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Accuracy of a real-time location system in static positions under practical conditions: Prospects to track group-housed sows

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ABSTRACT

Social interaction between animals may influence disease transmission paths. Therefore, the usage of real-time location systems gains in importance for livestock farms and research institutes as this technology helps to simultaneously obtain positions of a large number of animals and to evaluate them automatically. Thus, the aim of the project was to specify the accuracy of the real-time location system under practical conditions with regard to a possible future application. In practice, ear tags have proven their worth because pigs manipulate and therefore destroy other objects applied to them in the long term. Therefore, a real-time location system was used providing the sending unit integrated in an ear tag. Ear tags were tested in a sows' gestation stall in static positions. Measuring took place for 5 min per static position, whereas data was transmitted once per second (1 Hz) which led to 300 data points per position. Metal pen equipment led to lost or noisy positions. On average, 9% of data losses occurred and were inserted for the following data evaluation. A Haar wavelet was applied to reduce the noise. Filter settings were rated with the help of an error size consisting of the Euclidean error and an error for the variance of the filtered signal. An optimal filter setting could be achieved when only the 29 largest coefficients for the X axis and 20 largest coefficients for the Y axis were kept while all others were set to 0. Additionally, a *t*-test was performed to test whether an averaged number of coefficients over all ear tags and an optimal individual filtering of each single ear tag resulted in a significantly different filter result. P-values of the *t*-test were 0.15 (X coordinate) and 0.18 (Y coordinate) and therefore not significant. Thus, an averaged filter setting can be applied to all ear tags. The median accuracy of measured data described as Euclidean distance was 2.7 m before filtering and improved to 2.0 m after filtering. Considering the results of this system investigation, it shows that the system may be helpful for ensuing studies regarding e.g. animal behaviour, movement profiles, or social networks to uncover possible transmission paths for diseases.

1. Introduction

Infectious diseases in livestock spread on various pathways such as animal trade (van Duijkeren et al., 2008) and direct contacts (Morris, 1993). Among other influencing factors, contact structures determine the occurrence and dynamics of infectious diseases to a great extent. Especially, network analysis (Newman, 2010) helped to uncover transmission paths and advanced the development of adjusted epidemiological models, which were used to improve disease management. Patterns of pig trade have been widely analysed using network analysis (Lentz et al., 2011, 2016; Büttner et al., 2013a, 2013b; Ciccolini et al., 2012; Bigras-Poulin et al., 2007) but little is known about disease spread at pen level. This may be due to the fact that the contact structure of pigs is hard to capture. As a result, homogenous mixing is still assumed to predict disease spreading on pen level. In order to aim at an improvement of this situation, a real-time location system was tested for its applicability to reflect locations of sows and subsequently their proximity to each other.

Location systems have increasingly been gaining in importance for farms (Banhazi et al., 2012; Wathes et al., 2008). Especially in animal husbandry, technical solutions have become more meaningful due to growing stock sizes and declining employment rates (Frost et al., 1997). Matthews et al. (2016) gives an overview of automation in the pig industry. Of special interest are e.g. oestrus (Ostersen et al., 2010; Freson et al., 1998; Bressers et al., 1993) and lameness detection (Scheel et al., 2017; Traulsen et al., 2016; Pluym et al., 2013) as well as other health

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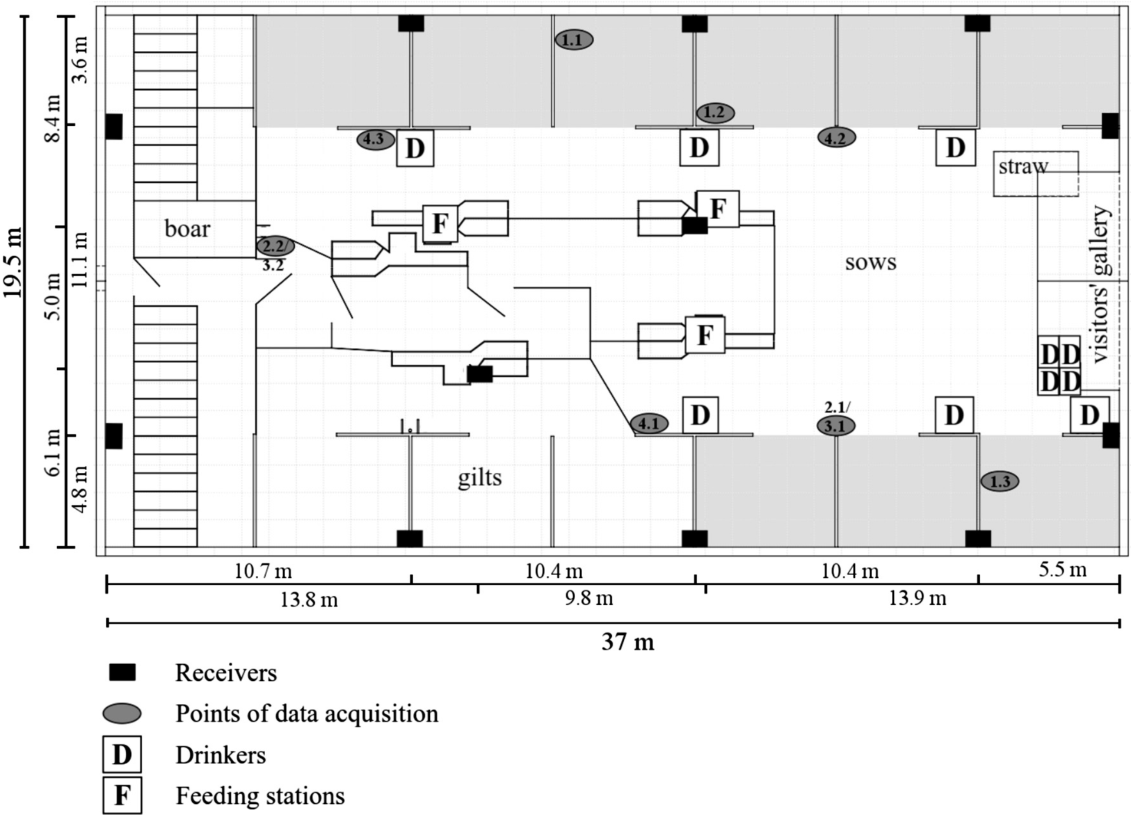

Fig. 1. Floor map of gestation stall in Futterkamp with receivers, points of data acquisition, drinkers, feeding stations, and resting areas (light grey areas). Points of data acquisition according to the different test designs used (see Fig. 2): 1.1: positions P. 01 – P. 03; 1.2: positions P. 04 – P. 06; 1.3: positions P. 07 – P. 09; 2.1: positions P. 19 – P. 22; 2.2: positions: P. 23 – P. 26; 3.1: positions P. 27 – P. 30; 3.2: positions: P. 31 – P. 34; 4.1: positions: P. 10 – P. 12; 4.2: positions: P. 13 – P. 15; 4.3: positions: P. 16 – P. 18.

or welfare issues (Kruse et al., 2011; Reiner et al., 2009; Exadaktylos et al., 2008; Ferrari et al., 2008). Also, scientists have demonstrated a growing interest in this new technology as it may help to analyse e.g. animal behaviour (Oberschätzl et al., 2015; Georg et al., 2012; Cornou et al., 2011), animal networks on pen level (Büttner et al., 2015a, 2015b), and the spreading of diseases (Chen et al. 2014, 2013). Additionally, technical solutions may be helpful to draw conclusions on animal welfare (Reimert et al., 2013; Špinka, 2012). As stated by Gygax et al. (2007), animals influence each other regarding their social interactions. Samarakone and Gonyou (2009) pointed out that sows may change their social behaviour according to group size. Hence, simultaneous recording of all herd members may be preferable but also challenging (Gygax et al., 2007). Until now, studies applied video recording and analysis or direct observations to obtain behavioural data. These techniques are time-consuming, lavish, and costly and therefore only practical for small herd sizes (up to 20 animals) (Gygax et al., 2007) or short periods of time. This is why high numbers of animals or a 24 h observation period require technical solutions.

Location systems comprise receivers and senders. Most systems work with senders attached to a neck collar (Ubisense, GEA, LPM). One system, however, uses transponders included in ear tags (SmartBow GmbH). Especially when working with swine, ear tags are more suitable and the only practicable solution so far, as pigs are very curious and show strong exploratory behaviour (Fraser et al., 1991). Practice has shown that other objects such as neck collars attached to sows are more likely to be chewed on and consequently are destroyed or lost more often. A further advantage of ear tags is that they are securely fixed to the ear of the animals so they cannot slip out of place like a transponder worn around the neck (Gygax et al., 2007; Rose, 2015).

Currently, tracking systems are predominantly used in cattle stock (Porto et al., 2014; Chen et al., 2013; Gygax et al., 2007; Pourvoyeur et al., 2006). One study has focused on goats (Georg et al., 2012). Studies with pigs are rare. Porto et al. (2012) investigated the technical possibilities of localising pigs with an active RFID system. Scheel et al. (2017) and Traulsen et al. (2016) worked with the acceleration data of the Smartbow system to detect lameness. Studies with swine may be rare because only ear tags can be used. Other transponders such as neck collars get easily chewed on and destroyed by pigs due to their exploratory behaviour (Fraser et al., 1991). The advantages of the Smartbow system compared to systems used earlier in pigs (Porto et al., 2012) are the small ear tag size, the low weight, and the higher operating frequency band. Further, the system transmits the 2-D position as well as the 3-D acceleration. This allows a wider range of application.

However, in practical application, technical solutions face some challenges. For example, electric signals may suffer from distraction by metal pen equipment and water (Deak et al., 2012; Maalek and Sadeghpour, 2013; Rose, 2015). Water sources can be drinking troughs or the animals themselves. This signal distraction is called noise and might lead to a longer signal runtime due to signal reflection or position losses due to signal absorption. The system interprets a longer runtime as a position more distant from the receiver. This leads to jumpy position changes even if the animal does not move. Noise complicates the correct detection of a target (Maalek and Sadeghpour, 2013) and therefore must be reduced with an additional application of a filter.

Under practical conditions, accurate localisation is challenged by this noise and signal absorption. This leads to the aim of the present study which was to specify the accuracy of a real-time location system under practical conditions to track group-housed sows in later epidemiological and behavioural studies. Prior to system operation in sows, the accuracy must be evaluated. Thus, the system was tested in a sows' gestation stall of a conventional farm under practical conditions. The ear tags were placed in static positions within the pen to obtain position data for accuracy testing. Especially epidemiological studies consider the contact intensity as it is an indicator for disease transmission. Sows rest 45–70% of the day (Maselyne et al., 2014; Rolandsdotter et al., 2009) and, at the same time, have intensive contact to other sows. This is why the accuracy of static positions is of special importance. A Haar wavelet (Haar, 1910) with different filter settings was applied to the dataset to find an appropriate filter setting. The task was, with the help of an error size, to detect an averaged filter setting applicable to all ear tags. Possible differences between individual and averaged filter settings were tested for significance.

2. Material and methods

2.1. Animals and housing

The experiment was carried out in cooperation with the research farm Futterkamp of the Chamber of Agriculture in Schleswig-Holstein, Germany. The conventional pig production is divided into breeding and fattening. In total, 400 sows and 1400 fattening pigs were kept.

The validation of the real-time location system took place in the sow's gestation stall (Fig. 1) in Futterkamp under production conditions. The inner dimension of the stall measures 37 m × 19.5 m and is divided into a larger pen for sows and a smaller one for gilts. Here, sows are group-housed with a group size of around 220 animals. The group of the gilts consisted of approximately 40 animals. Further, there was a pen for a boar, two selection compartments and crates. Location measurements were only performed in the area for the sows. This was equipped with slatted floor, six water troughs, four freely suspended nipple drinkers, and three feeding stations (Fig. 1). The sows had access to nine separate resting areas with a size of 4 m × 5 m (Fig. 1, light grey areas). Some areas were equipped with lying mats, others with concrete floor. Further, they had access to manipulable materials (straw in a rack, wooden bars, or brushes) and they had the possibility to contact the boar.

2.2. Real-time location system

In the present study, the SMARTBOW® real-time location system was used. This system comprises ear tags (dimensions: 52 mm × 36 mm × 17 mm; weight: 34 g) holding the sending unit and receivers obtaining the 2-D position data from the ear tags. Besides the 2-D position data, ear tags also provide 3-D acceleration data. However, information on acceleration of an animal was not used in the present study. The system works with an operating frequency band of 2.4 GHz. Power is supplied by an integrated 3 V battery. Battery runtime lasted approximately 20 weeks and depends on the frequency at which ear tags transmit their locations. In the present study, position transmission occurred once per second (1 Hz). Other location systems transmit the position with a frequency of less than 1 Hz (Porto et al., 2012) and up to 4 Hz (Arcidiacono et al., 2017a, 2017b). Chen et al. (2013, 2014) aggregated the collected data over 10 s intervals. The frequency used in the present study should be acceptable because sows walk 0.7–0.9 m per second (Gregoire et al., 2013; Thorup et al., 2007) but on the other hand also rest 45–70% of the day (Maselyne et al., 2014; Rolandsdotter et al., 2009). Hence, 1 Hz position transmission can be considered to be an appropriate compromise between data resolution and battery runtime.

The position signals of the ear tags were transmitted once per second to the 12 receivers installed along the walls and in the middle of the stall. To locate a position, at least three receivers were required. A central server analysed the received signals with trilateration algorithms and stored the data. The system used the Time Difference of Arrival (TDoA) technology for position determination. This means the runtime of radio signals between the ear tag and the receivers was recognised to determine the distance to the receiver. Additionally, the time differences between the single signals were captured to calculate the exact position of the sending unit (Zhang et al., 2010).

The number of required receivers is defined by the individual barn size and geometry as the distance between receivers should not exceed 25 m to guarantee accurate positioning. Thus, 12 receivers were installed in the gestation stall (Fig. 1). This number is necessary as, according to Langley (1999) and Mahfouz et al. (2008), non-geometrically sensor layouts may lead to an error referred to as Horizontal Delusion of Precision (HDOP). This reflects the reduction of localisation precision and thus describes the scattering of measured values. The precision depends on the angle between the receiving units while a higher number of receivers may reduce the error (Langley, 1999). To reduce the error rate, the 12 receivers were evenly distributed around the pen with a distance to each other of 10–19.5 m (Fig. 1). In this case, a smaller distance between receivers is useful because it may support a reduction in signal disturbance due to metal pen equipment (Maalek and Sadeghpour, 2013; Rose, 2015).

2.3. Determined static positions for accuracy testing

To measure the quality of static coordinates the following experiments were performed as shown in Fig. 2. Ear tags were secured to a measuring stick. A person carried the stick with the ear tags through the gestation stall and placed it in predefined static positions. Local measuring took place for 5 min per static position, whereas each second the 2-D position (X and Y coordinate) was transmitted. Consequently, 300 data points per position were recorded and evaluated. In total, 6500 s per ear tag were recorded, comprising static positions as well as periods of walking between the single static positions. Only static positions were precisely defined and evaluated subsequently. Experiments 1–3 took different heights into account to evaluate the influence of height on localisation. Experiment 1 (Fig. 2a) raised data at three different heights (0.1 m, 0.35 m, and 0.6 m) considering three different positions in the stable. This resulted in nine position records in total (three ear tags × three positions = nine position records). Additionally, the influence of proximity between ear tags was investigated in Experiment 2 (Fig. 2b). Here, the influence the ear tags might have had on each other

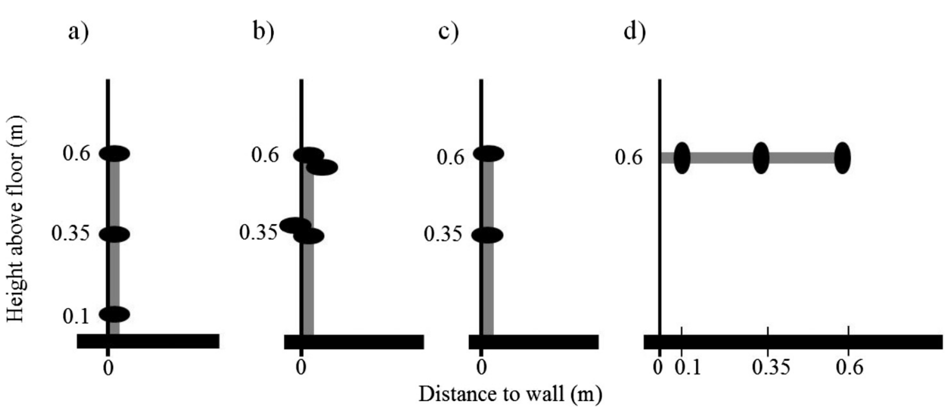

Fig. 2. Test design; sketches show measuring stick (grey) with attached ear tags (black ovals) at specific heights; (a) Experiment 1: 3 ear tags were secured at heights of 0.1 m, 0.35 m, and 0.6 m above the floor; data acquisition of positions P. 01 – P. 09 (see Fig. 1, points of data acquisition 1.1–1.3), (b) Experiment 2: 2 ear tags were simultaneously secured in heights of 0.35 m and 0.6 m above the floor; data acquisition of positions P. 19 – P. 26 (see Fig. 1, points of data acquisition 2.1–2.2), (c) Experiment 3: 2 ear tags were consecutively secured at heights of 0.35 m and 0.6 m above the floor; data acquisition of positions P. 27 – P. 34 (see Fig. 1, points of data acquisition 3.1–3.2), (d) Experiment 4: 3 ear tags were secured at distances of 0.1 m, 0.35 m, and 0.6 m away from the wall at a height of 0.6 m; data acquisition of positions P. 10 – P. 18 (see Fig. 1, points of data acquisition 4.1–4.3).

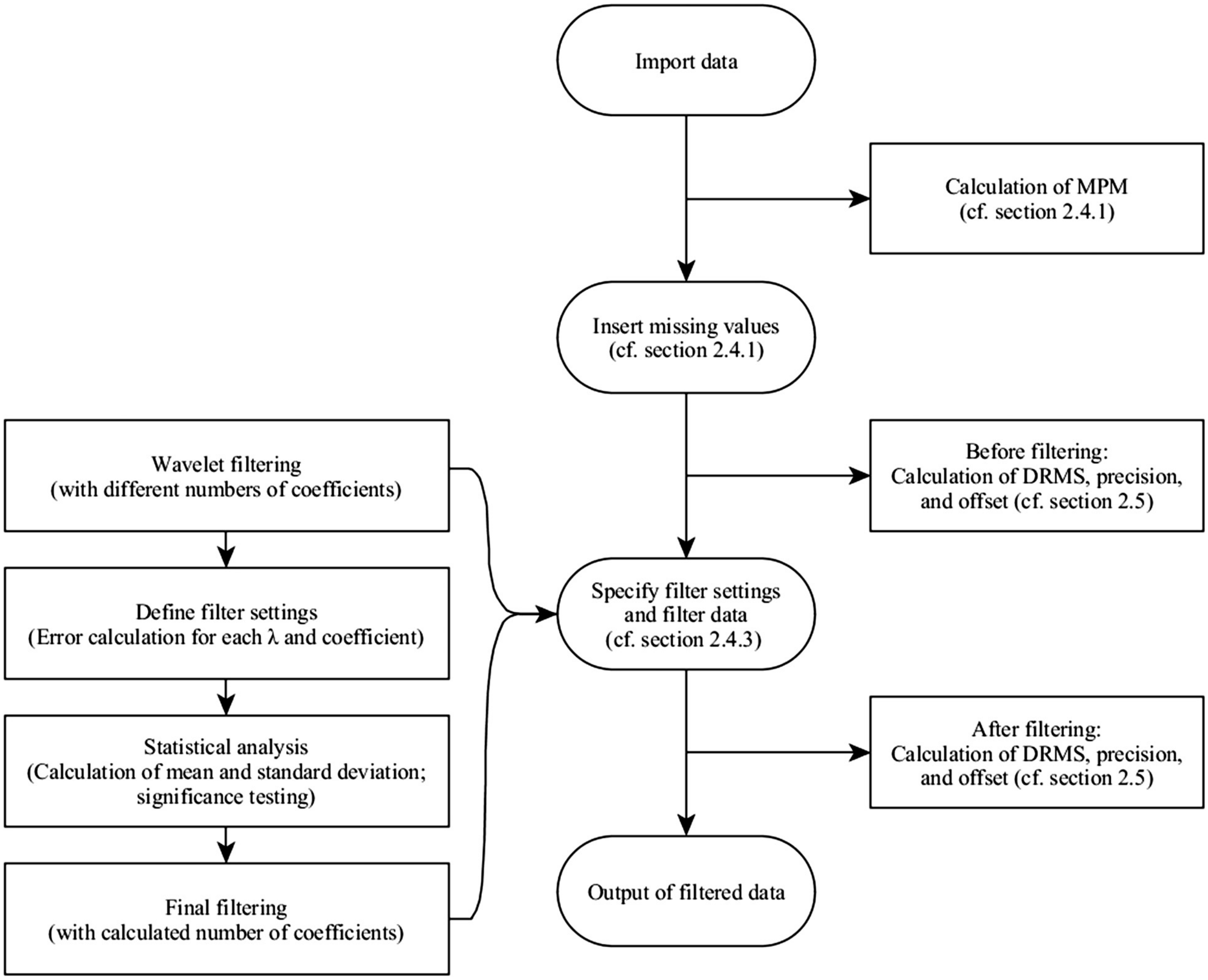

Fig. 3. Flowchart of data processing. (MPM: Missing percentage of measurements describes the data completeness; DRMS: Distance root mean squared describes the accuracy of the system).

when they were close to each other was explored. This might occur when sows were lying close together. Therefore, two ear tags were simultaneously secured at two different heights (0.35 m and 0.6 m) at two different positions. This led to eight position records in total. Experiment 3 (Fig. 2c) functioned as a reference for Experiment 2 and further analysed the position deviation that might have occurred between different transmitters. Here again, in total eight position records were collected. Data for the first three experiments were collected close to the cubicle walls. Data in Experiment 4 (Fig. 2d) were collected 0.6 m above the ground. This experiment evaluated the influence of the distance to the walls of the resting areas by horizontally holding the stick with three ear tags away from the wall. Here, three different positions were taken into account resulting in nine position records in total. Thus, the overall experimental design contained 34 position records (P. 01 to P. 34) according to Figs. 1 and 2.

2.4. Data processing

Fig. 3 shows the single steps of data processing from the import of the raw data to the output of the filtered data. The single steps are explained in detail in the following sub-sections.

2.4.1. Preparation of location data

After the import of the raw data, the number of transmitted pings was evaluated. Correspondingly, the missing percentage of measurements (MPM) was computed as the division of the lost measurements (LM) and the total number of measurements (TM) in seconds.

$$MPM = \frac{LM}{TM} \times 100 \quad (1)$$

LM specifies the number of pings that were not captured by the system due to signal absorption. It was computed by subtracting the number of transmitted pings from the total number of measurements (TM), while TM designates the number of pings that should have been recorded by the system (6500 pings for the present study). MPM can range between 0% and 100%, where 0% indicates that all pings (one per second) were transmitted and 100% indicates that no ping was transmitted. A low MPM is favoured because it shows a low rate of lost pings.

The shortest and longest time span with a ping loss in seconds was also registered. As lost pings had been inserted into the dataset, longer ping losses could result in position distortions. Sows move with a walking speed of around 0.7–0.9 m per second (Gregoire et al., 2013; Thorup et al., 2007). Therefore, longer ping losses may include unregistered walking routes or lying. To better evaluate the effects of these possible distortions, the share of 1 s losses was registered together with losses of up to 10, 20, 30, 60, or more than 60 s. The number of time spans lost was also captured. A high number of 1 s losses leads to considerably less data distortion because sows may not walk that far. Data losses of 10 s and more lead to distortions because sows may walk longer distances or visit places that remain unregistered during that time. Missing pings (9% on average in the present study) were inserted into the time series by dividing the distance between the past and following position by the number of lost pings. This was necessary to adjust the signal length for filtering which requires signals of the same length.

2.4.2. Discrete wavelet transform (DWT)

The discrete wavelet transform (DWT) is a valuable tool in signal processing (Madan et al., 2009). As signals are often disturbed by noise, relevant information might be hidden. The wavelet transform may help to reduce noise and with that reveal essential information. In the following, we may differentiate between four types of signals: original, measured, pure, and filtered signal (see Supplementary data). The original signal reflects the actual positions within the stall. Actual positions were only available for static positions, which is why this parameter is only theoretical and not available in practice. The measured signal represents the signal transmitted by the system. It comprises the pure signal (signal without noise) distorted by noise. The pure signal is supposed to reflect the original signal at the best. Due to system-related influences the pure signal may slightly differ from the original signal. Further, it is distorted by noise. Filtering helps to reduce the noise part and strengthens the pure signal. Consequently, filtering leads to the filtered signal (signal with noise reduction) which is supposed to approximate the pure and with that ideally the original signal.

Signals may comprise low as well as high frequencies (see Supplementary data). Pigs are inactive up to 70% of the day (Maselyne et al., 2014; Rolandsdotter et al., 2009) and walk slowly (Gregoire et al., 2013; Thorup et al., 2007). Thus, their activity level is best represented by low frequencies. Hence, the low frequencies reflect the original signal while high frequencies represent the noise part (see Supplementary data). With low frequencies, even small frequency changes are of importance. Therefore, a good frequency resolution is required. In contrast, at high frequencies, changes may occur more often. Additionally, in high frequencies a complete oscillation requires less time, which is why these frequencies request a good time resolution. Oscillations describe the temporal repetitive variation of a signal (see Supplementary data). DWT is based on a low- and high-pass filter and therefore balances a good frequency resolution with a good time resolution. Consequently, it works for both high and low frequencies as both parts are issued.

DWT comprises the mother wavelet ψ and the scaling function ϕ (see Supplementary data). The scaling function ϕ is a low-pass filter only letting through low frequencies, whereas the wavelet function ψ is a high-pass filter suppressing low frequencies.

DWT was applied to the entire signal, comprising static measuring points and time periods with carrying the ear tags from one position to the next. Data recording resulted in a signal with a length of 6500 s. If only static sequences were considered, a very strong smoothing of the signal could be used to achieve an optimal result. At the same time, this would also smooth movement and let it disappear. Hence, position changes of the ear tags had to be taken into account. Thus, the filtered result had to be optimised for a signal with movement and stagnation. During filtering, the signal was split into two sets of coefficients. Firstly, low-pass coefficients from the scaling function were called "approximation" and contained information about the signal. Secondly, high-pass coefficients from the wavelet function were called "detail" and contained the noise part (see Supplementary data). The coefficients from this first splitting were called "Level 1" coefficients. Accordingly, the approximation could be further split up into scaling and wavelet coefficients. Each additional splitting comprised a further level.

The filtering process was carried out following Madan et al. (2009). In the present study, different numbers of wavelet coefficients were taken into account for the subsequent inverse wavelet transform (IWT). Only a specific number of coefficients was considered for filtering while all other wavelet coefficients were set to 0, which reduced the noise. Finally, IWT was applied to receive a filtered signal with less noise. IWT reconstructs the input signal from the scaling and wavelet coefficients. As only a limited number of wavelet coefficients was used for the back-transformation, this resulted in a smoothened signal (Madan et al., 2009).

The discrete wavelet transform "dwt" of the R package "wavelets" was used for filtering. The pure signal, included in the measured signal, comprises constant and linear phases to reflect lying and walking behaviour in sows. Thus, different wavelets were tested (see Supplementary data) to decide for an appropriate one. The Haar wavelet (Haar, 1910) was chosen because this wavelet resembles best with the pure signal. The number of iterations was set to "Level 7". Previous tests have shown that higher levels do not further improve the filter results (see Supplementary data). Therefore, "Level 7" was sufficient for filtering.

2.4.3. Wavelet filter settings

A suitable filter is supposed to reduce the noise without dropping information about position changes of the sows. The chosen filter setting must be able to most explicitly reveal the inactivity or activity of the sows. Therefore, different filter options were compared to find an appropriate filter setting and, finally, filter the signal. The procedure is illustrated in Fig. 3 and described in detail below.

2.4.3.1. Wavelet filtering. The appropriate filter setting depends on the considered number of coefficients kept for filtering. Therefore, the signal was filtered with different numbers of coefficients. Previous tests, performed with the data obtained for this study, had resulted in an error curve that suggested an optimal number of coefficients between 20 and 30. Low values of the error curve indicate the optimal number of required coefficients for filtering. The error values were lowest within the mentioned range. However, for the present study, the considered number of coefficients was extended to a range of 5–70 coefficients to more accurately calculate an error curve.

2.4.3.2. Define filter settings. To specify the optimal number of coefficients, the filter results were rated with an error size. The filtered signal is supposed to approximate the true positions. With that, movement as well as rest times must be represented adequately. Hence, an appropriate error size must result in a good approximation. This is achieved by balancing the Euclidean distance, the signal variation, and the number of coefficients, whereby a low variation requires a low number of coefficients. Therefore, two error values were taken into account: firstly, the Euclidean error e_{euclid} and secondly, an error for the variation of the filtered signal, e_{var}. Errors were calculated for each filter setting.

The error e_{euclid} rates the Euclidean distance (Deza and Deza, 2016) between the single positions i of the measured signal $S\_measured_i$ and the single positions i of the filtered signal S_i. The measured signal was compared to the filtered signal because the original signal is only available for static positions. The complete measured signal with a length of 6500 s, however, also contains phases of walking. In addition, the filtered signal is expected to approximate the original signal. This error increases with progressing filtering because the filtered signal smoothens and with that the Euclidean distance between measured and filtered signal increases.

$$e_{euclid} = \sqrt{\frac{\sum_{i=1}^{n} \sum (S_i - Smeasured_i)^2}{l}}, \tag{2}$$

where l is the signal length. e_{euclid} assumes positive values in metres. In case of e_{euclid}, a low error value results in only marginal filtering. Thus, especially rest times would not be visible in the filter results. For this reason, the applied error size must be enhanced by e_{var}.

The error e_{var} was calculated to value the variation (Clarkson and Adams, 1933) of the filtered signal S.

$$e_{var} = \frac{\sum_{i=1}^{n} |(S_{i+1} - S_i)|}{l}, \tag{3}$$

where l is the signal length, S_i indicates the current filtered position, and S_{i+1} stands for the next filtered position of the following second. With proceeding filtering the signal becomes smoothed and the variation decreases. With that also e_{var} decreases. e_{var} assumes positive values in metres. Here, a low value is favoured.

The total error e is a combination of the two error sizes e_{euclid} and e_{var}. e_{var} of the given dataset proved to be smaller than e_{euclid} and therefore less influential. Static phases in the filtered signal led to a low e_{var} because the current and next position do not differ from each other. Therefore, an extremely low e_{var} may be expected when the activity level of the animals is low. This may be the case for pigs because they are lying up to 70% of the day (Maselyne et al., 2014; Rolandsdotter et al., 2009) which leads to long static phases with no variance in the signal. As a low variation in the filtered outcome is favoured, the influence of e_{var} is weighted with λ to stress this error. Therefore, the total error e is defined as

$$e = e_{euclid} + \lambda e_{var}. \tag{4}$$

λ has to be chosen carefully because it influences the achieved error curve as illustrated in Fig. 4. A low λ value underestimates e_{var} (Fig. 4a) while a high λ value leads to overestimation (Fig. 4b). In both cases only a rising or declining error line can be obtained with no indication of a suitable filter setting. An appropriate λ gives adequate influence to e_{var} and thus helps to create an appropriate error curve (Fig. 4c). Only this error curve may help to identify the required number of coefficients for filtering. Different λ values between 5 and 155 were tested to adequately weight the variance of the signal. A wider range was tested in advance to limit the obtained λ values to 5–155. With regard to using this error size e as a decision criterion for the number of coefficients, a low error is favoured.

2.4.3.3. Statistical analysis. All statistical analyses were performed in R (R Core Team, 2016).

Ideally, all ear tags should result in the same number of required coefficients. Therefore, filter errors for each ear tag with different filter settings were collected. For each λ value, the lowest and highest number of coefficients over all ear tags were registered. Furthermore, the mean and the standard deviation (SD) of all coefficients were calculated. The number of necessary coefficients depends on λ. Therefore, SD functions as a measure for an appropriate λ value. The mean provides the appropriate averaged number of coefficients for all ear tags because the number of coefficients for individual ear tags is normally distributed.

The optimal number of coefficients for individual ear tags may differ from the average number of coefficients. To test whether a lower or higher number of coefficients of the individual filtering results in significantly different filter results, a *t*-test was performed in R. For this purpose, total errors were calculated; firstly, with the average number of coefficients, and secondly, with the individual number of coefficients appropriate for a specific ear tag.

2.5. Accuracy testing before and after filtering

Usability of position data depends on the accuracy of the signal which is compared with the exact position of the respective ear tag. Hence, the stable was measured with a tachymeter using laser technology to determine the distances between walls and pen equipment. The original positions of the ear tags were obtained from the positions measured with tachymeter and then compared with the measured positions from the ear tag. Maalek and Sadeghpour (2013) described specific parameters to test the signal accuracy. For 2-D position data (X, Y coordinates), the distance root mean squared (DRMS), precision, and offset are valuable parameters. In order to rate the filter effect, the collected position measurements were evaluated twice, before and after filtering, thus allowing the capture of the filter effect on the parameters DRMS, precision, and offset.

2.5.1. Distance root mean squared (DRMS)

The accuracy of the measured positions is expressed by DRMS in metres which is an appropriate parameter of the measurement reliability. DRMS (Maalek and Sadeghpour, 2013) is calculated by means of the transmitted and the actual positions:

$$DRMS = \sqrt{\frac{\sum_{i=1}^{n} (x_i - x_{actual})^2}{n} + \frac{\sum_{i=1}^{n} (y_i - y_{actual})^2}{n}}, \tag{5}$$

where n is the total number of pings, x_i and y_i are the single positions i of the measured locations, and x_{actual} and y_{actual} are the actual reference locations. DRMS assumes positive values in metres. A low DRMS value close to 0 indicates very accurate measurements that were tracked near the original position. Nevertheless, under practical conditions such a low value can be rarely obtained due to distraction by metal pen equipment. Thus, values below 1 m are desirable.

2.5.2. Precision

The precision of the transmitted signal compares the standard deviation of the captured positions to their average value. Measurements that conglomerate are more precise and have little deviation, whereas spreading values are not very accurate. Considering the mean value of each axis (X and Y), precision (Maalek and Sadeghpour, 2013) is calculated as

$$Precision = \sqrt{\frac{\sum_{i=1}^{n} (x_i - \bar{x})^2}{n} + \frac{\sum_{i=1}^{n} (y_i - \bar{y})^2}{n}}, \tag{6}$$

where n is the total number of signal points, x_i and y_i are the single positions i of the measured locations, and $\bar{x}$ and $\bar{y}$ are the mean of the measured locations. Precision assumes positive values in metres. As the objective is to obtain precise data, low precision values below 1 m are favoured.

2.5.3. Offset

The mean of the captured locations can deviate from the actual location and, thus, results in an offset from the actual position. The difference between these two dimensions is described by the offset (Maalek and Sadeghpour, 2013):

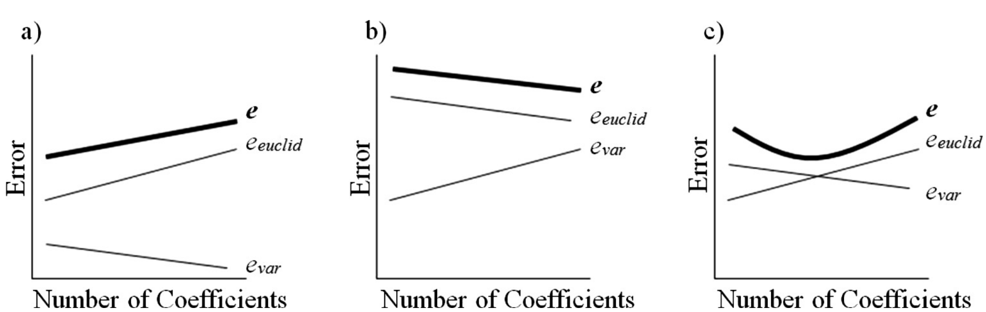

Fig. 4. Exemplary presentation of error curves and impact of λ; (a) λ value is too low, therefore only a rising error line can be obtained; (b) λ value is too high, therefore only a declining error line can be obtained; (c) λ value is optimal, therefore an error curve can be obtained.

Table 1
Overview of data completeness per ear tag in percent.

Ear tag	MPM	Longest	Shortest	1 s	< 10 s	< 20 s	< 30 s	< 60 s	> 60 s
80	12.08%	398	1	56.41%	7.14%	0.89%	–	3.25%	32.31%
81	12.13%	441	1	55.21%	8.16%	0.97%	–	–	35.65%
82	8.65%	13	1	86.69%	9.92%	3.39%	–	–	–
83	8.41%	12	1	85.44%	12.81%	1.75%	–	–	–
110	9.02%	7	1	82.35%	17.65%	–	–	–	–
111	8.66%	7	1	83.57%	16.43%	–	–	–	–
112	8.59%	4	1	89.14%	10.86%	–	–	–	–
113	9.19%	32	1	80.74%	15.01%	–	–	4.25%	–
140	8.96%	14	1	81.04%	13.64%	5.32%	–	–	–
141	8.92%	13	1	83.95%	14.27%	1.78%	–	–	–
142	8.72%	10	1	84.15%	15.85%	–	–	–	–
143	8.82%	12	1	82.94%	13.73%	3.33%	–	–	–
Mean	9.35%	80.25	1	79.30%	12.96%	1.45%	–	0.63%	5.66%

$$Offset = \sqrt{(x_{actual} - \bar{x})^2 + (y_{actual} - \bar{y})^2}, \quad (7)$$

where x_{actual} and y_{actual} are the actual reference position and $\bar{x}$ and $\bar{y}$ are the mean of the measured locations. Offset assumes positive values in metres. Preferably, the measured locations are close to the original position and hence, have a low offset value below 1 m.

3. Results

3.1. Evaluation of data completeness

The error of measurements is described by the missing percentage of measurements (MPM). Overall, roughly 8–12% with a mean of around 9% of pings were lost (Table 1). For all ear tags, the shortest ping loss was 1 s. For 10 out of 12 ear tags, the longest ping losses varied from 4 to 32 s. Only two ear tags showed extreme ping losses of 398 or 441 s, respectively. However, 80–90% of the losses lasted only 1 s. 9 out of the 12 used ear tags (75%) showed consecutive ping losses of less than 20 s.

3.2. Wavelet filter settings

The discrete wavelet transform (DWT) was used to filter the noised signal. Exemplary illustrations of the filter results for one ear tag are shown in Fig. 5, where the grey line reflects the measured signal while the black line shows the filtered signal for the X or Y coordinate, respectively. Fig. 5 displays the entire recorded signal with a length of 6500 s. Therefore, static phases as well as position changes can be found. Arrows indicate the performed position changes while the rectangles highlight some of the captured static positions (see Figs. 1 and 2).

An error size e was calculated to value the results. The influence of different λ values on e_{var} was tested. However, no single ideal λ value, where all standard deviations approximated the minimum, could be detected. The averaged filter settings were settled within a λ range of 105–107 for the X coordinate or 96–100 for the Y coordinate, respectively. The lowest standard deviation of coefficients for the X coordinate was within this λ range indicating that the smallest error occurred with 29 coefficients. For the Y coordinates the lowest standard deviation indicated that the smallest error occurred with 20 coefficients (Fig. 6).

Both above-mentioned λ ranges were evaluated. Exemplarily, the results of the mean λ values (X coordinate: λ = 106; Y coordinate: λ = 98) are shown in Table 2

. The t-test compared the two sets of errors. With a λ of 106, total errors (Table 2) for the X coordinate range between 3.49 m and 4.30 m for the averaged filter settings and between 3.39 m and 4.10 m for individual filter settings. For the X coordinate, the mean of the total errors (Table 2) for the averaged filtering with 3.79 m was not significantly different from the individual filtering with 3.65 m (t-test, p = 0.15). With a λ of 98 for the Y coordinate, total errors (Table 2) ranged between 3.13 m and 3.83 m for the averaged filter settings and between 2.99 m and 3.65 m for individual filter settings. Here again, the mean of the total errors (Table 2) for the averaged filtering with 3.39 m was not significantly different from the individual filtering with 3.27 m (t-test, p = 0.18). A t-test was also performed for the whole λ ranges (X coordinate: 105–107; Y coordinate: 96–100; results not shown). No λ value resulted in significant differences between the mean errors. Therefore, the averaged filter settings were used for filtering and further calculations.

3.3. Accuracy testing before and after filtering

Accuracy of the captured positions was evaluated twice: before and after filtering with the averaged filter settings. The accuracy of the captured data points is described by the distance root mean squared (DRMS) in metres. In total, data were recorded at 34 positions. Before filtering, the accuracy for all measurements was more than 1.2 m and escalated up to 5.2 m with a median of 2.7 m. 35% of the considered positions showed an accuracy of less than 2.0 m (Fig. 7a). Precision as a parameter for the closeness of data points fluctuated between 1.1 m and 2.8 m with a median of 1.4 m for the unfiltered data. Almost 90% of the recorded positions reached a precision below 2.0 m (Fig. 7b). Before

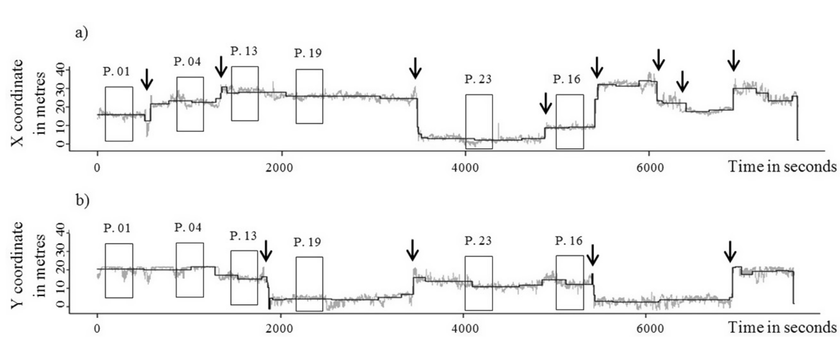

Fig. 5. Exemplary results of discrete wavelet transform with (a) 29 coefficients (X coordinate) and (b) 20 coefficients (Y coordinate) for one ear tag; Arrows indicate position change; Rectangles indicate static positions (e.g. P. 01) according to Figs. 1 and 2.

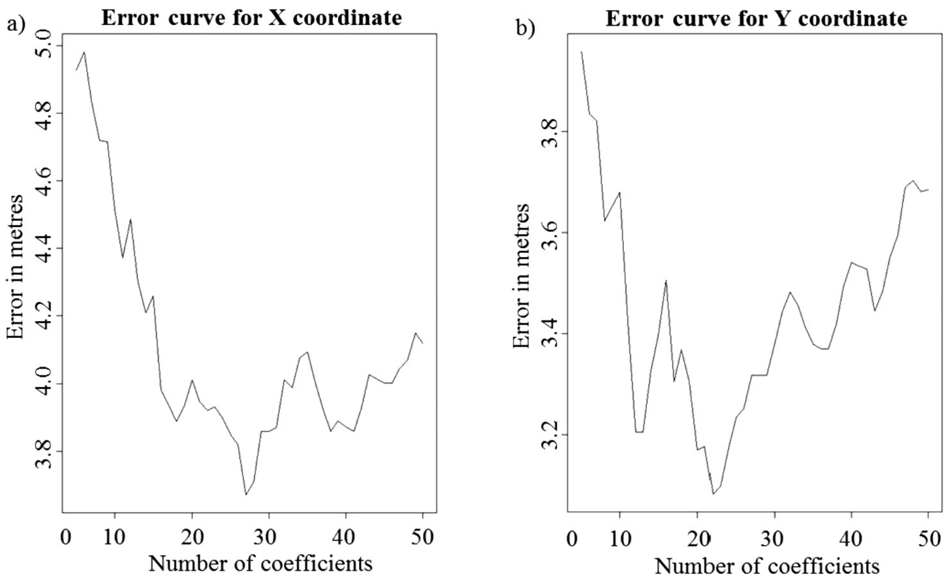

Fig. 6. Error curves for (a) X coordinate filtered with 29 coefficients (λ = 106) and (b) Y coordinate filtered with 20 coefficients (λ = 98).

Table 2
Total errors *e* (see Eq. (4)) in metres calculated with a λ value of 106 (X coordinate) or 98 (Y coordinate), respectively, for significance testing of the averaged and the individual filter settings.

Ear tag	Total error (averaged[a]) in metres		Total error (individual[b]) in metres	
	X	Y	X	Y
80	3.49	3.48	3.39	3.34
81	3.68	3.44	3.66	3.34
82	4.04	3.23	3.74	2.99
83	3.65	3.36	3.49	3.21
110	3.76	3.13	3.68	3.11
111	4.30	3.66	4.10	3.52
112	3.57	3.29	3.53	3.14
113	3.76	3.17	3.57	3.05
140	3.70	3.17	3.56	3.08
141	3.86	3.63	3.67	3.52
142	3.51	3.35	3.49	3.31
143	4.15	3.83	3.92	3.65
Min	3.49	3.13	3.39	2.99
Max	4.30	3.83	4.10	3.65
Mean	3.79	3.39	3.65	3.27

[a] Signal filtered with 29 coefficients for X coordinate and 20 coefficients for Y coordinate.
[b] Signal filtered with number of coefficients that are optimal for the specific ear tag.

filtering, 47% of the considered positions showed an offset to the origin of less than 2.0 m (Fig. 7c). The offset describes the distance between measured and original position. It ranged between 0.07 m and 5.0 m with a median of 2.2 m.

Data filtering resulted in a higher accuracy for measured positions which then ranged between 0.6 m and 4.5 m with a median of 2.0 m. Half of the positions achieved an accuracy of less than 2.0 m after filtering, while 24% of the considered positions (8 positions) were still above a 3 m limit (Fig. 7a). Strong improvement could be obtained for precision. All considered positions ranged between 0 m and 1.5 m after filtering. Even the median decreased from 1.4 m to 0.4 m (Fig. 7b). After filtering the offset ranged between 0.3 m and 4.5 m. 53% of considered positions deviated less than 2.0 m from the origin. However, the median decreased only slightly from 2.2 m to 1.9 m (Fig. 7c).

Besides the accuracy, the correct locating might be of importance for some problems. Therefore, the locating in the correct cubicle, the distance reproduction between ear tags, and the position reproduction of ear tags was evaluated.

Exemplarily, Fig. 8a shows measured positions before and after filtering to evaluate the location in the correct cubicle. Three ear tags were arranged on top of each other to include different heights. There was a large variance between measurements of the same ear tag. All ear tags were located in the correct cubicle after filtering apart from one.

Ear tags located in the same place should reflect the same position. Thus, the position reproduction of ear tags was evaluated (Fig. 8b and c). Comparing simultaneously with consecutively recorded data, it became clear that filtered positions differed to different extents.

Fig. 8d shows the measured positions before and after filtering of three ear tags which lay 0.25 m apart to evaluate the distance reproduction between ear tags. The measured positions showed a high variance. The distance of 0.25 m was not displayed after filtering. Rather, positions of filter results deviated to different extents from the original position and suggested a different order of the ear tags.

4. Discussion

4.1. Evaluation of data completeness

On average 9% of positions were not transmitted. This may be due to signal absorption from water sources or metal pen equipment (Deak et al., 2012; Maalek and Sadeghpour, 2013; Rose, 2015). Further, at least three receivers are required to locate an ear tag. The ear tags send their signal to receivers in clear view. Therefore, localisation may be noised when a person or an animal moves between the ear tag and the receivers. However, the signal is rarely shielded to all directions which is why positions can still be located. For practical application, it has to be kept in mind that sows lying on an ear tag may shield the signal, which may lead to data losses depending on the sow's rest time duration. Also in cow studies sensors that slip out of place or animal head movements led to incorrect positioning (Arcidiacono et al., 2017a, 2017b; Gygax et al., 2007). Finally, battery life may also affect the localisation. Data completeness is important as missing values were inserted and signal length was adjusted for further evaluation. With regard to the subsequent filtering, this was of special importance as the filter result is dependent on the signal length. Thus, a standardised signal length was essential for the comparability of results. The insertion of missing values simplifies the reconstruction of the signal. Accordingly, inserted values do not represent the actual positions of sows but rather suggest possible positions. That is why, especially with longer missing time spans, data distortions may occur. Only two considered ear tags (16%) showed ping losses of more than 60 s. Data of six additional ear tags showed occasional ping losses between 10 s and 60

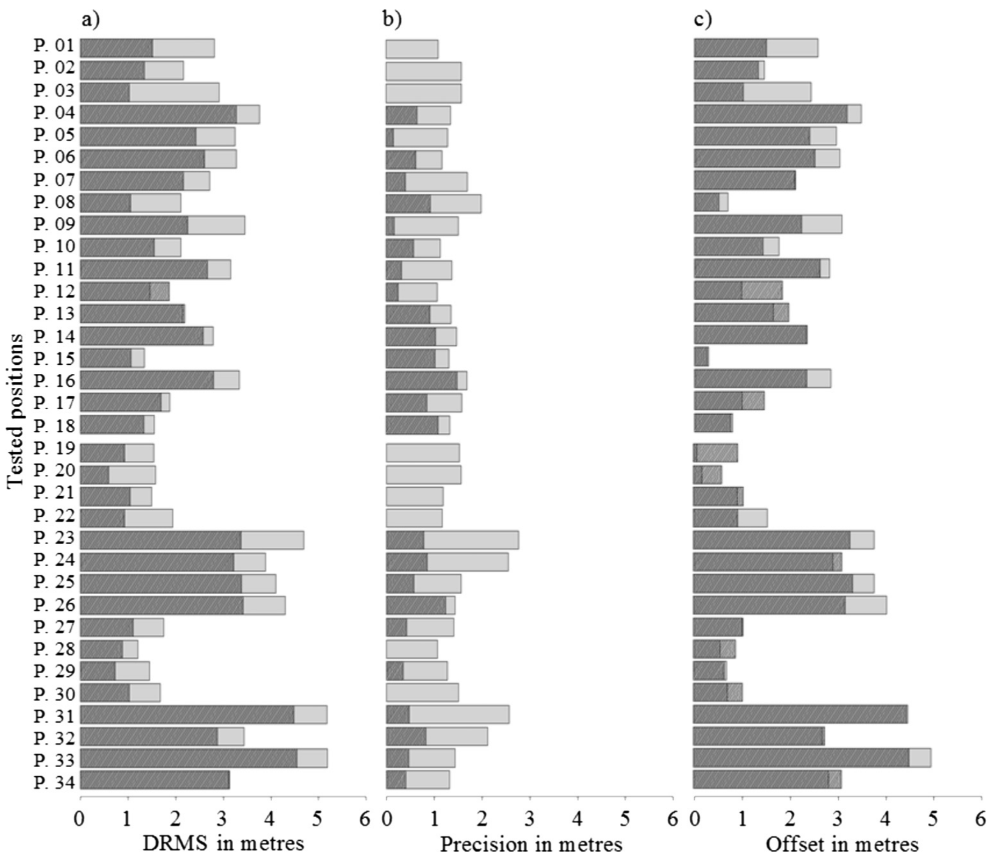

Fig. 7. (a) Accuracy (DRMS), (b) Precision, and (c) Offset of tested positions (P. 01 – P. 34; for explanation see Figs. 1 and 2) before and after filtering; Light bars: Value before filtering; Hatched bars: Value after filtering.

s. Losses of 10 s or more may be regarded as critical for further data evaluation due to the fact that sows may walk approximately 0.7–0.9 m per second (Gregoire et al., 2013; Thorup et al., 2007). As a matter of fact, the covered distance lengthens over time. Long data losses may also include contact with others, stays in specific areas, or phases of inactivity that would not be registered. Real-time location systems may suffer from data losses but compared with video analysis, data collection is more extensive and detailed. Technical solutions may record data over 24 h periods while videos are often evaluated by scan-sampling. In scan-sampling, data is recorded only at predetermined time intervals. Therefore, one has to deal with more extensive data losses. Further, data of only small numbers of animals may be collected to be able to distinguish between the animals. Recently, robust image analysis simplifies video analysis as it helps to detect animal behaviour such as lying, walking, or eating (Porto et al., 2013, 2015; Giancardo et al., 2013; Kashiha et al., 2013; Oczak et al., 2013). However, the problem of recognising single animals still needs to be addressed especially for large groups (Kashiha et al., 2013). Further, Arcidiacono et al. (2017b) compared video analysis with acceleration data and found that acceleration data is superior to video analysis. In this regard, technical solutions with real-time location systems outclass conventional methods such as video analysis. The severity of long ping losses depends on the data usage and the problem under consideration. With regard to epidemiological studies and contact structures, data completeness is very important to capture the contact structure. However, 80% of the ping losses of tested positions were shorter than 10 s. This leads to the conclusion that data completeness is sufficient for further usage to construct social networks, address epidemiological problems, and study animal behaviour concerning the time of day or the length spent in specific sections of the pen. To investigate precise interaction between pigs, such as tail biting, video analysis might be more favourable. However, if the contact structure in large groups of animals should be investigated, RTLS will be the only suitable solution.

4.2. Wavelet filter settings

Metal pen equipment and water sources may lead to noised data (Deak et al., 2012; Maalek and Sadeghpour, 2013; Rose, 2015). The discrete wavelet transform (DWT) is a useful tool to adequately filter noised signals. The presented application of DWT for signal filtering was already described by Madan et al. (2009). As stated by Liò (2003), it is appropriate to assume that only a specific number of the largest wavelet coefficient represents the signal. Small wavelet coefficients are more likely to contain noise (Liò, 2003). Therefore, the appropriate number of required coefficients for an optimal filter result was determined with help of the error size *e*. The results showed that a higher number of coefficients was required for the X coordinate. A higher number of coefficients stands for a less intensive filtering of the X coordinate. Accordingly, this result indicated less noise distorting the signal on this axis. The difference in behaviour between the X and Y coordinate is only minimal and may be system-related. The mean of coefficients over all ear tags indicated that the average number of coefficients for the filtering were 29 (X coordinate) or 20 (Y coordinate) coefficients, respectively. This number of coefficients was sufficient for a signal with a length of 6500 s. When the ear tags are applied to animals, data can be obtained over several days or weeks. With that, also signal length increases. Longer signals may require more coefficients. Also, other activity patterns may influence the required number of coefficients for filtering. When transferring these results to other datasets, this has to be taken into account. Hence, the required number of coefficients must be reinvestigated in subsequent studies.

Besides wavelet filtering, other data optimisation methods can be found in literature. Chen et al. (2013) averaged positions over time units of 10 s, indicating data volume decreases by 10%, which may be necessary to handle large amounts of information. On the other hand, this approach leads to information losses due to the data compression. Oberschätzl et al. (2015) applied cluster analysis methods to assign

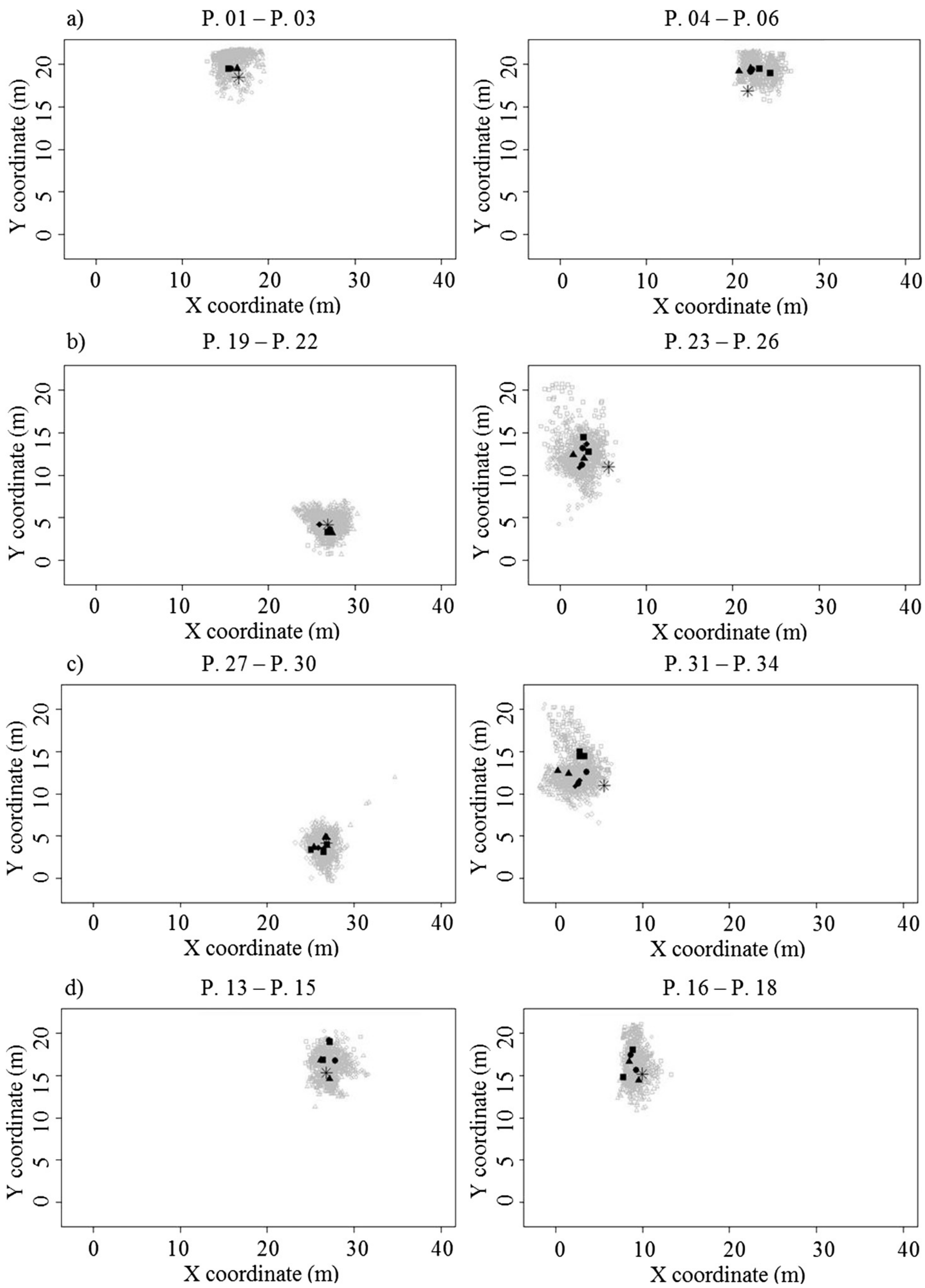

Fig. 8. Unfiltered measurements (blank grey symbols ○△□◇) and filtered positions (filled black symbols ●▲■◆) in comparison to the original position (*); illustrated on the floor map of the gestation unit for selected positions (see Figs. 1 and 2); (a) Experiment 1: 3 ear tags on top of each other according to Fig. 2a; data acquisition points 1.1–1.2 (Fig. 1), (b) Experiment 2: 2 ear tags simultaneously at the same place according to Fig. 2b; data acquisition points 2.1–2.2 (Fig. 1), (c) Experiment 3: 2 ear tags consecutively at the same place according to Fig. 2c; data acquisition points 3.1–3.2 (Fig. 1), (d) Experiment 4: 3 ear tags away from the wall according to Fig. 2d; data acquisition points 4.1–4.2 (Fig. 1).

animals to specific barn areas. They also addressed the problem of information loss because cluster analysis may reduce the data volume by up to 95%. Great influence on usability of compressed data may be the definition of area size as Oberschätzl et al. (2015) stated that small barn areas may not be represented correctly and therefore lead to false results. Further, the activity level of the observed animal species has to be taken into account when compressing data for evaluation. Active animals change their position more often. Here, data compression would lead to tremendous information losses and false records (Oberschätzl et al., 2015). However, sows spend between 45 and 70% of the day lying with single resting phases of up to 7 h (Maselyne et al., 2014; Rolandsdotter et al., 2009). This shows that sows are rather inactive and hence, with regard to adequate sized barn areas and time resolution, cluster analysis may be feasible without great information loss.

The optimal number of coefficients calculated for each individual ear tag differed from each other. The filtering of a single ear tag with a specific number of coefficients may be feasible. But with regard to practical implementation, a common filter setting which can be used for all ear tags is necessary. Therefore, filter results were tested for possible significant differences between the individual and the averaged filter settings. The p-values from the *t*-test were greater than 0.05 (0.15 and 0.18) and therefore not significant. This indicates that the usage of an averaged value for the coefficients is possible because the filter results did not differ significantly. Consequently, an averaged filter setting for all ear tags is sufficient for filtering and necessary for a practical implementation.

4.3. Accuracy testing before and after filtering

With a median accuracy of 2.7 m in the present study, the location system exceeds the manufacturer-declared indoor accuracy of 2.0 m. But after filtering, the median accuracy improved to 2.0 m while half of the recorded data stayed below 2.0 m. The accuracy of Experiment 1 (P. 01 – P. 09) shows that localisation in heights of 0.35 m (P. 02, P. 05, and P. 08) and 0.6 m (P. 03, P. 06, and P. 09) is slightly better than in a height of 0.1 m (Fig. 7a). This may be because walls and other animals may impair clear view between ear tag and receivers and hence, lead to signal distractions. In addition, the used system only delivers the 2-D position. Here, the signal is expected in a default height. Any deviation of the default height may influence the localisation. Data acquisition point 1.2 (P. 04 – P. 06) is less accurate than the positions of data acquisition points 1.1 and 1.3 (P. 01 – P. 03 and P. 07 – P. 09). This may be due to the proximity to the walls of the lying cubicle which might lead to a stronger signal distraction. The Experiments 2 and 3 (P. 19 – P. 34) indicated that ear tags did not substantially influence each other when they are close together. Nevertheless, positions P. 23 – P. 26 and P. 31 – P. 34 of data acquisition points 2.2 and 3.2 showed a lower accuracy than positions of data acquisition points 2.1 and 3.1 (P. 19 – P. 22 and P. 27 – P. 30). These positions were surrounded by metal pen equipment and presumably suffered from strong signal disturbances which was demonstrated by a low accuracy. The results of Experiment 4 (P. 10 – P. 18) suggest that close proximity to the walls influenced localisation negatively (Fig. 7a). Further, the distance between the three ear tags at data acquisition points 4.1–4.3 was not reflected by the system (Fig. 8d). Different research topics require varying degrees of accuracy. Issues of special interest are the interaction between animals (Büttner et al., 2015a, 2015b; Oberschätzl et al., 2015; Abeyesinghe et al., 2013; Croft et al., 2005; Durrell et al., 2004), usual location areas (Chen et al., 2013, 2014; Oberschätzl et al., 2013; Gygax et al., 2007), the time of day and length spent in different sections (Gygax et al., 2007; Galindo and Broom, 2000; Óden et al., 2000), or epidemiological studies (Chen et al., 2013, 2014; Duncan et al., 2012; Corner et al., 2003). Social interactions and contact structures between animals require a high accuracy to reveal proximity between animals. Gygax et al. (2007) used the recorded position data to detect proximity between cows. Animals were recognised to be neighbours when their distance was 2.0 m or less. Chen et al. (2014) constructed contact networks considering an animal distance of 0.3 m. The system accuracy must be very precise to detect proximity between animals. The tested system only delivers the 2-D position which is why the height marginally influences the localisation of the ear tags. Additionally, it must be considered that pig stalls include a lot of metal pen equipment which can lead to signal distraction or absorption. Thus, the proximity between ear tags was not always adequately reflected by the system used in the present study as illustrated in Fig. 8. Nevertheless, exact localisation of animals may be less important with regard to their stays in specific housing areas. This was also shown by Oberschätzl et al. (2015), who considered aggregated positions. Most ear tags were located in the correct cubicle and therefore allowed the consideration of the spatial distance between animals. Further, accuracy is less important if only the activity of the animals is to be evaluated.

In addition to the accuracy, precision and offset was calculated. These two parameters influence the accuracy. Results showed a median precision of 1.4 m before filtering which could improve to 0.4 m after filtering. Imprecise data resulted from noised measurements and can be handled quite well with a wavelet filter which reduces the variance. The median offset was 2.2 m before filtering but did not improve much afterwards (1.9 m). In fact, in several cases the offset even increased slightly. The offset may result e.g. from incorrect calibration or drift effects. These errors severely distort the signal and are hard to handle with filtering. Consequently, the wavelet filtering seems to have no major positive effect on the offset parameter. Fig. 8 suggests that measured positions drift towards the walls. It can only be speculated whether this is due to incorrect calibration or not. So finally, this parameter seems to be the main reason why the accuracy does still not drop below the 2.0 m limit. Furthermore, the system did not consider the height of the ear tags when calculating the current position. This may have an influence on the positioning. Thereby, it has to be taken into account that the system was tested under practical conditions. This means that metal pen equipment or water sources like the animals themselves may shield the signal (Deak et al., 2012; Maalek and Sadeghpour, 2013; Rose, 2015) and thus, result in a less accurate positioning.

In the present study, only the accuracy of static positions was considered. Due to the fact that sows rest 45–70% of the day (Maselyne et al., 2014; Rolandsdotter et al., 2009), the accuracy of static positions was regarded as more important for disease transmission. The probability of disease transmission rises with contact length and therefore, rest times play a major role. In contrast, when sows pass each other in the corridor, contact duration is only about 5 s (Jensen, 1980).

It shows that under practical conditions the real-time location system faces multi-factorial influences such as metal, water, animals, and impacts caused by the system itself. Nevertheless, data collected with the help of this system is suitable for subsequent studies as stated above.

5. Conclusions

The social structure and possible disease transmission paths between sows may be uncovered with the help of real-time location systems. Thus, the aim of the present study was to specify the accuracy of a real-time location system under practical conditions for later application. An averaged filter setting which can be used for all ear tags could be detected. Optimal filter results for the tested signal could be obtained with 29 coefficients for the X coordinate and 20 coefficients for the Y coordinate. With that, the accuracy of the system could be improved from 2.7 m to 2.0 m. Further, the noise was suppressed, which can be underlined by a strong decrease in precision from 1.4 m to 0.4 m. Knowledge concerning the system accuracy is of great importance for subsequent epidemiological and social network studies.

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Appendix A. Supplementary material

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.compag.2017.09.020.

References

Abeyesinghe, S.M., Drewe, J.A., Asher, L., Wathes, C.M., Collins, L.M., 2013. Do hens have friends? Appl. Anim. Behav. Sci. 143 (1), 61–66.
Arcidiacono, C., Porto, S.M.C., Mancino, M., Cascone, G., 2017a. A threshold-based algorithm for the development of inertial sensor-based systems to perform real-time cow step counting in free-stall barns. Biosys. Eng. 153, 99–109.
Arcidiacono, C., Porto, S.M.C., Mancino, M., Cascone, G., 2017b. Development of a threshold-based classifier for real-time recognition of cow feeding and standing behavioural activities from accelerometer data. Comput. Electron. Agric. 134, 124–134.
Banhazi, T.M., Lehr, H., Black, J.L., Crabtree, H., Schofield, P., Tscharke, M., Berckmans, D., 2012. Precision livestock farming: an international review of scientific and commercial aspects. Int. J. Agric. Biol. Eng. 5 (3), 1–9.
Bigras-Poulin, M., Barfod, K., Mortensen, S., Greiner, M., 2007. Relationship of trade patterns of the Danish swine industry animal movements network to potential disease spread. Prev. Vet. Med. 80 (2–3), 143–165.
Bressers, H.P.M., Te Brake, J.H.A., Engel, B., Noordhuizen, J.P.T.M., 1993. Feeding order of sows at an individual electronic feed station in a dynamic group-housing system. Appl. Anim. Behav. Sci. 36 (2–3), 123–134.
Büttner, K., Krieter, J., Traulsen, A., Traulsen, I., 2013a. Static network analysis of a pork supply chain in Northern Germany - characterisation of the potential spread of infectious diseases via animal movements. Prev. Vet. Med. 110 (3), 418–428.
Büttner, K., Krieter, J., Traulsen, I., 2013b. Characterisation of contact structures for the spread of infectious diseases in a pork supply chain in Northern Germany by dynamic network analysis of yearly and monthly networks. Transboundary Emerg. Dis. 62, 188–199.
Büttner, K., Scheffler, K., Czycholl, I., Krieter, J., 2015a. Network characteristics and development of social structure of agonistic behaviour in pigs across three repeated rehousing and mixing events. Appl. Anim. Behav. Sci. 168, 24–30.
Büttner, K., Scheffler, K., Czycholl, I., Krieter, J., 2015b. Social network analysis -

centrality parameters and individual network positions of agonistic behavior in pigs over three different age levels. SpringerPlus 4, 185.
Chen, S., Sanderson, M.W., White, B.J., Amrine, D.E., Lanzas, C., 2013. Temporal-spatial heterogeneity in animal-environment contact: implications for the exposure and transmission of pathogens. Sci. Rep. 3, 3112.
Chen, S., White, B.J., Sanderson, M.W., Amrine, D.E., Ilany, A., Lanzas, C., 2014. Highly dynamic animal contact network and implications on disease transmission. Sci. Rep. 4, 4472.
Ciccolini, M., Dahl, J., Chase-Topping, M.E., Woolhouse, M.E.J., 2012. Disease transmission on fragmented contact networks: livestock-associated Methicillin-resistant Staphylococcus aureus in the Danish pig-industry. Epidemics 4 (4), 171–178.
Clarkson, J.A., Adams, C.R., 1933. On definitions of bounded variation for functions of two variables. Trans. Am. Math. Soc. 35 (4), 824–854.
Corner, L.A.L., Pfeiffer, D.U., Morris, R.S., 2003. Social-network analysis of Mycobacterium bovis transmission among captive brushtail possums (Trichosurus vulpecula). Prev. Vet. Med. 59 (3), 147–167.
Cornou, C., Lundbye-Christensen, S., Kristensen, A.R., 2011. Modelling and monitoring sows' activity types in farrowing house using acceleration data. Comput. Electron. Agric. 76 (2), 316–324.
Croft, D.P., James, R., Ward, A.J.W., Botham, M.S., Mawdsley, D., Krause, J., 2005. Assortative interactions and social networks in fish. Oecologia 143 (2), 211–219.
Deak, G., Curran, K., Condell, J., 2012. A survey of active and passive indoor localisation systems. Comput. Commun. 35 (16), 1939–1954.
Deza, M.M., Deza, E., 2016. Encyclopedia of Distances. Springer, Berlin/Heidelberg, Germany.
Duncan, A.J., Gunn, G.J., Lewis, F.I., Umstätter, C., Humphry, R.W., 2012. The influence of empirical contact networks on modelling diseases in cattle. Epidemics 4 (3), 117–123.
Durrell, J.L., Sneddon, I.A., O'Connell, N.E., Whitehead, H., 2004. Do pigs form preferential associations? Appl. Anim. Behav. Sci. 89 (1–2), 41–52.
Exadaktylos, V., Silva, M., Aerts, J.M., Taylor, C.J., Berckmans, D., 2008. Real-time recognition of sick pig cough sounds. Comput. Electron. Agric. 63 (2), 207–214.
Ferrari, S., Silva, M., Guarino, M., Aerts, J.M., Berckmans, D., 2008. Cough sound analysis to identify respiratory infection in pigs. Comput. Electron. Agric. 64 (2), 318–325.
Fraser, D., Phillips, P.A., Thompson, B.K., Tennessen, T., 1991. Effect of straw on the behaviour of growing pigs. Appl. Anim. Behav. Sci. 30 (3–4), 307–318.
Freson, L., Godrie, S., Bos, N., Jourquin, J., Geers, R., 1998. Validation of an infra-red sensor for oestrus detection of individually housed sows. Comput. Electron. Agric. 20 (1), 21–29.
Frost, A.R., Schofield, C.P., Beaulah, S.A., Mottram, T.T., Lines, J.A., Wathes, C.M., 1997. A review of livestock monitoring and the need for integrated systems. Comput. Electron. Agric. 17 (2), 139–159.
Galindo, F., Broom, D.M., 2000. The relationships between social behaviour of dairy cows and the occurrence of lameness in three herds. Res. Vet. Sci. 69 (1), 75–79.
Georg, H., Bender, S., Ude, G., 2012. Feasibility test of a positioning system to measure grazing behaviour of goat kids. Landtechnik 67 (2), 136–139.
Giancardo, L., Sona, D., Huang, H., Sannino, S., Manago, F., Scheggia, D., Papaleo, F., Murino, V., 2013. Automatic visual tracking and social behaviour analysis with multiple mice. PLoS ONE 8 (9), e74557.
Gregoire, J., Bergeron, R., D'Allaire, S., Meunier-Salaun, M.-C., Devillers, N., 2013. Assessment of lameness in sows using gait, footprints, postural behaviour and foot lesion analysis. Animal 7 (7), 1163–1173.
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. Comput. Electron. Agric. 56 (1), 23–33.
Haar, A., 1910. Zur Theorie der orthogonalen Funktionensysteme. Math. Ann. 63, 331–371.
Jensen, P., 1980. An ethogram of social interaction patterns in group-housed dry sows. Appl. Anim. Ethol. 6 (4), 341–350.
Kashiha, M., Bahr, C., Ott, S., Moons, C.P.H., Niewold, T.A., Ödberg, F.O., Berckmans, D., 2013. Automatic identification of marked pigs in a pen using image pattern recognition. Comput. Electron. Agric. 93, 111–120.
Kruse, S., Traulsen, I., Salau, J., Krieter, J., 2011. A note on using wavelet analysis for disease detection in lactating sows. Comput. Electron. Agric. 77 (1), 105–109.
Langley, R.B., 1999. Dilution of precision. GPS World 10 (5), 52–59.
Lentz, H.H.K., Koher, A., Hovel, P., Gethmann, J., Sauter-Louis, C., Selhorst, T., Conraths, F.J., 2016. Disease spread through animal movements: a static and temporal network analysis of pig trade in Germany. PLoS ONE 11 (5), e0155196.
Lentz, H.H.K., Konschake, M., Teske, K., Kasper, M., Rother, B., Carmanns, R., Petersen, B., Conraths, F.J., Selhorst, T., 2011. Trade communities and their spatial patterns in the German pork production network. Prev. Vet. Med. 98 (2–3), 176–181.
Liò, P., 2003. Wavelets in bioinformatics and computational biology: state of art and perspectives. Bioinformatics 19 (1), 2–9.
Maalek, R., Sadeghpour, F., 2013. Accuracy assessment of Ultra-Wide Band technology in tracking static resources in indoor construction scenarios. Automat. Constr. 30, 170–183.
Madan, R., Singh, S.K., Jain, N., 2009. Signal filtering using discrete wavelet transform. Int. J. Recent Trends Eng. 2 (3), 96–98.
Mahfouz, M.R., Zhang, C., Merkl, B.C., Kuhn, M.J., Fathy, A.E., 2008. Investigation of high-accuracy indoor 3-D positioning using UWB technology. IEEE Trans. Microw. Theory Tech. 56 (6), 1316–1330.
Maselyne, J., Saeys, W., de Ketelaere, B., Briene, P., Millet, S., Tuyttens, F., van Nuffel, A., 2014. How do fattening pigs spent their day? In: Proceedings of the 6th International Conference in the Assessment of Animal Welfare at Farm and Group Level, 157.
Matthews, S.G., Miller, A.L., Clapp, J., Plotz, T., Kyriazakis, I., 2016. Early detection of health and welfare compromises through automated detection of behavioural changes in pigs. Vet. J. 217, 43–51.
Morris, M., 1993. Epidemiology and social networks: modeling structured diffusion. Sociol. Method. Res. 22 (1), 99–126.
Newman, M.E.J., 2010. Networks: An Introduction. Oxford University Press Inc., New York.
Oberschätzl, R., Haidn, B., Harms, J., Peis, R., Stitzelberger, I., Rose, T., Bernhardt, H., 2013. Automated recording of behaviour of dairy cows a comparison of different technical approaches. Landtechnik 68 (8), 400–405.
Oberschätzl, R., Haidn, B., Peis, R., Kulpi, F., Völkl, C., 2015. Validation of automated processed position data for assessing dairy cow behaviour. Landtechnik 70 (1), 3–8.
Oczak, M., Ismayilova, G., Costa, A., Viazzi, S., Sonoda, L.T., Fels, M., Bahr, C., Hartung, J., Guarino, M., Berckmans, D., Vranken, E., 2013. Analysis of aggressive behaviours of pigs by automatic video recordings. Comput. Electron. Agric. 99, 209–217.
Óden, K., Vestergaard, K.S., Algers, B., 2000. Space use and agonistic behaviour in relation to sex composition in large flocks of laying hens. Appl. Anim. Behav. Sci. 67, 307–320.
Ostersen, T., Cornou, C., Kristensen, A.R., 2010. Detecting oestrus by monitoring sows' visits to a boar. Comput. Electron. Agric. 74 (1), 51–58.
Pluym, L.M., Maes, D., Vangeyte, J., Mertens, K., Baert, J., van Weyenberg, S., Millet, S., van Nuffel, A., 2013. Development of a system for automatic measurements of force and visual stance variables for objective lameness detection in sows: SowSIS. Biosys. Eng. 116 (1), 64–74.
Porto, S.M.C., Arcidiacono, C., Anguzza, U., Cascone, G., 2013. A computer vision-based system for the automatic detection of lying behaviour of dairy cows in free-stall barns. Biosys. Eng. 115 (2), 184–194.
Porto, S.M.C., Arcidiacono, C., Anguzza, U., Cascone, G., 2015. The automatic detection of dairy cow feeding and standing behaviours in free-stall barns by a computer vision-based system. Biosys. Eng. 133, 46–55.
Porto, S.M.C., Arcidiacono, C., Cascone, G., Anguzza, U., Barbari, M., Simonini, S., 2012. Validation of an active RFID-based system to detect pigs housend in pens. J. Food Agric. Environ. 10 (2), 468–472.
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. Comput. Electron. Agric. 108, 221–229.
Pourvoyeur, K., Stelzer, A., Gassenbauer, G., 2006. The local position measurement system lpm used for cow tracking. In: IEEE International Conference on Multisensor Fusion and Integration for Intelligent Systems, pp. 536–540.
R Core Team, 2016. R: A Language and Environment for Statistical Computing. R Foundation for Statistical Computing, Vienna, Austria.
Reimert, I., Bolhuis, J.E., Kemp, B., Rodenburg, T.B., 2013. Indicators of positive and negative emotions and emotional contagion in pigs. Physiol. Behav. 109, 42–50.
Reiner, G., Hübner, K., Hepp, S., 2009. Suffering in diseased pigs as expressed by behavioural, clinical and clinical–chemical traits, in a well defined parasite model. Appl. Anim. Behav. Sci. 118 (3–4), 222–231.
Rolandsdotter, E., Westin, R., Algers, B., 2009. Maximum lying bout duration affects the occurrence of shoulder lesions in sows. Acta Vet. Scand. 51 (1), 44.
Rose, T., 2015. Real-time Location System SERIES 7000 from Ubisense for Behavioural Analysis in Dairy Cows. Dissertation. Christian-Albrechts-University Kiel, Kiel.
Samarakone, T.S., Gonyou, H.W., 2009. Domestic pigs alter their social strategy in response to social group size. Appl. Anim. Behav. Sci. 121 (1), 8–15.
Scheel, C., Traulsen, I., Auer, W., Müller, K., Stamer, E., Krieter, J., 2017. Detecting lameness in sows from ear tag-sampled acceleration data using wavelets. Animal 1–8.
Špinka, M., 2012. Social dimension of emotions and its implication for animal welfare. Appl. Anim. Behav. Sci. 138 (3), 170–181.
Thorup, V.M., Tøgersen, F.A., Jorgensen, B., Jensen, B.R., 2007. Biomechanical gait analysis of pigs walking on solid concrete floor. Animal 1 (5), 708–715.
Traulsen, I., Breitenberger, S., Auer, W., Stamer, E., Müller, K., Krieter, J., 2016. Automatic detection of lameness in gestating group-housed sows using positioning and acceleration measurements. Animal 10 (6), 970–977.
van Duijkeren, E., Ikawaty, R., Broekhuizen-Stins, M.J., Jansen, M.D., Spalburg, E.C., de Neeling, A.J., Allaart, J.G., van Nes, A., Wagenaar, J.A., Fluit, A.C., 2008. Transmission of methicillin-resistant Staphylococcus aureus strains between different kinds of pig farms. Vet. Microbiol. 126 (4), 383–389.
Wathes, C.M., Kristensen, H.H., Aerts, J.M., Berckmans, D., 2008. Is precision livestock farming an engineer's daydream or nightmare, an animal's friend or foe, and a farmer's panacea or pitfall? Comput. Electron. Agric. 64 (1), 2–10.
Zhang, D., Xia, F., Yang, Z., Yao L., Zhao, W., 2010. Localization Technologies for Indoor Human Tracking. In: 5th International Conference on Future Information Technology (FutureTech) 2010, pp. 1–6.