Automatic detection of mounting behaviours among pigs using image analysis

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Abstract

Excessive mounting behaviours amongst pigs cause a high risk of poor welfare, arising from skin lesions, lameness and stress, and economic losses from reduced performance. The aim of this study was to develop a method for automatic detection of mounting events amongst pigs under commercial farm conditions by means of image processing. Two pens were selected for the study and were monitored for 20 days by means of top view cameras. The recorded video was then visually analysed for selecting mounting behaviours, and extracted images from the video files were subsequently used for image processing. An ellipse fitting technique was applied to localize pigs in the image. The intersection points between the major and minor axis of each fitted ellipse and the ellipse shape were used for defining the head, tail and sides of each pig. The Euclidean distances between head and tail, head and sides, the major and minor axis length of the fitted ellipse during the mounting were utilized for development of an algorithm to automatically identify a mounting event. The proposed method could detect mounting events with high level of sensitivity, specificity and accuracy, 94.5, 88.6 and 92.7%, respectively. The results show that it is possible to use machine vision techniques in order to automatically detect mounting behaviours among pigs under commercial farm conditions.

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1. Introduction

Mounting behaviours in pigs can be defined as when a pig lifts its two front legs and puts the two legs or its sternum on any part of the body or head of another pig; the mounted pig may stand or sit down during the mounting or move away to avoid being mounted (Hintze et al., 2013). Both male and female pigs perform mounting behaviour, with different frequencies (Rydhmer et al., 2006; Hemsworth and Tilbrook, 2007), and the behaviour occurs more frequently in overcrowded conditions (Faucitano, 2001). Mounting behaviour amongst pigs can increase the risk of injuries, such as bruises and damage to the skin when pigs mount one another and scratch the back with the claws of the forelimbs (Faucitano, 2001; Harley et al., 2014), and lameness or leg fractures (Rydhmer et al., 2004). These injuries and the general unrest in the group can have considerable negative economic consequences (Rydhmer et al., 2006). Although the level of activity declines with increasing weight, mounting behaviour (Thomsen et al., 2012), and skin lesions and lameness (Teixeira and Boyle, 2014), happen during the entire growing period of pigs. Investigations of the mounting behaviour of pigs have already been made in different studies. However, these have generally been carried out using direct visual observations to sample behaviour under experimental conditions, reflected by a small number of pigs in the pen. Hintze et al. (2013) developed an ethogram of different types of mounting behaviours and their consequences. According to their classification, sexual mounts were longer than non-sexual mounts and were associated with more screaming, which is an indicator of stress and reduced welfare in pigs, by the mounted animal.

Image processing techniques have increasingly been applied to pig farm management in recent years and different studies have been carried out on the development of machine vision tools for pig production. By using a CCD camera the amount of pigs' water usage was estimated automatically with an accuracy of 92% based on their head distances to the drinking nipples in the images (Kashiha et al., 2013). Pig herds have been monitored using the optical flow method developed by Gronskyte et al. (2015) for obtaining undesirable events in the slaughterhouse with high overall sensitivity and specificity. Lu et al. (2016) proposed automatic weight estimation of pigs using image processing systems. In order to identify aggressive behaviours among pigs, motion history features have been applied (Viazzi et al., 2014) resulting in an overall high accuracy and sensitivity. Thermal comfort and lying patterns of groups of pigs have also been investigated with a high degree of accuracy by applying image processing techniques (Shao and Xin, 2008; Costa et al., 2014; Nasirahmadi et al., 2015). Recently some more state-of-art image capture methods have been applied in farms in order to improve animal welfare and monitor performance. A Vicon 3D optoelectronic motion analysis system and the Kinect motion sensor have been used for pig lameness detection (Stavrakakis et al., 2015) and the proposed method could distinguish the sound from lame pigs. For estimation the weight of pigs (Kongsro, 2014) and broilers (Mortensen et al., 2016) 3D Kinect cameras have been used. Furthermore, backfat thickness of Holstein-Friesian cows was estimated using a time-to-flight camera by Weber et al. (2014).

Every year approximately 100 million male piglets are castrated in the EU countries to control risk of boar taint and undesirable male behaviours. Surgical castration is a painful and stressful event (Prunier et al., 2006; Hintze et al., 2013), and its abolition is currently being proposed. If systems with entire male pigs are adopted in consequence, employing an automated machine vision method as a non-contact way for monitoring mounting behaviours in pig farms could help to inform farm managers about the number of mounting events and identify pens requiring intervention. It would also facilitate large scale research into methods to reduce this behavioural problem. A method using low cost CCTV cameras would be more economically acceptable for farm mangers than one requiring investment in expensive high resolution cameras. However, no studies have yet been done on the topic of automated detection of mounting and the feasibility of a low-cost system for this requires evaluation. Hence, the main object of this research was to develop an automatic method for detection of mounting behaviours among pigs under commercial pig farm conditions by means of machine vison techniques and development of image analysis algorithms.

2. Material and methods

2.1. Animal and data collection

The study was carried out at a commercial pig farm in the UK and started after placement of pigs in the pen at about 30 kg live weight. A 20 day period of data collection was used to generate sufficient occurrences of mounting behaviour. Each pen had a dimension of 6.75 m wide × 3.10 m long, with a fully slatted floor, and contained 22 - 23 pigs of mixed gender (entire males or females). All pens were equipped with a liquid feeding trough and one drinking nipple. During the experiment lights were switched on and video recording of the pigs in two of the pens were made. Each research pen was equipped with a CCVT camera (Sony RF2938, EXview HAD CCD, Board lens 3.6 mm, 90^{o}, Gyeonggi-do, South Korea) which was located centrally at 4.5 meters above the ground and pointing directly downward to get a top view. Video images from the cameras were recorded simultaneously for 24 h during the day and night and stored in the hard disk of a PC using Geovision software (Geovision Inc. California, USA) with a frame rate of 30 fps, at a resolution of 640 × 480 pixels. After downloading the recorded data, the video files were directly observed and labelled in order to evaluate peak times of mounting activity (Hintze et al., 2013). A sufficient number of occurrences of the behaviour for testing the automated approach were obtained using five days of 24 h activity selected from the available sample. Two periods were selected (2 h between 09:30 to 11:30 AM; 3 h between 14:30 to 17:30 PM) for each day and pen, during which the number of mounting events was increased compared to other periods. The selected video files were then used for extracting frames for further processing.

2.2. Image processing

In this study CCTV cameras were used, and distortions are common for the low-end lenses of such cameras (Geys and Gool, 2007）. In order to remove barrel distortion in the images, camera calibration was carried out using the ‘Camera Calibration Toolbox’ of MATLAB® (the Mathworks Inc., Natick, MA, USA) and 25 extracted images of a pattern plane were taken in different orientations for each camera (Wang et al., 2007) and projected on the pen surface. The extracted image samples used for the mounting analysis were subjected to a four-step image processing (Fig. 1).

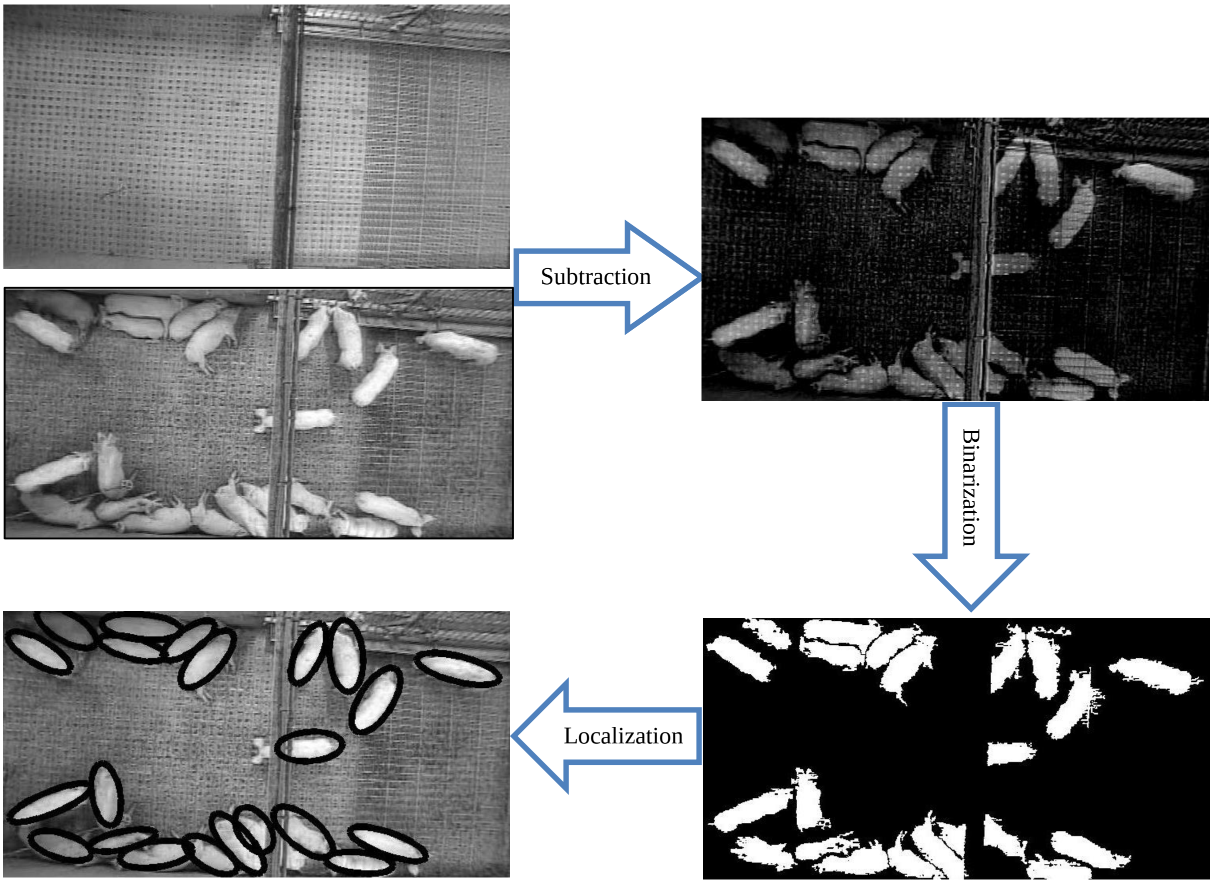

Fig.1. Image processing steps in this study; background (top left), grey image (middle left), subtracted image (top right), binary image (down right) and fitted ellipse (down left).

First step: in order to extract foreground objects (pigs) from the background (pen), a background subtraction method was used.

Second step: a global threshold was applied using Otsu's method (Otsu, 1979) and the threshold was used to convert the greyscale image into a binary image.

Third step: disk structure of erosion and dilation for smoothing the edges was used, and then small objects were removed from images by applying a morphological closing operator (Gonzalez and Woods, 2007).

Forth step: to localize each pig body as an image, an ellipse fitting algorithm was applied (O'Leary, 2004; Nasirahmadi et al., 2015) and ellipse parameters such as ''major axis length”, ‘‘minor axis length”, ‘‘orientation” and ‘‘centroid” were calculated for all fitted ellipses.

2.3. Mounting behaviour detection

The detection rule for pig mounting events in frame sequences is based on distance between pigs, as normally a mounting pig gets close to another pig and then lifts its two front legs and puts them on any part of the recipient or mounted pig (Fig. 2). The mounted pig may stand, sit down or run away, and the duration of mounting can be short (<1s), medium (1-10s) or long (>10-60s) (Hintze et al., 2013). Fig. 2 illustrates a video sequence for a mounting event in a pen, where in frames (f1-f2) the distance between two pigs (mounting and mounted) became less; this distance could be between the centre of two pigs or the head of one pig to the tail of the next one. The mounting event happened in frames (f3-f5), in frame (f6) the mounting/mounted pig moved away and the event finished.

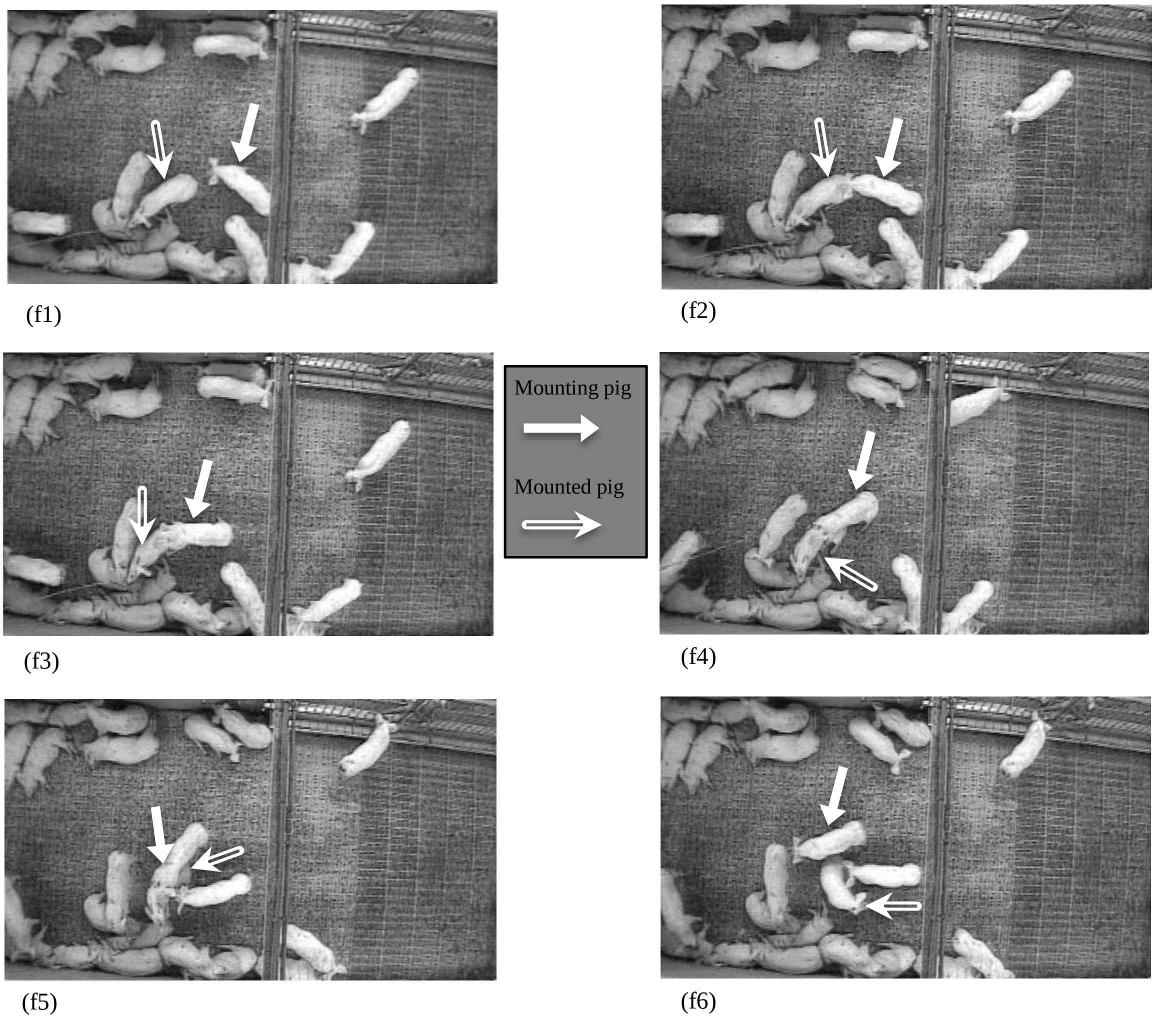

Fig.2. Mounting behaviour in pig. (f1- f2) getting close, (f3-f5) mounting happened, (f6) getting away/ mounting finished.

In order to find the distance between two pigs in a mounting event, it was necessary to identify the head, tail and two sides of pigs. As a tool, analysis of the body contour of a pig was suggested by Kashiha et al. (2013), but in this study the long distance from the lens (camera) to the object (pig), low quality of images and the background noise made the method inaccurate.

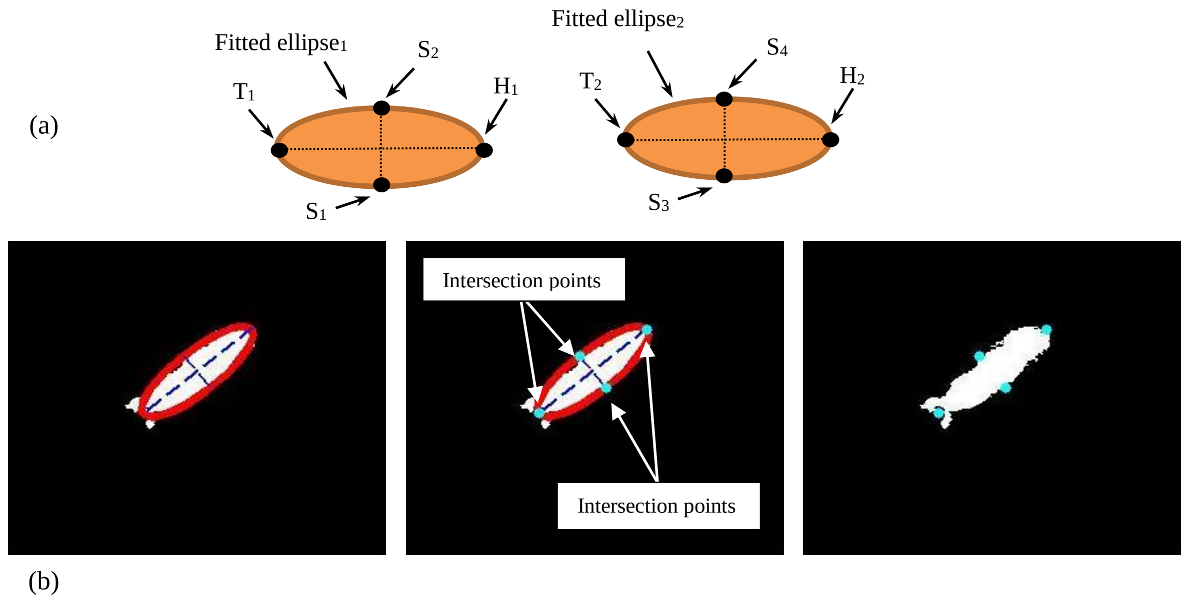

Fig.3. Intersection points of major and minor axis and ellipse for finding the position of head, tail and sides in pigs. (a); T,H and S in two fitted ellipses, (b); the T, H and S in a pig in binary image.

Therefore, in this work, the intersections of the major and minor axis with the ellipse have been considered as tail/head and sides respectively (Fig. 3), named as T, H, S and then the Euclidean distance (Ed) $(Ed\ (H_i, T_j)) = \sqrt{\sum_{i=1}^{n}(H_i - T_i)^2}$ and $(Ed\ (H_i, S_j)) = \sqrt{\sum_{i=1}^{n}(H_i - S_i)^2}$ of each pair calculated as follows:

Matrix of head and/or tail for n pigs (T, H): $$\begin{bmatrix} T_1 & H_1 \\ T_2 & H_2 \\ . & . \\ . & . \\ . & . \\ . & . \\ . & . \\ . & . \\ T_{n-1} & H_{n-1} \\ T_n & H_n \end{bmatrix} \quad (1)$$

Matrix of pig sides for n pigs (S, S): $$\begin{bmatrix} S_1 & S_2 \\ S_3 & S_4 \\ . & . \\ . & . \\ . & . \\ . & . \\ . & . \\ . & . \\ S_{2n-3} & S_{2n-2} \\ S_{2n-1} & S_{2n} \end{bmatrix} \quad (2)$$

$$\xrightarrow{(Eq.1)} Ed(T_1, \begin{bmatrix} H_2 \\ H_3 \\ \cdot \\ \cdot \\ H_{n-1} \\ H_n \end{bmatrix}), Ed(T_2, \begin{bmatrix} H_1 \\ H_3 \\ \cdot \\ \cdot \\ H_{n-1} \\ H_n \end{bmatrix}) \;....\; Ed(T_n, \begin{bmatrix} H_1 \\ H_2 \\ \cdot \\ \cdot \\ H_{n-2} \\ H_{n-1} \end{bmatrix}) \qquad (3)$$

$$\xrightarrow{(Eq.1)} Ed(T_1, \begin{bmatrix} T_2 \\ T_3 \\ \cdot \\ \cdot \\ T_{n-1} \\ T_n \end{bmatrix}), Ed(T_2, \begin{bmatrix} T_1 \\ T_3 \\ \cdot \\ \cdot \\ T_{n-1} \\ T_n \end{bmatrix}) \;....\; Ed(T_n, \begin{bmatrix} T_1 \\ T_2 \\ \cdot \\ \cdot \\ T_{n-2} \\ T_{n-1} \end{bmatrix}) \qquad (4)$$

$$\xrightarrow{(Eq.1)} Ed(H_1, \begin{bmatrix} H_2 \\ H_3 \\ \cdot \\ \cdot \\ H_{n-1} \\ H_n \end{bmatrix}), Ed(H_2, \begin{bmatrix} H_1 \\ H_3 \\ \cdot \\ \cdot \\ H_{n-1} \\ H_n \end{bmatrix}) \;....\; Ed(H_n, \begin{bmatrix} H_1 \\ H_2 \\ \cdot \\ \cdot \\ H_{n-2} \\ H_{n-1} \end{bmatrix}) \qquad (5)$$

$$\xrightarrow{(Eq.1\ and\ 2)} Ed(T_1, \begin{bmatrix} S_3 \\ S_4 \\ \cdot \\ \cdot \\ S_{2n-1} \\ S_{2n} \end{bmatrix}), Ed(T_2, \begin{bmatrix} S_1 \\ S_2 \\ \cdot \\ \cdot \\ S_{2n-1} \\ S_{2n} \end{bmatrix}) \;....\; Ed(T_n, \begin{bmatrix} S_1 \\ S_2 \\ \cdot \\ \cdot \\ S_{2n-3} \\ S_{2n-2} \end{bmatrix}) \qquad (6)$$

$$\xrightarrow{(Eq.1\ and\ 2)} Ed(H_1, \begin{bmatrix} S_3 \\ S_4 \\ \cdot \\ \cdot \\ S_{2n-1} \\ S_{2n} \end{bmatrix}), Ed(H_2, \begin{bmatrix} S_1 \\ S_2 \\ \cdot \\ \cdot \\ S_{2n-1} \\ S_{2n} \end{bmatrix}) \;....\; Ed(H_n, \begin{bmatrix} S_1 \\ S_2 \\ \cdot \\ \cdot \\ S_{2n-3} \\ S_{2n-2} \end{bmatrix}) \qquad (7)$$

Based on the typical behaviour of pigs, they normally move forward and mount with their front legs onto a part of the mounted pig's body. As a result, in a sequence of frames, the distance from the head of one pig to the other pig (head or tail) could be obtained from its direction of movement, as well as the distances between head of one pig to both sides of other pigs. By finding the region of interest (ROI) for each participant pair (two pigs) with an Ed (Eq. 1) less than a defined value (here, about half of the major axis length), the possibility of mounting events has been investigated in the algorithm, and the *x*-*y* coordinates of the centre of the two pigs in the ROI recorded for the next steps. Note that as the mounting event is performed, the Ed between the head of first pig and the tail/head or side of the second one has been reduced from the previous frame and the two pigs considered as one in the algorithm;

here the length of two pigs (length of major axis in fitted ellipse) will be changed to approximately 1.3 to 2 pig lengths if the pig is mounting from behind the second one, and the length of major and minor axis will be around 1.3-1.8 pig lengths if the pig is mounting from the side of another pig. So, if the length of the ellipse(s) was between the aforementioned value and the *x*-*y* coordinates of the ellipse located in the ROI, the mounting behaviour was declared. Furthermore, if two pigs were standing close to each other without any mounting event, the algorithm just fitted an ellipse to each of the pigs and no mounting behaviour was specified.

3. Results and discussion

Fig. 4 shows the Ed between two points (H/T, H/S of one pig to another one); it could be inferred that the distances between the mounting and mounted pig declined before the mounting event happened. The algorithm only detected an Ed less than 43 (in pixels) (Fig. 5) as the ROI in this study. Fig. 5 illustrates the changes in Ed before and after the ROI for a mounting behaviour has been identified; when the Ed=0 the mounting events happened (during time 5-14 s, 17 s, 27-33 s and 35 s) and it can be seen that there was a discontinuous mounting event. The major axis length of the fitted ellipse for both mounting and mounted pigs for a mounting event which happened from the back is shown in Fig. 6. According to the diagram, the length of each pig was around 80 (pixels) (see Table 1) and, as the mounting event happened at second 5, the algorithm considered the mounting and mounted pigs as one pig and fitted an ellipse with a bigger major length. At the beginning of the mounting event, the length of the major axis was larger and it then declined over time as the mounting pig demonstrated pelvic thrusts (Hintze et al., 2013). Fig. 7 illustrates the major and minor axis length of mounting and mounted pigs when the mounting event occurred from the side. Here, the major length during the mounting event was around 1.4 pig lengths, while the major axis length in the mounting event was approximately 2 times one pig's minor length.

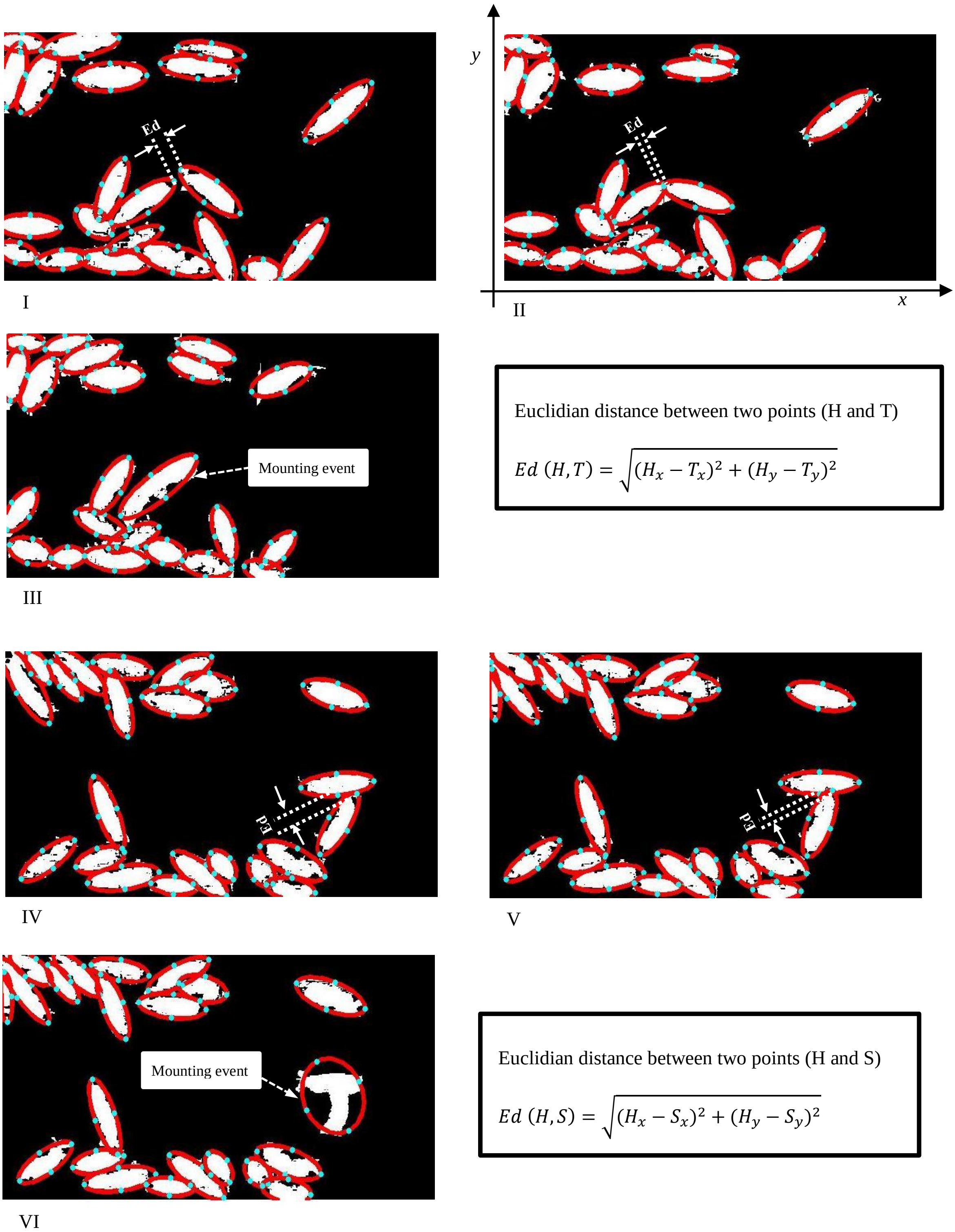

Fig.4. The Ed between Tail and Head of two pigs during a mounting event. For a mount from behind: (I and II) the Ed declined, (III) mounting happened from the back giving a bigger ellipse. For a mount from the Side: (IV and V) the Ed declined, (VI) mounting happened from the side giving a bigger ellipse.

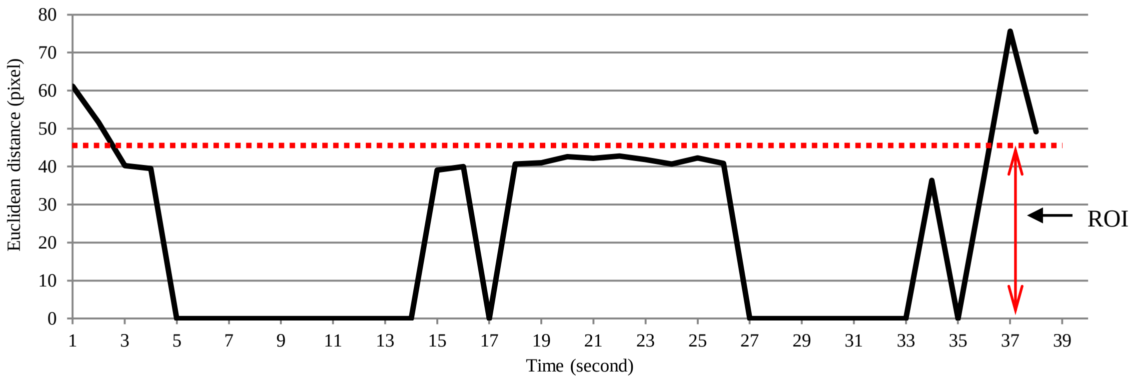

Fig.5. Euclidian distance between two pigs (mounting and mounted) and the ROI.

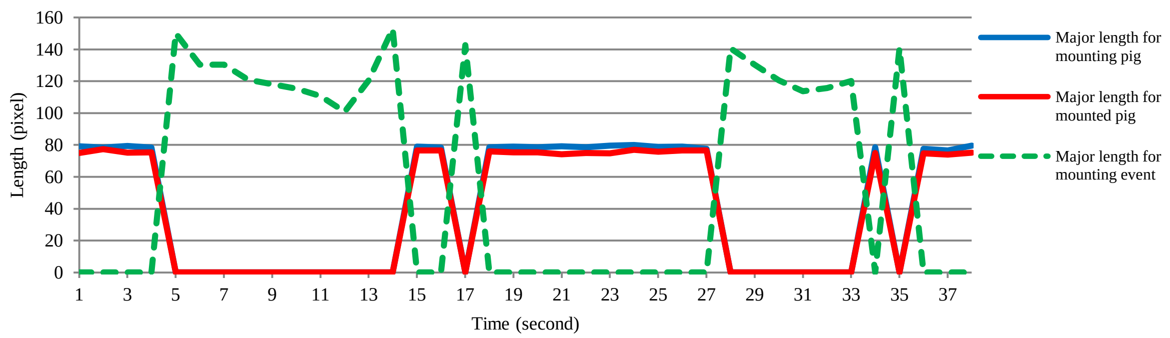

Fig.6. The major axis length of mounting and mounted pigs, along with the mounting event length, for a mounting event from the behind.

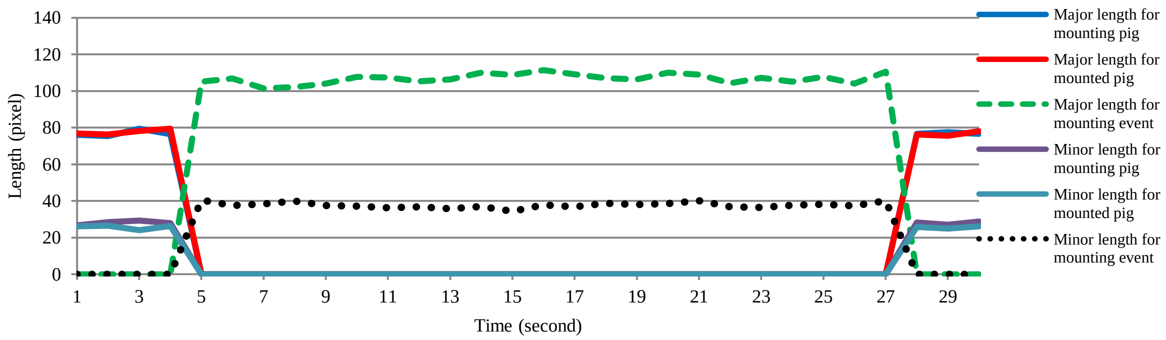

Fig.7. The major and minor axis length of mounting and mounted pigs along with mounting event length, for a mounting event from the side.

Table 1. Mean and standard deviation (SD) of major and minor axis length of pigs in ROI before and after of the mounting event.

Time (second)	1	2	3	4	27	28	29
Major axis length (pixel) ± SD	76.4±0.5	75.8±0.6	77.8±0.4	76.8±0.6	76.4±0.2	76.9±0.6	77.3±0.9
Minor axis length (pixel) ± SD	26.4±0.3	27.4±0.8	27.3±1.1	26.7±0.6	26.5±0.9	25.9±1.2	27.1±0.9

From the 200 h of recorded videos, a total of 120 mounting events were visually obtained. In general, 1800 s of mounting events and 7,200 frames (4 frames per second) were obtained from both pens during the study. The mounting events were manually validated from the recorded video frames by an expert. The validation scales used for finding the performance of the detection system were defined as in Table 2 (Firk et al., 2002; Pourreza et al., 2012; Tsai and Huang, 2014).

Table 2. Definition of validation parameters

Scale	Definition	Value
True positive (TP)	Mounting event considered as mounting event	4753
False positive (FP)	Non-mounting event considered as mounting event	247
True negative (TN)	Non-mounting event considered as non-mounting event	1925
False negative (FN)	Mounting event considered as non-mounting event	275

$$\text{Sensitivity} = \frac{TP}{TP + FN} \times 100 \longrightarrow \frac{4753}{4753 + 275} = 94.5\% \tag{8}$$

$$\text{Specificity} = \frac{TN}{TN + FP} \times 100 \longrightarrow \frac{1925}{1925 + 247} = 88.6\% \tag{9}$$

$$\text{Accuracy} = \frac{TP + TN}{TP + FP + TN + FN} \times 100 \longrightarrow \frac{4753 + 1925}{4753 + 247 + 1925 + 275} = 92.7\% \tag{10}$$

The result obtained from the validation of the algorithm shows a good mounting detection rate with satisfactory sensitivity (94.5%), specificity (88.6%) and accuracy (92.7%). According to the criteria of Table 2, some mounting frames were not recognized and there were some false positives. These errors sometimes occurred because the project was carried out in a commercial farm where there was a water pipe in the middle of each pen (2.5 m from the floor) and some mounting events happened in this invisible area. Furthermore, when the apparent mounting event happened near a pen wall and/or when the mounting pig contacted or tried to contact a pig from a neighbouring pen, drank from the attached nipple drinker or licked the wall (Hintze et al., 2013), and due to the low image quality, the system could not properly distinguish the wall and pigs.

It is clear that the mounting behaviours in pigs need different detection methods from those of some other species due to differences in the nature of their behaviours. For example, the mounting behaviour in cows contains a few seconds of following behaviours (Tsai and Huang, 2014), in which the mounting cow closely follows the mounted cow, and then a jumping or mounting event happens. Tsai and Huang, (2014) have shown that, because of following behaviours in cows, using the motion analysis of mounting events could be a good technique for mounting detection. In contrast, mounting in the pig often happens without any preceding following. Furthermore, the mounted pig may be sitting down or moving away during the event, so using the recommended method for cows may not be applicable in pig behaviour detection.

This study has shown that binary image and fitted ellipse features can be used to extract features related to mounting behaviour among pigs. However, the system could not identify all mounting events, because the CCTV camera could not always detect the pig's body and make a clear distinction between pigs and wall or pigs and background (pen). This problem might be overcome by using 3D image data (i.e. time-to-flight, Microsoft Kinect sensor) which has the advantages of elimination errors related to animal colours, background and different ambient lighting (Kongsro, 2014), animal body detection in more detail (Weber et al., 2014) and pictures with higher resolution. However, using expensive cameras with better colour and object detection in commercial farms, in an environment with high levels of humidity, dust and ammonia, and their associated detrimental effects on electronics, may not be economically acceptable for farm managers. So possibilities for improving the algorithm for images from simple CCTV cameras or using other methods need to be considered in future research.

To date, no previous studies have been carried out to automatically detect pig mounting behaviours. The technique proposed here can automatically detect mounting events among pigs, even in commercial farm conditions. The method could be a valuable tool to aid farmers to increase animal welfare and health, and reduce injuries and economic losses, particularly as the use of entire males becomes more common. As the pigs grow larger, the mounted pigs may have increased risk of injury (Clark and D'Eath, 2013), and may be mounted more frequently by other pigs. So, with accurate information about the mounting events, the farmer can move quickly to address problem pens or seek interventions. Additionally, automated tracking of the time course and frequency of mounting behaviours within pens could facilitate the work of researchers exploring methods of prevention or alleviation of this behavioural problem.

4. Conclusion

In this study, automatic detection of mounting events among pigs, based on ellipse fitted features, was reported. A background subtraction method has been used for finding pigs in images and, after removing noise from binary images, *x*-*y* coordinates of each binary image were used for localization of each pig in image (ellipse fitting technique). The Ed distances from head/tail of one pig to another and head/tail to sides of second pig were calculated for defining the ROI and, as the mounting event happened in the ROI, the size of two pigs combined (new fitted ellipse) altered to that of 1.3-2 pigs. The performance of the algorithm showed a high level of accuracy, so this method could contribute in the future as an important and economically feasible technique in commercial pig farms. This automatic method is an important step for developing an automatic system for making the farm management easier, cheaper and more efficient in use of manpower.

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