Full title: Automatic Monitoring of Pig Locomotion Using Image Analysis

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Abstract

The purpose of this study is to investigate the feasibility and validity of an automated image processing method to detect the locomotion of pigs housed under experimental conditions. Top-view video images were captured for forty piglets, housed ten per pen. On average, piglets had a weight of 27 kg (SD = 4.4 kg) at the start of experiments and 40kg (SD=6.5) at the end. Each pen was monitored by a top-view CCD camera. The image analysis protocol to automatically quantify locomotion consisted localising pigs through background subtraction and tracking them over time. To validate the accuracy of detecting pigs “In Locomotion” or “Not In Locomotion”, they were compared to offline manually labelled behavioural data ('In Locomotion' versus 'Not In Locomotion'). This is the first study to show that locomotion of “pigs in a group” can be determined using image analysis with an accuracy of 89.8 %. Since locomotion is known to be associated with issues such as lameness, careful monitoring can give an accurate indication of the health and welfare of pigs.

Keywords: Locomotion; ellipse fitting; pig; eYeNamic; image analysis

1. Introduction

Over 60 billion animals were slaughtered in 2010 for food production (Prakash and Stigler, 2012). This strong demand for animal products forces producers to increase their capacity with fewer available resources per animal. To reconcile market forces with animals’ need for individual care, farmers might use automatic tools to monitor their welfare and health (Schön and Puppe, 2004).

The increased number of animals per farm has resulted in new welfare problems due to lack of time for individual animal care (HSUS, 2010). Welfare issues can lead to pain and suffering in livestock. Pain and suffering are forms of stress on livestock and stressed animals can show compromised growth, production and reproduction (Lauber, 2007). Animals experiencing pain normally deviate from their normal behaviour by altering locomotion (either an increase or decrease) (Anil et al., 2002). This deviation can be detected and reported to farmer using automated tools, thus avoiding a compromised growth.

Monitoring locomotion in animals can serve different purposes. Researchers have previously investigated different approaches to monitor locomotion in pigs. For instance Cornou and Lundbye-Christensen (2010) fitted sows with a neck collar containing an accelerometer. They used time series of acceleration measurements in order to automatically classify locomotion types common among group-housed sows. They described five locomotion types using univariate and multivariate models: feeding (FE), rooting (RO), walking (WA), lying sternally (LS) and lying laterally (LL). By grouping the locomotion types into active (FE, RO, WA) vs. passive (LS, LL) categories, this method allowed them to classify 96% of the active category and 94% of the passive category correctly. It was discussed that this method could be directly employed to automatically detect the onset of oestrus. Another application was mentioned to be monitoring the approach of farrowing since the locomotion level of sows is expected to increase during the last 24 h before farrowing.

Although earlier studies involved innovative technologies that could be utilised to monitor pig locomotion, many of them require animals to be fitted with sensors or tags. Using these tags raises biosecurity risks (Hernandez-Jover et al., 2008) and pigs endure extreme pain in

the installation process (Leslie et al., 2010). Vision-based pig identification technology, however, is a non-intrusive technique that can measure locomotion accurately.

Image processing has also been employed to assess locomotion in livestock. In one study, Lind et al. (2005) introduced a system to automatically track pig locomotor behaviour. They administrated seven pigs different doses of drugs and quantified locomotion in sessions of 60 minutes. This method allowed them to track pigs with a repeatability coefficient of 0.6%.¹ In another study, Cangar et al. (2008) developed an automatic real-time monitoring technique to identify locomotion and posture of eight pregnant cows in the 24 hours prior to calving. On average, 85% of standing and lying conditions and 87% of eating and drinking bouts were classified correctly. In addition, professional video tracking software is available that can automatically record marked animal locomotion, movement and interaction (Spink et al., 2001).

Yet current vision systems need pigs to walk in front of the camera one by one (Lind et al., 2005) or to be marked (Kashiha et al., 2013). Otherwise, they can only provide locomotion for the animals as a group (Costa, 2007). The disadvantage of the latter is that variation in locomotion between pigs cannot be measured.

Existing tools such as Ethovision (Noldus et al., 2001) need marking pigs for tracking them in a group. The objective of this study is to monitor unmarked pigs' locomotion in a group-housed environment through automated quantification of locomotion levels using continuous image analysis.

¹ The coefficient of repeatability will be low if the variability between the repeated measurements is low.

2. Materials and Methods

2.1. Animals and housing

The experiments for this study were carried out at Agrivet research farm, Merelbeke, Belgium. Forty pigs, Rattlerow Seghers x Piétrain Plus, were selected after the battery period, balanced for sex, live weight and former litter and battery mates and randomly assigned (10 per pen) to four fully slatted and concrete floor pens ($2.25\text{ m} \times 3.60\text{ m}$). Each pen was equipped with a double feeder space and one drink nipple. Animals had ad libitum access to food (commercial grower diet) and water for the whole experimental period. Pigs had a timer-controlled 12-hour light period from 07:00 h – 19:00 h. Barn temperature was kept by Hotraco IRIS climate control equipment on an average of 22 centigrade, with a minimum of 18.6 centigrade and a maximum of 25.4 centigrade over the total experimental period. On average, piglets weighed 27 kg (SD = 4.4 kg) at the start of experiments and 40kg (SD = 6.5) at the end.

This study was approved by the Ethical Committee of the Faculty of Veterinary Medicine at Ghent University, Belgium.

2.2. Equipment and data collection

Video recordings of the pigs were made at 25 frames per second. To capture top-view images, Panasonic WV-BP330 cameras with resolution of 720x576 pixels and CS-mount DC-Servo ALC 5.5-12mm lenses were installed in the rafters of the barn at height of 180 cm, in the location shown in figure 1. Since 1991, camera technology has been used as a non-disturbing method to

monitor animals and to implement algorithms in research and field applications (Van der Stuyft et al., 1991).

Figure 1. Ground plan of the 4 pens in research barn in Agrivet, Merelbeke.

Using MPEG Recorder software from Noldus, and a black and white Panasonic WV-BP330 camera, images were recorded during 13 days, for 12 hours per day. Images were captured between 07:00 and 19:00, resulting in 156 hours of video. Videos were recorded in MPEG-1 format, a frame width of 720 pixels, a frame height of 576 pixels, and a data rate of 64 kbps. To provide light in the barn, six 36-watt, 120 cm Sylvania Luxline Plus white fluorescent tube lamps were installed at a height of 200 cm in the locations shown in figure 1.

2.3. Development of the automated locomotion quantification protocol

The processing flowchart to monitor locomotion in a pen is shown in figure 2. First, for each pen, the feeder and the pen floor area were initially determined manually. The feeder needed to be excluded from the image since it could affect the segmentation accuracy. In addition, the pen floor had to be excluded to eliminate the camera cover appearing in the segmented image. These regions are shown in figure 3. To eliminate light effects, the histogram of the image was then equalised using adaptive histogram equalization (Sherrier and Johnson, 1987).

Figure 2. Image processing flowchart to monitor locomotion in a pen

Figure 3. Pen floor area and feeder selected by the user

In a second step, each image was binarised to eliminate the background. The binarisation procedure was as follows: 1) the image was filtered using a 2-D Gaussian low-pass filter; 2) a global threshold was calculated using Otsu's method (Otsu, 1979); 3). The image was subsequently hard-thresholded resulting in figure 4a; 4) To remove small objects such as slat edges from the image, a morphological closing operator using a disk-shaped structuring element with a size of 10 pixels (Gonzalez and Woods, 2001) was performed on it. The morphological closing operation is a dilation followed by an erosion, using the same structuring element for both operations. Conducting this operation resulted in figure 4b.

Figure 4. Segmented image before (a) and after (b) applying morphological operators

Third, each image was segmented in order to find the location of the pigs. To segment the image, the pigs' bodies were extracted as ellipses (Zhang et al., 2005) within each pen. The procedure for fitting ellipses to the binary image as displayed in figure 4b was as follows: 1) using the direct least-squares ellipse-fitting method (Zhang et al., 2005), ellipses were fitted to objects in the image; 2) ellipse parameters such as "Orientation", "Major Axis Length", "Minor Axis Length" and "Centroid" were calculated for all objects in the image. To avoid incorrectly identifying other shapes in the pen as pigs, a minimum of 230 or 90 pixels and a maximum of 430 or 140 pixels were considered for the major and minor axes of an ellipse, respectively. FIGURE 5a illustrates these parameters, and figure 5b shows the ellipses fitted to the pigs' bodies (figure 4.b). For this method, it is important that the area of the space between each floor

slat is smaller than a piglet's body area, which was always the case for the animals in the current study.

Figure 5. a. Ellipse parameters; b. Ellipses fitted to pigs' bodies

The following steps shown in figure 2 are explained in the sections below.

2.3.1. Image Locomotion

Image Locomotion (IL) is defined as amount of movement an object produces in pixels. Using the ellipse models presented in the previous section, IL is mathematically explained as shown in the following equation. IL is composed of two steps: 1) Angular motion (moving from ellipse E_1 to E_2 in figure 6); 2) Linear motion (moving from ellipse E_2 to E_3 in figure 6). To make IL independent from pig body size, it has to be divided to L .

$$IL = (|Linear\ motion| + |angular\ motion|)/L = (|\vec{T}| + |\left(\angle \vec{T}\right) * \frac{L}{2}|)/L = T/L + \tan(\theta_T + \theta_1)/2 \quad (1)$$

Where:

IL is the Image Locomotion; in pixels

$\vec{T}$ is the movement vector (from ellipse E_1 to ellipse E_2); in pixels

$T = |\vec{T}|$ is the size of the movement vector; in pixels

Θ_T is the difference of orientation between ellipses E_1 and E_2 ; unit-less

L is average of size of the major axis of ellipses E_1 and E_2 ; in pixels

$\angle$ is the angle operator

Figure 6. Ellipse fitted to pig's image: (a) at time "t-1"; (b) at time "t"; T is the distance travelled;

2.3.2. Image Locomotion Detection

IL was monitored over time and Image Locomotion Status (ILS) was determined based on the following parameter:

$$ILS = \frac{IL}{L} \quad (2)$$

Where:

ILS is the Image Locomotion Status; unit-less

IL is the Image Locomotion; in pixels

L is the average size of the major axis of ellipses E_1 and E_2 (figure 6); in pixels

The next step was to decide, based on ILS, whether a pig was In Locomotion (IL) or Not In Locomotion (NIL). Based on the ILS parameter and an experimental threshold of 0.4, locomotion was determined as shown in table 1. This means if a pig moves more than 40 % of his body length (L in equation 1), he is considered to be IL. Otherwise he is NIL.

Table 1- Locomotion of pigs

2.3.3 Manual labelling

As a reference, the manual "labelling" of recorded videos was done by an ethologist experienced in labelling. Human visual observations of the pigs' behavioural locomotion were performed off-line on videos using 2-min instantaneous scan-sampling in four 30-minute sessions on 6 selected days. Preliminary observations allowed for the selection of two morning sessions (session 1:

09:30-10:00 h and session 2: 11:00-11:30 h) and two afternoon sessions (session 3: 16:00-16:30 h and session 4: 17:30-18:00 h), to compare automated with manually labelled behavioural locomotion. The behaviour of each individual pig was labelled using the Observer XT 10.2 software (Noldus, Wageningen, The Netherlands). Therefore, 30 scan samples per pig per day were obtained. For each scan sample, all 10 individual pigs of one pen were scored as either IL or NIL. Locomotion behaviour was defined as walking, running, and/or performing other behavioural activities such as exploring or manipulating pen fixtures, manipulating pen mates, agonistic behaviour, feeding, drinking, or other behavioural activities that include physical movements of any body part. Sensitiveness of this method is 5 cm. If a pig was not performing behaviours of the “In Locomotion” behavioural category it was considered Not to be In Locomotion. Finally, the number of IL pigs was tallied, to calculate the number of IL pigs per pen.

It should be noted that not all data were labelled, since labelling is an extremely time-consuming process. The data that were not labelled were analysed by Image Locomotion Detection technique introduced above.

3. Results

3.1. Validation

In order to validate the automated image processing technique, image-detected locomotion was compared with labelling results, as shown in Table 2. There were 24 half-hour intervals, each of which consisted of 15 scan samples. In each of these scan samples 10 pigs were scored for their locomotion, which means that in total there were $24 \times 15 \times 10$ or 3600 scan samples per pen.

Table 2- Locomotion in 4 pens, comparing labelling and automated image analysis

In total, 14400 frames were analysed, which were recorded from four pens. Out of 5896 IL pigs, 5297 were identified correctly, while 162 false positive identifications (**Error! Reference source not found.**) and 599 false negative identifications (10.2 %) were recorded. This leads to an overall accuracy of 89.8 % for a stocking density of 1.23 pig/m².

3.2. Continuous data analysis

After validating the method all 13 days of the experiment data were analysed. There were in total 13 (days)* 12 (hours) * 3600 (seconds) * 10 (pigs) or 5.616 million (432k per day) scan samples per pen to analyse. Figure 7 shows average of IL pigs per pen during the days of the experiment.

Figure 7. Average of IL pigs during 13 days of the experiment detected by ILS algorithm

4. Discussion and conclusion

Automatic monitoring of animals has been tested with many different animals (Brendle and Hoy, 2011; Venter and Hanekom, 2010). Moreover, for farm managers this technology seems promising for monitoring purposes (Kashiha et al., 2013), mainly thanks to the broad applications automated animal monitoring has to offer. Camera technology in particular has made it possible to monitor every second of animal behaviour and has also proven especially suitable to study group behaviour (Pastorelli et al., 2006).

Monitoring animal locomotion in group is an essential aspect of analysing different behaviours. Some of the more specific behavioural aspects that can be focused on are locomotor

behaviour (Lepron et al., 2007), lameness detection (Kramer et al., 2009), agonistic behaviour (Szendrő and Dalle Zotte, 2011) and freezing behaviour (Vanheukelom et al., 2012). Moreover, this technology can help to monitor a large number of welfare measures taken to improve the animals' wellbeing (Botreau et al., 2007), such as “ease of movement” and “thermal comfort”. Hence, there are many possible applications for which the use of this technique can be attractive.

Although methods such as acceleration measurement (Lind et al., 2005) have been used to monitor pig locomotion in previous studies, automatic detection of the locomotion of unmarked pigs in a group by image processing has never been reported in the literature. The existing techniques require marking colour (Spinka et al., 2004) or IDs (Kashiha et al., 2013) on pigs. In this study, however, an innovative approach using movement calculation of ellipses fitted to pigs' bodies was chosen to investigate the possibilities of automated locomotion detection for fattening pigs using vision technology. It was shown that pig locomotion detection is possible by localising individual pigs in the group by fitting ellipses onto their top-view body image and tracking those ellipses over time.

Among the previous methods used for pig locomotion monitoring, the moving pixels calculation method used in eYeNamic tool was the most successful (Leroy et al., 2006). This tool calculates the difference in image intensity between consecutive frames. From this difference image, the binary ‘locomotion image’ $I_a(x, y, t)$ is derived, containing the pixels for which the intensity change exceeded a certain threshold. A summation of the number of these pixels yields the total amount of locomotion at time t (figure 8). As this technique has been the most successful to date, it might be interesting to examine how it compares to the method proposed in this study. Since eYeNamic cannot determine number of IL pigs, one development phase was

launched to determine a threshold for number of pixels to decide how many pigs in a pen were IL. In the validation phase, data presented in Table 2 were also analysed with eYeNamic. Table 3 shows the results of this comparison. Upon these results ILS method reports 10.2% of error in detecting number of IL pigs while eYeNamic categorizes locomotion of pigs with an error of 39.2 %. In addition, false positives were 2.75% and 11.8% respectively. Thus, ILS method yields a higher accuracy in detecting locomotion of pigs.

Figure 8. Locomotion calculation in eYeNamic tool

Table 3- Comparison of labelling, ILS technique and eYeNamic tool in detecting number of IL pigs in a pen (NIL includes standing, lying and standing; IL includes running and walking)

The introduced technique was also robust against body shape variations in standing and lying position. This made it quite suitable for the purpose of this study since there was considerable variation in brightness between pigs' different postures and locations. It is worth mentioning that the occurrence of false positives in detection of locomotion is unavoidable. Incorrect classification was due to several factors: 1) Segmentation was often an issue in resting zone since pigs tended to lie down socially (in contact with each other and sometimes with some overlapping) thereby complicating the segmentation task; 2) there were sometimes mistakes in labelling IL pigs; Nevertheless, while this method is dependent on contrast between floor and pig surface it could still detect IL pigs in a light intensity range of 11.7 and 176.1 lux with an accuracy of 89.8 %.

Although this method would theoretically work with a wide range of light intensity and contrast between pigs and floor, background subtraction and segmentation of pigs' bodies can be a challenge. Therefore, authors would suggest setting the thresholds using the data of the day before. This means at the end of a day, thresholds are calculated to be used on the day after.

The method allows doing behavioural research at group level without the need of additional sensors and software and without the need to mark the animals (for tracking purposes), or to interfere with them in any other way. It saves costs and makes researchers able to add functionality to video cameras. It is certainly a valuable tool for research purposes and has an advantage of being non-intrusive.

Combining this method with identification techniques such as using ear-tags (Allen et al., 2008), animal husbandry management can be improved. However, there are still challenges to use the proposed technique in practical settings. Due to experiments requirements, stocking density in images used in this study was as low as 1.23 pig/m^2 while in a real farm setting, stocking density will be as high as 1.67 pig/m^2 (Schinkel et al., 2009). The higher the stocking density, the more difficult segmenting the pigs in the image will be. This could in turn have a negative effect on accuracy of locomotion detection. One way to address this problem is to calculate locomotion by comparing consecutive frames (Leroy et al., 2006).

Locomotion monitoring can have many applications such as stressor response analysis. By combining locomotion with other parameters such as occupation¹, one could analyse pigs' behaviours including playing, resting, drinking, feeding and manipulation behaviour. These possibilities will be investigated in future work.

In conclusion, this protocol, which can measure locomotion with an accuracy of 89.8 %, might contribute in future as a practical tool in livestock husbandry since health, welfare and performance are all variables that are related to locomotion.

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¹ Occupation is calculated by dividing the total number of object pixels, relative to the total number of pixels in a given area

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