a normalised duration by adding to each CP-data the weighted time of its neighbours unless it exceeded an arbitrary fixed threshold of 1.2 h (24 h $\times$ 0.05). Indicators of data quality were summarised in terms of duration (corrected and normalised), data rate and sampling period, as mean and coefficient of variation (CV) within and between tags.

A daily time-budget can only be analysed if the cows are reliably detected by the system. Each tag, among a total of N1 attached to cows, was not always in the most favourable visibility situation, as it could be (i) out of service, (ii) in an area not covered by the CowView system (parlour, sick bay, outside the barn), (iii) masked by another cow or by itself (badly positioned on the neck), by other equipment, by a steel tube, a pillar and a concrete wall or a wooden partition. These items could either completely mask one or more antenna or interfere with the UWB signals by generating multipath propagation (e.g. reflection on steel) or wave slowdown (e.g. transmission through wood). These phenomena decrease the quality of the triangulation, producing missing values or additional and unpredictable positioning noise. The indicators of data quality were obtained in the same way as above for fixed tags, i.e. duration (corrected and normalised), data rate and sampling period, as mean and coefficient of variation (CV) within and between tags, for the previously declared usable P2 days, and for a usable number N2 of cows (among N1) detected without interruption in the barn.

In exactly the same way as for GPS data, even though our CP-data was already pre-filtered, we observed abnormal and spatial discontinuities in our data making some positions jump. A basic smoothing algorithm is generally advised, consisting of a non-recursive median filter (Behmann, Hendriksen, Muller, Buscher, & Plumer, 2016) applied on the (x,y) data using the shortest temporal window, i.e. three successive points. To give an idea of its impact on the measure of displacement, the daily Euclidean distance travelled by each tag was calculated on the smoothed data. This raw distance includes the distance travelled by the cow (when walking, as already processed by the CowView system), its agitation (when moving its head), and the positioning noise.

Finally, three datasets were produced to meet the objectives of the study:

(i) DSFIX gathering the CP-data collected from the 12 fixed performance tags during the P2 usable days, to evaluate the RTLS technology,
(ii) DSCOW gathering the normalised and smoothed CP-data collected from the N2 usable attached tags collected during the P2 usable days, to evaluate the CowView system,
(iii) DSMOV gathering the normalised and smoothed CP-data collected from all the attached tags (N1) during all the days (P1), to refine the mapping.

2.3. *Conversion of the real-time location system dataset to density images*

In contrast with GPS data, RTLS position data are (i) here limited to two dimensions, (ii) restricted to the area covered by the antennas (i.e. 81.10 $\times$ 41.15 m^2 here) and (iii) sampled with a given squared spatial definition (1 $\times$ 1 cm^2 here). Consequently, a 2D-image map of size 8110 $\times$ 4115 pixels can be produced to visualise the overall spatiotemporal information in the form of occupancy, i.e. where several position points of identical coordinates (potentially from different tags) have their duration (ms) accumulated in the third available dimension of the 2D-image, i.e. the pixel value. We retained this representation which allowed each dataset to be summarised in a unique density image similar to the heat map currently used to visualise animal distribution in the geographic information system (GIS) (Barbari et al., 2006; Daigle, Banerjee, Montgomery, Biswas, & Siegford, 2014).

To automatically convert the different datasets to a density image, a dedicated program was developed in ImageJ v1.50c image processing software macro language (Schneider, Rasband, & Eliceiri, 2012) based on an algorithm that integrates a specific image transformation method based on histogram modelling (see comments in Fig. 4). This histogram equalisation procedure allows the extremely high dynamic image produced to be directly visualised, taking advantage of the full but limited capabilities of the screen, with an enhancement of lower local contrast area. Moreover, the overlay plane of the image is used to display the virtual map of the image drawn by CowView.

2.4. *Image analysis and CowView evaluation*

The image analysis tools, generally bundled with professional software, enable image manipulation (contrast adjustment, zoom, lookup table) and image quantification (geometrical and intensity measurement) that are useful for manipulating and diagnosing high-resolution and high-dynamic-range images. All the following measurements have been automated in ImageJ v1.50c image processing software macro programs to make the analysis more reproducible and less tedious.

```
macro "MacroConvertRTLS2image [X]" {            //Simplified imageJ macro converting PC-data into a density image
  newImage(imaCV, "32-bit black", 4115, 8110, 1); //create an image of the barn size and PC-data resolution
  for (numF=0;numF<list.length;numF++) {        //for each logged file (24h) in the data-base (123 days)
          for(i=0; i<rows.length; i++){         //for each row (one PC-data of one tag)
                  previousI=getPixel(x,y);              //read previous pixel intensity at the tag's position
                  setPixel(x,y,previousI+elapsedT);     //write new pixel intensity adding the elapsed time
          }
  }
  run("Median...", "radius=1");                 //reduce salt-and-pepper noise mainly due to outliers
  run("Bin...", "x=5"+" y=5"+" bin=Sum");       //resample /5 using "Sum" to preserve the quantitative information
  run("Log"); run("Divide...", "value="+log(10)); //log (base 10) to normalize intensity
  getStatistics(area, mean, min, max, std);     //calculate statistics on the log-normal intensity distribution
  run("Subtract...", "value="+mean);            //transform intensity using a sigmoid model fitted with the image statistics
    run("Divide...", "value="+std);             //        model : y=1/(1+exp(-(x-mean)/sd)))
    run("Multiply...", "value=-1");             //        enhance the medium intensity : spots of interest (e.g. mineral point)
    run("Exp");                                 //        flatten both extremes (1) dark intensity = moving area (e.g. alley)
    run("Add...", "value=1");                   //                              (2) high intensity = staying area (e.g. cubicle)
    imageCalculator("Divide create 32-bit", "ImageInitToOne","PreviousImage");
  resetMinAndMax();                             //normalize to adapt the new image distribution to the image display
  run("Jet");                                   //apply the "Jet" look up table (LUT) to maximise contrast
  filestring=File.openAsString(mapFile);        //read barn map
  Overlay.addSelection("white", 1);             //put barn map in the overlay plan to analyse animal x barn interactions
}
```

Fig. 4 – Simplified ImageJ macro converting CP-data into a viewable density image—only the useful image processing functions have been preserved and commented for a comprehensive description of the algorithm.

2.4.1. *Precision of the real-time location system technology – in ideal conditions*

To check that each tag was well and reproducibly localised in the virtual map, we conducted a performance study on the DSFIX dataset. We only performed static and relative validation rather than dynamic (Gygax et al., 2007) or absolute validation which would have necessitated a precise tacheometer and a complex protocol (Anderson et al., 2013) that would have been just as difficult to reproduce as to extrapolate. The focus of interest here was precision, i.e. the dispersion of measurement in x and y (positioning noise) for each fixed tag and the stability of this dispersion over all the area covered and in the long-term. Once the DSFIX dataset was converted into a density image, the mean position of each fixed tag (centre of mass) could be (1) compared to the virtual map using alignment criteria and (2) tested for correlation with the dispersion. Given that our positioning CP-data included not only x,y values but also duration (end minus start timestamp), instead of standard deviation measurement, we preferred to compute circular error probability at the 95% level (CEP-R95) (Anderson et al., 2013) defined as the radius of a circle centred on the mean position and in which 95% of the values occur. All these measurements are realised using ImageJ. All this information gives an idea of the positioning noise and in turn of the optimal grid resolution of our density image (pixel size) and its possible spatial stability (between tags variability).

2.4.2. *Accuracy of the CowView system – in real farm conditions*

The CowView system constructs the time-budget based on spatiotemporal interaction between each animal (reduced to a tag) and its environment (a virtual 2D-map with labelled area). A first and qualitative approximation of the accuracy is a visual match-up between the density image obtained from the DSCOW dataset and the virtual map overlay. A second and quantitative but global approximation of the accuracy is comparing the accumulated density, i.e. a measure of integrated intensity in the different labelled areas of the raw density image representing the mean level of activity, against activity data available in the literature (Gomez & Cook, 2010; Uzal & Ugurlu, 2010) and generally obtained by observation methods. ImageJ was used for both qualitative and quantitative approximations of these mean levels of activity.

2.5. *From density image to new behavioural pattern detection*

The density image helped reveal new spots of accumulated positioning data (high pixel intensity) potentially corresponding to cows' activities or behaviours of biological interest. The visual emergence of these spots and their possible segmentation were made possible by the long-term accumulation of density images using the biggest dataset (DSMOV), a strategy adapted to low-luminosity imaging that enhances signal-to-noise ratio. These spots of interest localised in the virtual barn could then be interpreted as specific behavioural patterns by crossing with visual observation of the animals in the barn.

2.5.1. *Gold standard by video analysis*

To obtain gold standard measurements, the new spots were continuously video-recorded for 24 h in Pen 5. Videos were digitised at 25 images s^{-1} using Media Recorder 2 (Noldus, Wageningen, The Netherlands). The corresponding behavioural patterns were analysed by a single experienced ethologist working to strict criteria (Shane et al., 2016) and using The Observer V11.5 software (Noldus, Wageningen, The Netherlands). Behavioural data were coded as an expression profile, i.e. a start "in activity" date (resolution of 1 ms) and a duration (resolution of 1 ms) without distinction of animal and without allowing for several animals on the same activity at the same time. As the video recorders were not connected to any source of clock synchronisation, the dates were kept in the local reference time system.

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2.5.2. Automatic detection by real-time location system data analysis

To obtain automatic measurements, we first performed contrast adjustments on the logged density image (the procedure is described in the comments to Fig. 4) coloured with a 16-colour LUT. This step can reveal several boundary surroundings for each spot-of-interest. Three segmentation criteria were used: (i) an image analysis criterion, i.e. the identification of a constant local minimum all around the spot, (ii) a spatial criterion, i.e. the relative correspondence between the image spot's area and the real surface of the spot where the animal × place interaction occurred, and (iii) a temporal criterion defined as the relative difference between the overall time spent by cows at this spot obtained from the video analysis and the volume of the density image in the spot reflecting the amount of time the tags localised to that spot. Using imageJ, we surrounded each boundary manually using the drawing tools available. These drawings were converted to masks, i.e. a binary image in which the spot of interest is “1” and the other is “0”. We then developed a program in ImageJ macro language to automatically generate profiles of presence of a cow in the spot from the moment when its coordinates (x, y) were localised in the spot of the mask image, with a start “in the spot” date (resolution of 1 ms) and a duration (resolution of 1 ms), for all the tags attached to the cows, for strictly the same period (24 h), for each spot of interest, without distinction of animals. For each spot, several boundaries were tested to identify the optimal area of interaction.

2.5.3. Validation of new behavioural patterns

Each profile of presence in a spot was compared to the corresponding gold standard profile continuously, i.e. without any additional discretisation and using the classical indicators of evaluation processed from the contingency table (Tullo et al., 2016). For instance, the true-positive (TP) lapse of time was processed as the sum of common lapses of time when both measurement methods (video and RTLS) agreed in detecting one animal in the specified activity. True-negative (TN), false-positive (FP) and false-negative (FN) were calculated in the same way, enabled us to compute the following performance indicators for the entire period of scan (24 h).

True-Positive Rate (%TPR) = 100*TP/(FN + TP), also dubbed ‘sensitivity’
False Negative Rate (%FNR) = 100*FN/(FN + TP)
True-Negative Rate (%TNR) = 100*TN/(FP + TN) also dubbed ‘specificity’
False-Positive Rate (%FPR) = 100*FP/(FP + TN)
Positive Predictive Value (%PV+) = 100*TP/(TP + FP)
Negative Predictive Value (%PV−) = 100*TN/(TN + FN)
Accuracy (%ACC) = 100*(TP + TN)/(TP + FP + TN + FN)

As the two clocks were not assured to be perfectly synchronised – and even if they were, we cannot be sure that the dating in the CowView system was not affected by phase shifting (delay) due to the filtering procedure – we processed all indicators of performance for different steps of artificial delay in a temporal window of 30 s before and after the absolute date. All calculations were performed with a Visual Basic for Applications (VBA) program developed under Microsoft Excel v2013.

3. Results

Each daily CSV file collected contained approximately 190 Mb of data for a normal day. The 12 fixed performance tags plus 190 tags each attached to a different cow were detected at least once by the system, and never with more than 168 at the same time.

Among the 123 consecutive days, 6 periods representing a total of 14 days appeared to be incomplete due to either electric failure in the barn or loss of connection between the data logger PC and the CowView system. Thus the P2 declared usable for statistics is 109 non-consecutive days. Among the 190 attached tags, 106 tags were always seen without interruption during these 109 days. These tags were declared usable and used for further statistics and image analysis.

3.1. Data assessment

On average, each fixed tag was localised 23.9 h per day once corrected, i.e. nearly 0% MV (Table 1). Sampling period varied between tags from 1116 to 1226 ms (1177 ms on average) but was constant for each tag between days. This result encouraged us to develop a data processing procedure taking into account the individual sampling period, e.g. for the calculation of speed. Because these CP-data are not raw but clustered positioning data, their rate was approximately one new point per minute.

On average, each attached tag was localised 21.4 h per day once data had been corrected (Table 1) but each missing period never exceeded 60 s. This means that resampling the CP-data to 1 point per minute would lead to no missing values. Some variability of the daily MV rate was observed between tags (10%) and within tag (5%). The resulting 11% of MV were imputed by our algorithm, leading to a normalised time of 24 h compatible with daily time-budget analysis. The data rate (on average 14 points per min) was also variable, notably for the moving point (on average 8 points with null-duration among 14 per min). On average, tags on cows were found to travel 8.3 km per day, but this measure seems noisy as it varied by 21% within tag and 30% between tags and appeared to be 7 times higher than daily distance travelled by each cow (1200 m on average) as processed by the CowView system.

3.2. DSFIX dataset and real-time location system evaluation

DSFIX was summarised as a density image (Fig. 5) using the algorithm in Fig. 4. The positioning accuracy processed from the raw density image gave 95% of the positioning points in a 16 cm-radius circle with a relatively low variation of 19% between tags. This variation did not correlate with *x* or *y* direction in the barn (Table 1). Mean position of each tag (centre of the circle) was visually checked based on real position in the barn and projected position in the virtual map. All the tags physically aligned were found to virtually align, and all the

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Table 1 – Evaluation of the spatiotemporal reliability and accuracy of the system processed separately for the fixed tags and the cow-mounted tags from the 109 usable days. Each value is a descriptive statistic of each indicator [Mean (CV% within tag/CV% between tags)]. Corrected durations are given in hours per day (h d^{-1}), data rates are given in points per minute (p min^{-1}), sampling period (SP) in ms, missing values (MV) in %, distance travelled by the tags in m d^{-1}, circular error probability at 95% (CEP-R95) in cm. The spatial dependency between CEP and the *x* or *y* direction is estimated by Pearson's coefficient of correlation.

Tags	N		Daily recovered CP-data						CEP	Cor (CEP,DIR)	
			Duration	Data rate (p min^{-1})		SP	MV	Distance	R95	(r^2)	
			(h d^{-1})	Total	Moving	(ms)	(%)	(m d^{-1})	(cm)	X	Y
Fixed	12	Mean	23.9	1	0	1177	0	129	16	0	0.06
		CV-within	0	51	–	0	0	108	–		
		CV-between	1	22	–	2	1	60	19		
On cows	106	Mean	21.4	14	8	1176	11	8290			
		CV-within	5	13	20	0	5	21			
		CV-between	10	18	28	3	10	30			

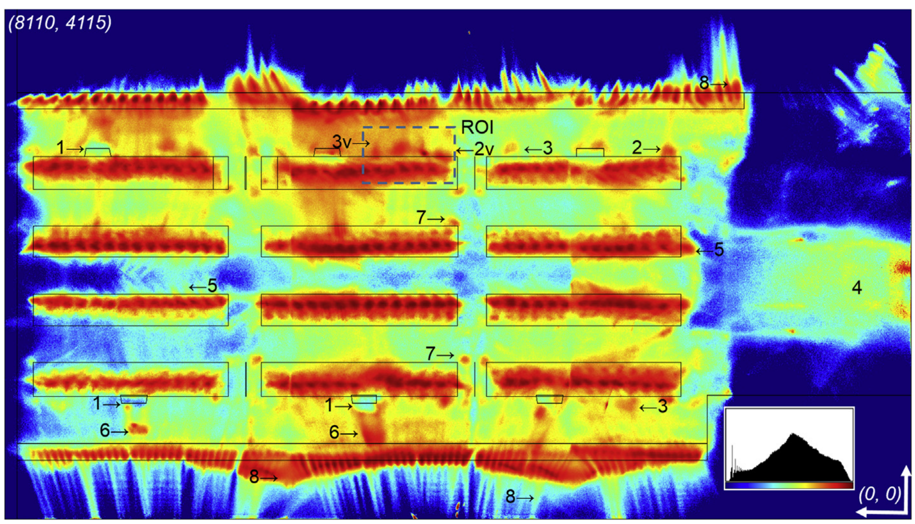

Fig. 5 – Density image without any contrast adjustment of 106 cows × 109 days (DSCOW dataset) in which each pixel intensity represents a level of occupancy. The original virtual map of the barn is put in overlay (black) and used for quantification of global time-budget information. The histogram of the image in the right lower corner depicts a well-equalised distribution of the transformed logged-intensity and false-colour correspondence, hot colour being associated with high level of occupancy (e.g. the resting area; more specifically each dark red spot where the tags are localised for long periods of time) and cold colour being associated with lower level of occupancy (e.g. the cyan colour in the waiting area (4) where cows are only passing). Some representative points of interest are numbered: (1) the drinkers which do not have the expected high density, (2) mineral blocks, (3) brushes, (4) the waiting area before milking, (5) positioning noise in the cubicle, (6) unexpected high-density spots potentially associated to drinking activity, (7) corner wall on which the cows would rub, and (8) vertical positioning noise at the feeding table. The letter v indicates a spot-of-interest validated by comparison with video analysis in the region-of-interest (ROI). The white arrows are 5 m.

tags within an area of activity were found in the corresponding polygon.

3.3. DSCOW dataset and CowView validation

DSCOW was composed of 352 million CP-data that were summarised as a density image (Fig. 5) using the algorithm in Fig. 4. It took 6 h to produce this image on a PC equipped with an Intel Core i5 microprocessor running at 2.9 GHz. The raw intensity of each square pixel of 1 cm^2 was given by the accumulated time spent by the 106 cows during the 109 days at this location. The histogram of this image spread from 0 to 4,708,712 ms, i.e. at least one given 1 cm^2 position was visited for a maximum of 1.3 h. These intensities had log-normal distribution, making the raw image difficult to visualise. Once logged, the histogram equalisation procedure based on a sigmoid transformation plus the use of an appropriate LUT optimised the image content to the capabilities of the display, thus enabling the visual diagnosis. The viewable density image was compared to the virtual map (Fig. 5) by checking the fit between the labelled region-of-interest (Fig. 2) and effective occupancy by cows. For basic activities already processed in CowView, the matching was good, except for the drinker fixed on a small 1.5 m-high concrete wall, which created a blind area for tag detection (Fig. 5 arrow 1). Quantitative analysis of the image for basic activities at feeding table (5.5 h d^{-1}), in cubicle (12.8 h d^{-1}) and others (5.7 h d^{-1}) were consistent with data obtained with visual observations on 205 cows × 16 barns × 24 h (Gomez & Cook, 2010), respectively 4.3 h d^{-1} (±1.1), 14.6 h d^{-1} (±2.4) and 5.2 h d^{-1} (±1.3). Conversely, quantitative analysis of the image for drinking activity (0.04 h d^{-1}) is far from the 0.48 h d^{-1} (±0.09) obtained with 24 cows × 1 barn × 10 days × 4 seasons (Uzal & Ugurlu, 2010). This result corroborates the visual diagnosis (Fig. 5 arrow 1).

3.4. DSMOV dataset and video analysis

DSMOV is the complete dataset and thus the most suitable to reveal new spots once summarised as a density image (not shown) very similar to Fig. 5. The mineral block and automatic brush were both visually identified in pen 5 (Fig. 5 – ROI – arrows 2v and 3v) matched with the floor plan (Fig. 1). This same matching is fairly easily realisable in the other pens. In order to validate these accumulations of presence as a behavioural pattern, 24 h of continuous video was recorded between 22nd and 23rd January 2016, a period during which 23 cows were present in pen 5. From 8 h (mineral point) to 12 h (brush) were necessary to analyse the video and extract the profile for both activities, i.e. when the cow was assumed to be (i) licking the mineral block as its nose was completely in the bucket and (ii) brushing (a grooming behaviour) as the mechanical brush was turning. The cows were seen licking the mineral block or brushing themselves for a cumulative time of 0.5 h and 7.6 h, respectively, spread over 75 or 140 different visits, respectively.

In parallel, the CP-data corresponding to the same period were extracted from DSMOV. Since one period was not analysable as the logger was accidentally interrupted, only 22 h in common between video and RTLS were analysed. One profile of 22 h was automatically generated from the CP-data localised inside each spot segmented according to a growing area, defined as the volume of intensity in the initial area corresponding to the overall time spent at this point obtained from the video analysis, i.e. 0.5 h in 0.2 m^2 for the mineral block and 7.6 h in 3.6 m^2 for the brush (Fig. 6). This procedure took only few minutes on our PC, which makes it compatible with real-time implementation. Among 190 tags, only the 23 tags corresponding to the 23 cows present in the pens were seen at least once in the different spots.

All the indicators of performance (TPR, TNR…) were computed for each comparison of the gold standard profile against an RTLS profile extracted from different growing areas and with an artificial delay introduced in the date. Figure 7 depicts a typical plot of each indicator according to delay, here in the case of the mineral point with a detection area of 0.58 m^2. Here, a peak of sensitivity (53%) was obtained for a delay of 14 s and this delay was constant whatever the spot area (results not shown). Sensitivity (TPR = 1−FNR) and the PV+ were affected by the delay, whereas specificity (TNR = 1−FPR), accuracy and PV− remained relatively unaffected and always stayed very high (>90% – not shown) whatever the spot area. Concerning the brush, the delay was 11 s, all the indicators were affected by the delay, and ACC, PV− and TNR were always above 75% (not shown) whatever the spot area.

Figure 8 plots two of the more interesting indicators of performance for several areas of each spot-of-interest. For the mineral point, sensitivity grows quickly as the area of detection is enlarged with TPR reaching up to 90%, whereas PV+ stays low and slowly tails away, i.e. the rate of true-positives among positive detections stays between 10 and 20%. For the brush, the evolution of both indicators in relation to spot area is slower. Sensitivity appears to be saturated at 80%. Conversely, PV+ is always above 60%.

4. Discussion

The RTLS dataset collected during this on-farm study was processed using the same free image processing software to assess, filter and then convert positioning data into density images. The method depicted here to analyse these images

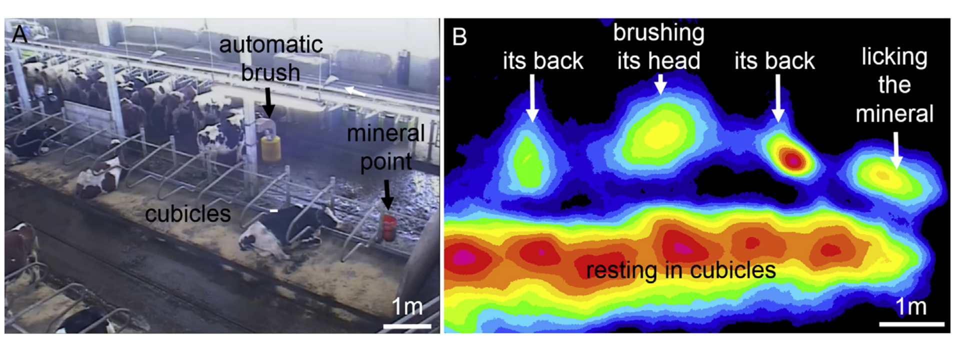

Fig. 6 – Snapshot from the video (A) and the corresponding region-of interest (B) extracted from the DSMOV density image after contrast adjustment and 16-colour LUT application allowing a multi-level local segmentation of the spots of interest 2v for the mineral point and 3v for the brush (ROI – Fig. 4 – pen 5). The white arrows indicate the boundary of the spot whose volume is equal to the total duration declared as "on activity" from the video analysis, 7.6 h for the brush for the brush (here sum of 3 areas pointed by the arrow) and 0.5 h for the salt lick. When cows are brushing either their back or their head, their body is mostly positioned parallel to the cubicles. The white bar gives scale.

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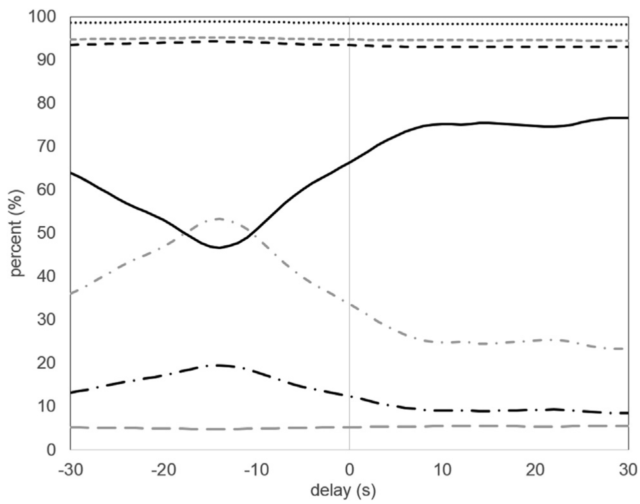

Fig. 7 – Indicators of performance computed between the profile extracted for the mineral point (detection area of 0.58 m^2) and the profile extracted from video in which an artificial shift (delay in s) has been introduced. The best performance is obtained for −14 s, i.e. the timestamp of the video is behind the real local time. False-Negative Rate (FNR): solid, Accuracy (ACC): dash, Negative Predictive Value (PV−): dot, True-Positive Rate (TPR): dash dot in grey, True-Negative Rate (TNR): short dash in grey, Positive Predictive Value (PV+): long dash dot, False-Positive Rate (FPR): long dash in grey.

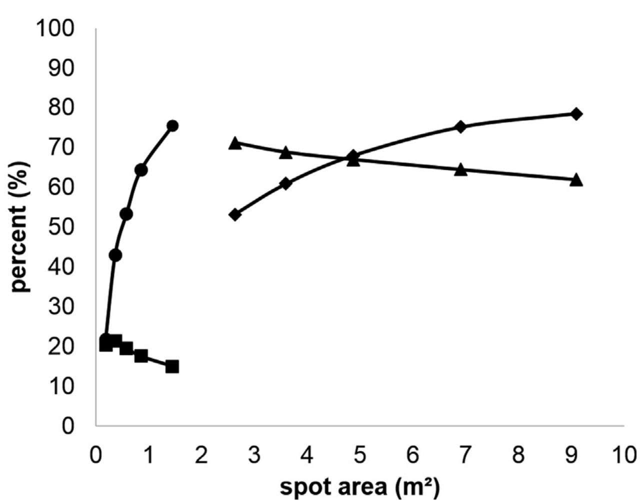

Fig. 8 – Two main indicators of performance for positive detection (TPR, also dubbed 'sensitivity', and PV+) computed for the mineral point and the brush as a function of spot area (m^2). TPR of mineral: circle, PV+ of mineral: square, TPR of brush: diamond, PV+ of brush: triangle.

proved to be well adapted to performing a qualitative and quantitative validation of the possibility of converting positioning data into animal behaviour. Moreover, the approach could be implemented in real-time once the density image is entirely converted to a labelled image, where each pixel value corresponds to an activity.

Having ideally-positioned fixed performance tags in the barn was essential to assess data availability, which is a primary condition for 24/7 analysis of animal behaviour. Here, all the missing periods were attributed to our datalogger and not to the RTLS system (CowView) which achieved almost a 0% miss rate of static data. These positioning data were also very precise, at 95% in a radius of 0.16 m, which is better than the 0.5 m guaranteed by the manufacturer of CowView. This precision processed from the density image was independent of position in the barn, a property that is not always ensured with this kind of technology (Behmann et al., 2016). These overall performances are high and stable over the long term, in the expected range of UWB positioning (Gygax et al., 2007). This was an essential prerequisite before considering converting positioning data to images for image analysis. Note however that we managed to obtain these results with few tags ideally-positioned in the barn.

The tags attached to the 106 cows that were always present in the barn were, on average, not localised for 2.6 h per day, i.e. 11% of the time. Nevertheless, this is a cumulative duration of frequent losses that never individually exceeded 60 s, and in any case is far more than the 30 min necessary for milking during which location is not guaranteed, as the milking parlour was not under sensor coverage. There might be several causes for not detecting tags, e.g. when the cow is at the feeding table or resting in the cubicle, its head is near the floor and the tag can be masked by its environment (feeding table or cubicle tubing). Huhtala, Suhonen, Makela, Hakojarvi, and Ahokas (2007) were the first to report similar observations. Furthermore, we observed high variability in the missing-value rate between tags and to a lesser extent within tags (between days). Therefore, the cows were not localised with the same accuracy in space or time. This could be explained either by cows changing behaviour pattern over the course of this long 123-day period or by the varying quality of detection by the sensors, e.g. tags moving on the collar. Anderson et al. (2013) reported that it was important but difficult to keep a sensor constantly on the top of a cow's neck. This is always a serious limitation with many animal-attached sensor devices. Raw daily distance travelled by the tag also appeared highly variable. These results corroborate Anderson who suggested never extrapolating results obtained in static conditions up to dynamic conditions and emphasised the need to evaluate all sources of noise. Visual inspection of the density image helps pinpoint problematic area in the barn: the feeding table area where the tags may be detected as moving by several metres even though the cow may be static, more or less depending on place at the feeding table, which may explain the unrealistic distances travelled by the tags and the observed variabilities, and some drinkers where no tags were detected, probably due to obstacles between the drinker and the antennas. The density image enabled the system to be reset in a different way, e.g. the position and number of sensors or refinement of the mapping. Farmers could be asked to follow some practical recommendations, e.g. to adjust the on-neck tag position when necessary (which will necessitate automatic detection of noisy tags) or to adapt barn layout as a function of RTLS limitations. For instance, a buck of salt localised on a wall, near a cubicle and in a zone of traffic is incompatible with automatic pattern detection.

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Once the positioning data had been pre-processed, the transformation of the density image to a labelled image was also biologically relevant from a temporal standpoint. These results appeared to be a prerequisite before considering the automatic detection of cow–environment interactions. In our conditions, only presence at drinkers seemed undetectable, whereas Tullo et al. (2016) used the same CowView device and obtained good sensitivity (85%) of detection at the drinker in their barn configuration. We identified two new spots of interest in the image: the mineral point and the mechanical brush, both of which are particularly well-revealed in pen 5. The floorplan of the barn (Fig. 1) helps understand the presence of spots in the other pens. The indicators of performance that we calculated by comparing the results of the image analyses (from RTLS) to visual observations of cows' behaviour (using video) revealed that the results of the image analysis were sensitive to the time shift between RTLS and the video, and also to the area of detection for the positioning data. In addition, the absence of identification of each cow may have caused TN to be strongly underestimated and TP to be slightly overestimated. Because we were more interested in the detection of activity (TP) and less in TN, we focused our attention on both FPR and PV+ which were also more impacted by a delay of several seconds than other indicators (ACC, PV−, FNR), and so consequently less informative here. Others indicators of performance could also be studied (Arcidiacono et al., 2017). For both patterns, we obtained quite good sensitivity (>75%), similar to figures obtained in similar conditions (Shane et al., 2016; Tullo et al., 2016) but for relatively large areas, i.e. 1.4 m^2 for the mineral point and 7 m^2 for the brush, which may increase the detection of false visits. Proportion of good detection was very low at the mineral point. This result may be explained by the fact that many cows use the bucket containing the mineral to rub, and the cows stay longer next to the point than really licking it, which as an event is rare in frequency and short in duration as the video analysis quantified 0.5 h for 23 cows, i.e. 80 s per cow per day. Thus in this particular case of rare and quick events, the accuracy ($\pm$1 s) of the video coding may also impact the results. The strategy to get information on the use of the mineral point and the brush is to retain a large area (e.g. 1.45 m^2 for the mineral point, allowing 75% sensitivity) that is much bigger than the real object, i.e. a 36 cm-diameter bucket here.

We analysed the continuous data (time) which is sensitive to shift and compared it to video which is sensitive to human bias (Shane et al., 2016) but still the gold standard for most behaviours. It could be useful to analyse the data in frequency after merging it into behavioural bouts. Activity profiles were extracted in the simplest way, i.e. binary presence/absence in the area, which could be enhanced using learning algorithms (Behmann et al., 2016). Nevertheless, discriminating fine behaviours with certainty quickly necessitates a multisensor approach where the first challenge is to choose and then adapt the high technology to the animal (Ginane et al., 2015).

5. Conclusion

Here we have acquired a "big data" set and proposed an easy-to-implement data mining approach based on image analysis. We showed that indoor positioning data had similar weakness to data from GNSS solutions, e.g. in terms of missing values and positioning noise, and necessitated a pre-processing algorithm adapted to each specific environment and application. Our approach could be advantageously proposed by the RTLS dealers to buyers to give an evaluation of system performance in the real-use-case environment.

We demonstrated that image analysis can be used empirically to refine the barn mapping and use it to automatically extract 24/7 profiles of presence in several zones of interest from animal tracks and, potentially, in real-time. The patterns of animal activity, which mirrored those defined by ethologists, give a unique opportunity to study time-budget information in the long-term, but there is still room for improvement. For instance, a cow detected as present in the resting area may be either idling or lying, which does not have the same biological signification (Veissier et al., 2004). Leg-attached accelerometers are generally well suited to distinguish lying from standing animals (Robert, White, Renter, & Larson, 2009). Additional activity sensors, such as those contained in an inertial measurement unit, could help in smoothing tracks and transforming data from sensors into more precise animal behaviours (Shamoun-Baranes et al., 2012) (Ginane et al., 2015). GIS tools and methods could be equally appropriate (Daigle et al., 2014). Commercial systems using a multi-sensor approach to refine behaviour classification are also increasingly making it to market (e.g. the RumiWatchSystem, Agroscope Research Station, Switzerland).

At present, there is strong societal pressure to keep cattle outdoors at pasture. Although the work we carried out was done in a barn with a RTLS system, the method we propose could be applied to very large datasets from GPS technology, which is appropriate to detecting the position of animals outdoors. We anticipate that miniaturisation and the Internet-of-Things will raise prospects for 24/7 tracking of herbivores indoors and outdoors and pave the way to many other PLF applications that our approach could help identify.

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Concerning any potential conflict of interest, the main authors (INRA) declare that this study was performed at their own initiative, for public and scientific-interest research purposes, and that the data were analysed entirely objectively. The commercial partner (GEA) was involved in furnishing the raw data and the settings of the CowView system with a lot of transparency, and also helped understand the raw results. GEA neither censored results nor influenced the discussion for their own interest.

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