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Automatic identification of marked pigs in a pen using image pattern recognition

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ABSTRACT

The purpose of this work was to investigate feasibility of an automated method to identify marked pigs in a pen in experimental conditions and for behaviour-related research by using image processing.

This study comprised measurements on four groups of piglets, with 10 piglets per group in a pen. On average, piglets had a weight of 27 ± 4.4 kg at the start of experiments and 40 kg ± 6.5 at the end. For the purpose of individual identification, basic patterns were painted on the back of the pigs. Each pen was monitored by a top-view CCD camera.

Ellipse fitting algorithms were employed to localise pigs. Consequently, individual pigs could be identified by their respective paint pattern using pattern recognition techniques. Taking visual labelling of videos by an experienced ethologist as the gold standard, pigs could be identified with an average accuracy of 88.7%. It was also shown that behaviours such as resting can be monitored using the presented technique.

1. Introduction

At present, over 60 billion animals are slaughtered yearly for food production (Prakash and Stigler, 2012). The increasing demand for animal products fosters intensive animal husbandry. Market demands force producers to increase the number of animals in their flock or herd with fewer available resources (per animal). To meet the demands of the market while providing enough care to the individual animals, farmers might use automatic tools to monitor welfare and health of their animals (Botreau et al., 2007; Harris et al., 2001; Morris et al., 2012). While existing systems facilitate an efficient use of land and labour, the increased number of animals per farm has resulted in new welfare problems because time is too limited to provide individual animal care (HSUS, 2010).

One of the essential components of welfare in animal husbandry is providing adequate food and water (Botreau et al., 2007) which requires a substantial number of man-hours. In normal situations pigs show a stable diurnal drinking pattern (Madsen et al., 2005). Abnormal decrease or increase of food or water use can be due to health problems or other factors such as environmental changes or interruptions in feed delivery (Madsen and Kristensen, 2005). A sudden, 20–30% drop in water use or drinking visits often indicates that swine influenza has taken hold (Bernick, 2007). It is possible to give early alarm in case of such happenings, using image processing techniques. However, since individual pigs are anticipated to face these problems, it is important that feeding and drinking are detected for each pig individually. This could, in turn, help to prevent the disease from spreading among the pen. Since video analysis of pigs has numerous other applications (Van der Stuyft et al., 1991; Xin, 1999; Kollis et al., 2007) analysing pigs' behaviours using videos is an added value without extra cost for farmers.

Other researchers previously investigated different approaches to monitor livestock using image analysis. Cangar et al. (2008) used geometric image variables to classify specific behaviours such as standing, lying, eating or drinking of cows. They could categorize 85% of the standing and lying and 87% of the eating or drinking behaviour of the eight cows 24 h before calving using those variables. Farah et al. (2011) proposed a method to track rats and determine their motion pattern in cages under normal laboratory conditions. They employed a sliding window approach based on gradient and intensity features consisting of a fitness cost function based on the histograms of oriented gradients, the histograms of intensity (HI), the quantity of motion and edge density to track

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the animal. They succeeded in achieving adequate tracking with an average error less than 5%. Ahrendt et al. (2011) developed a pig tracking system algorithm based on support maps. These support map segments were subsequently used to build up a 5D-Gaussian model of the individual pigs, their position and shape. Using this method, they could track a minimum of three pigs for at least 8 min. Aydin et al. (2010) applied an automatic image monitoring system to assess the activity of broiler chickens with different gait scores (ability to walk). Poursaberi et al. (2009) developed an algorithm based on image analysis to classify the behaviour of turkeys in real time and automatically. They chose four behaviours, namely turning, lying, standing and wing flapping to represent different behaviours for welfare assessment. Finally, they fitted ellipses to turkey's body parts and made a model to categorize above behaviours.

In this paper, an approach is presented to identify the pigs in experimental conditions and for behaviour-related research in a fully automated way based on continuous image analysis. To the authors' knowledge there currently is no tool available that uses vision technology to automatically identify marked pigs in a pen. Other researchers previously investigated techniques such as pig identification using ear-tags (Prola et al., 2010; Burose et al., 2010) but there are biosecurity risks raised by this method (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 which has never been implemented.

2. Materials and methods

2.1. Animals and housing

Experiment of this work was carried out in Agrivet research farm, Merelbeke, Belgium. Forty pigs, Rattlerow Seghers × Piétrain Plus, were selected after the battery period and assigned to four fully slatted pens (2.25 m × 3.60 m) made of concrete, so there were 10 pigs per pen. 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 h light period from 07:00–19:00 h. Barn temperature was kept on average at 22 °C, with a minimum of 18.6 °C and a maximum 25.4 °C over the total experimental period by Hotraco IRIS climate control equipment. On average, piglets had a weight of 27 ± 4.4 kg at the start of experiments and 40 kg ± 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

During the experiment, video recordings of the pigs in four pens were made. Cameras were installed in the rafters in the location shown in Fig. 1 to capture top-view images. Since 1991 top-view camera has been known as a non-disturbing method for monitoring animals and provides a way to implement algorithms in research and field applications (Van der Stuyft et al., 1991).

Using MPEG Recorder software from Noldus and black and white Panasonic WV-BP330 camera, images were recorded in light intensity of a minimum of 11.7 lux and a maximum of 176.1 lux during 13 days for 12 h per day, between 07:00 and 19:00, resulting in 156 h of video. Videos were recorded in MPEG-1 format, with a frame rate of 25 frames per second, frame width of 720 pixels, frame height of 576 pixels and data rate of 64 kbps. The reason why black and white cameras were used was that they were already installed in the barn. To provide light in the barn, six 58 W, 120 cm Gamma white fluorescent tube lamps were installed at a height of 200 cm in locations shown in Fig. 1.

To be able to identify pigs individually, a specific pattern was stamped on the back of each pig using blue dye mark of blue MS Long spray, Belgian MS Schippers. These patterns were cut on rubber in size of 8 $*$ 12 cm and stamped on pigs' back. On average, the patterns had to be renewed every third day. The reasons this method was used were: (1) it was cheap; (2) it was easy to be implemented; (3) it was computationally feasible; (4) black and white cameras were already available in the barn. Fig. 2 shows the identification patterns used to identify 10 individual pigs and Fig. 3 shows a frame of a video recorded in the experiment. The patterns selected were required to be discernible using the identification method explained in Section 2.3.

To develop algorithms for continuous automated identification of pigs the ID and location of each pig are needed to be known during a certain period. As a reference or gold standard of IDs, manual or visual "labelling" of recorded videos was done by an experienced ethologist. Subsequently, a comparison was made between data obtained by manual labelling and data from automatic identification. Manual labelling is a very time consuming work and since labelling of 1 h of video takes at least 3 h, 468 h were needed to

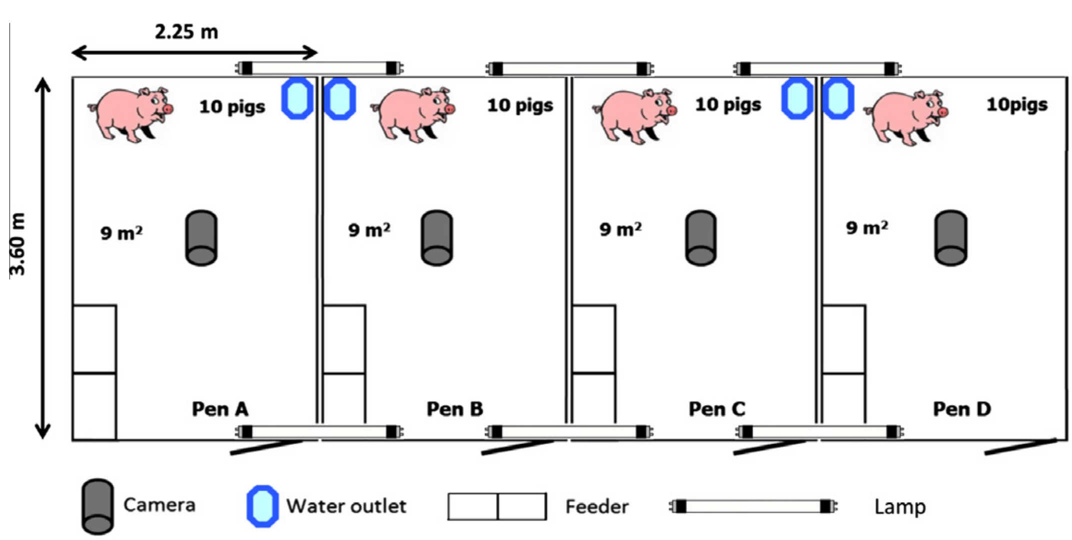

Fig. 1. Ground plan of the 4 pens in research barn in Agrivet, Merelbeke.

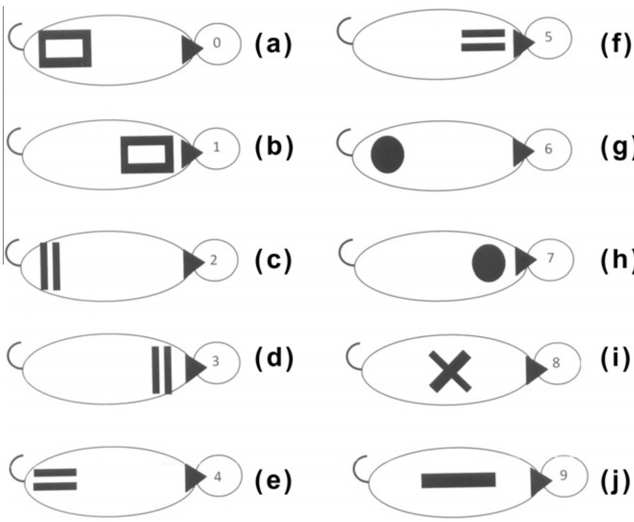

Fig. 2. Patterns applied to identify 10 pigs in a pen.

Fig. 3. A frame of a video in the database.

label videos of our experiments (156 h of videos). Since it was not possible to label all the data collected, video samples of 10 min every 2 h were labelled, so that time-of-day effects would have been eliminated. Location of each pig was pinpointed in scan samplings of 2 min (one single frame each 2 min). Therefore 30 samples per pig per day were analysed. The rest of data that were not labelled manually were analysed by localising and tracking

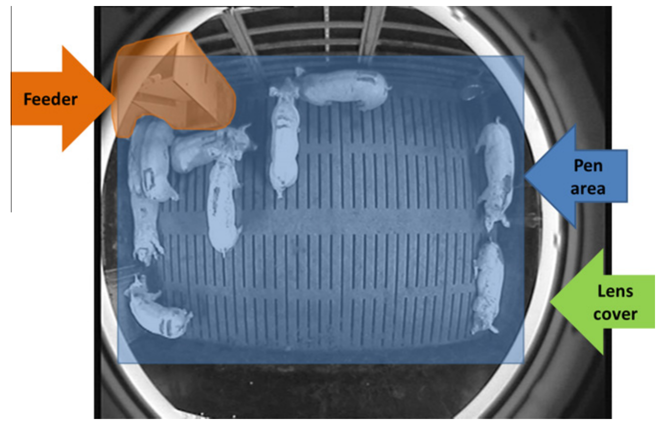

Fig. 5. Pen floor area and feeder selected by the user.

pigs. Results of these analyses are presented in Section 3 of the paper.

2.3. Automated identification of pigs

There are several ways to analyse these patterns (Zhang and Lu, 2004). In this work a method to identify patterns, namely Fourier description of patterns (Zhang, 2002; Zhang and Lu, 2004; Zhang and Wu, 2011) was employed. This method is capable of describing objects in an image under very noisy image conditions with numerous variations in the pattern sought (Zhang and Lu, 2004; Reddy and Chatterji, 1996).

The processing flowchart to identify marked pigs in a pen is shown in Fig. 4. The first step to process these patterns was to segment the image in order to find the location of the pigs and the location of the applied identification pattern. To segment the image, first the feeder and the pen floor area were determined. The former was needed to be excluded since it could affect the segmentation accuracy. The latter was necessary to exclude the camera cover appearing in the image from segmentation. These regions are shown in Fig. 5. Thereafter to eliminate light effects, histogram of the image was equalised using adaptive histogram equalization (Sherrier and Johnson, 1987). Original and histogram equalised images are shown in Fig. 6a and b together with related histograms. Afterwards, the image was binarised to eliminate the background. The binarisation procedure was as follows. First, the image was filtered using a 2-D Gaussian low-pass filter. Then, a global threshold was calculated using Otsu's method (Otsu, 1979). The image was hard-thresholded subsequently resulting in Fig. 7a. To remove small objects from the image, a morphological closing operator using a disk-shaped structuring element with size of 10 pixels (Gonzalez and Woods, 2001) was performed on it, resulting in Fig. 7b.

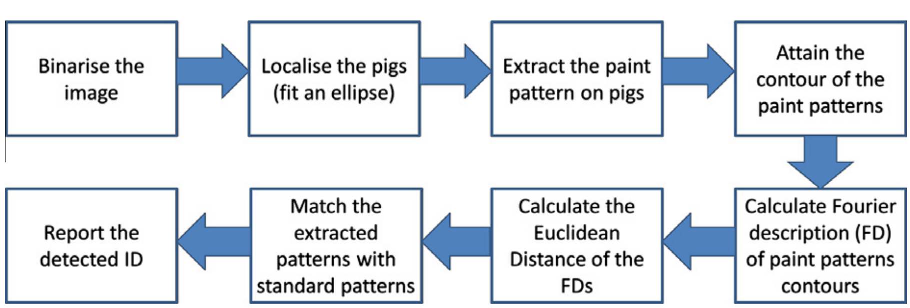

Fig. 4. Flowchart of identification of marked pigs in a pen.

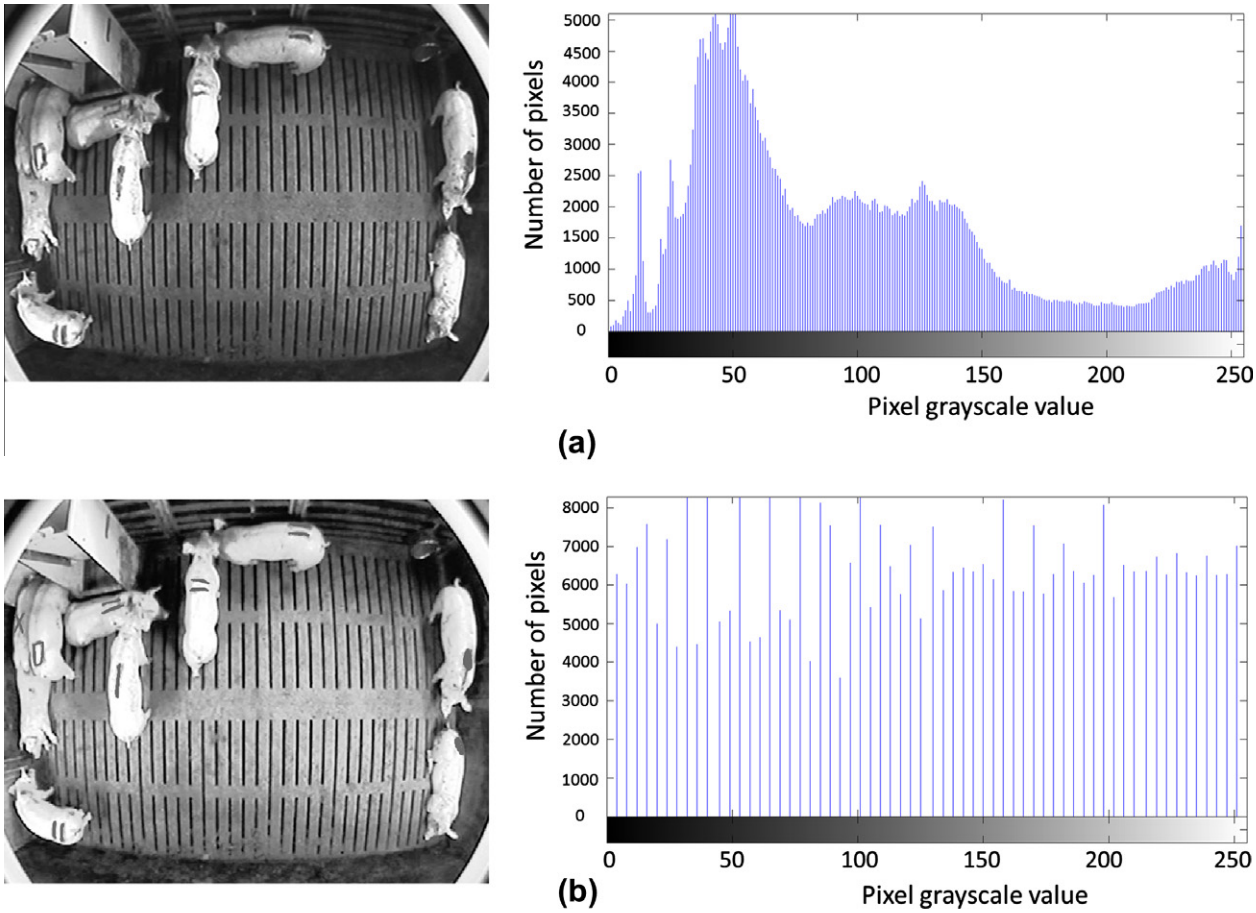

Fig. 6. (a) Original pen image and (b) histogram equalised pen image.

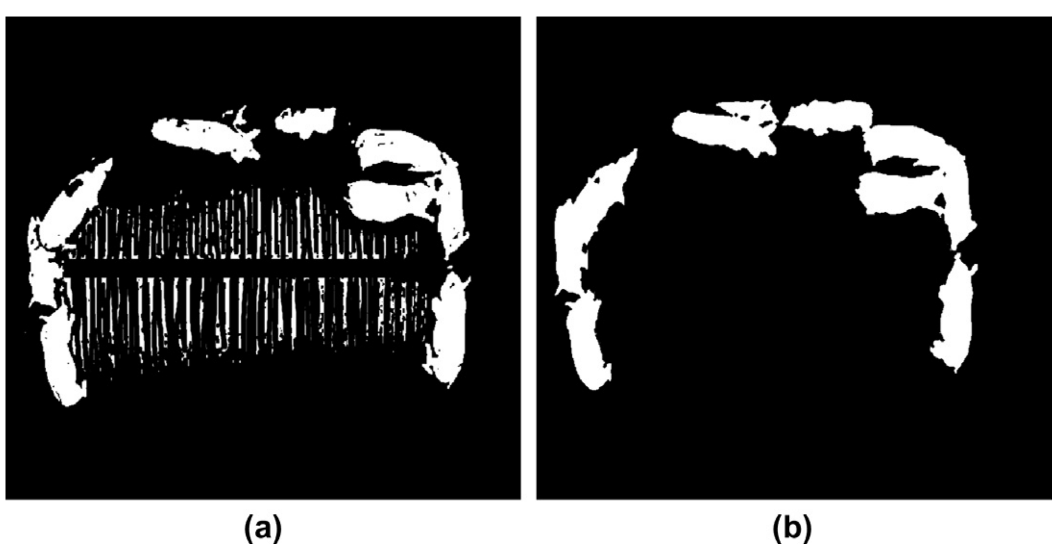

Fig. 7. Segmented image before (a) and after (b) applying morphological operators.

Thereafter the pig's body was extracted as ellipses (Zhang et al., 2005; Tillett, 1991) as bright regions related to pigs had a rather high contrast with the background (pen floor). The procedure for fitting ellipses to the binary image of Fig. 7b was as follows: First, using direct least-squares ellipse-fitting method (Zhang et al., 2005) ellipses were fitted to objects in the image. Subsequently, ellipses parameters such as "Orientation", "Major Axis Length", "Minor Axis Length" and "Centroid" for all objects in the image were calculated. Not to take other shapes in the image mistakenly as pigs, a minimum of 230 and a maximum of 430 pixels for major axis and a minimum of 90 and a maximum of 140 pixels for minor axis of an ellipse were considered. Fig. 8a illustrates these parameters and Fig. 8b shows the ellipses fitted to the pigs' body (Fig. 7b). It should be noted that in this method it is only important that the

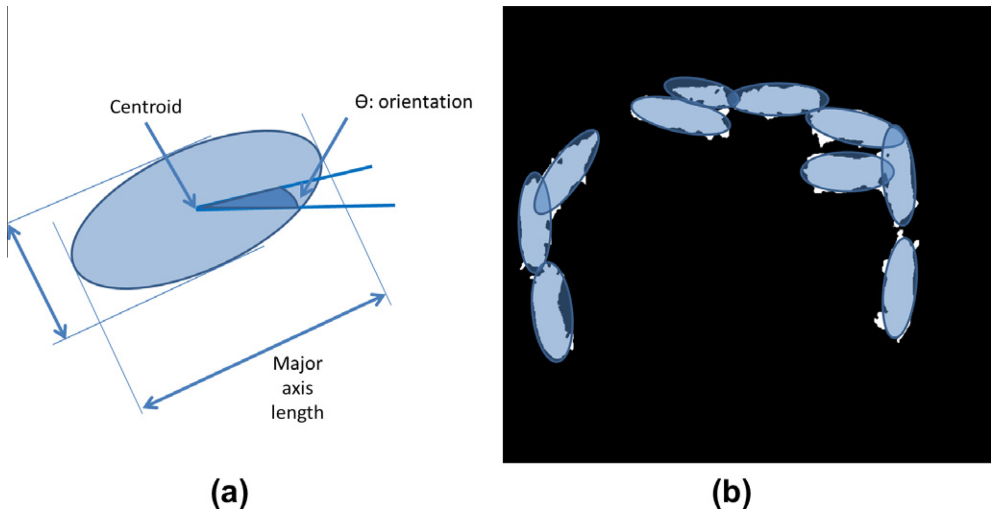

Fig. 8. (a) Ellipse parameters and (b) ellipses fitted to pigs' body.

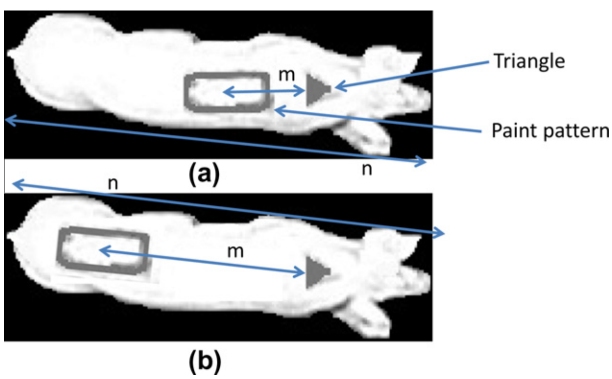

Fig. 9. (a) Location of paint patterns in relation to the triangle painted on neck; for IDs 0, 2, 4: $m > 0.4 * n$; For IDs 1, 3, 5 and 7: $m < 0.4 * n$.

area of each floor slit is smaller than a piglet's body area which is practically always the case.

Fig. 9a and b shows a target pattern. For the limited number of pigs in our experiment, the number of identification patterns was limited to five, so each pattern was used for two pigs in a pen, applied either to the front or to the back of pigs' body respectively (Fig. 2). To allow individual identification of pigs who had the same paint pattern (Fig. 2) it was necessary to find where on pigs' body the pattern was painted. This was achieved by painting a triangle on the neck of pigs. The base of the triangle had a distance of m (Fig. 9a and b) from the centre of the paint pattern. If m was bigger than 40 per cent of the pig body length (n in Fig. 13a and b) IDs 0, 2, 4 and 6 (Fig. 2a, c, e and g) could be detected. On the other hand, IDs 1, 3, 5 and 7 (Fig. 2b, d, f and h) could be verified if $m > 0.6 * n$ while IDs 8 and 9 were used only once and did not need to be checked with the triangle on the neck. This gave each pig a unique ID. Moreover, the reason why ten unique patterns were not used was that this triangle had applications in other research works carried out based on our experiments. For instance, it was used to analyse animals' movement behaviours such as chasing in which back and front side of pig's body movement is needed to be tracked.

The next step was the extraction of the applied identification pattern on each marked pig. Similar to the extraction of pigs from the binary image, identification pattern on each pig was extracted since the pattern was the biggest dark region on the animal's body

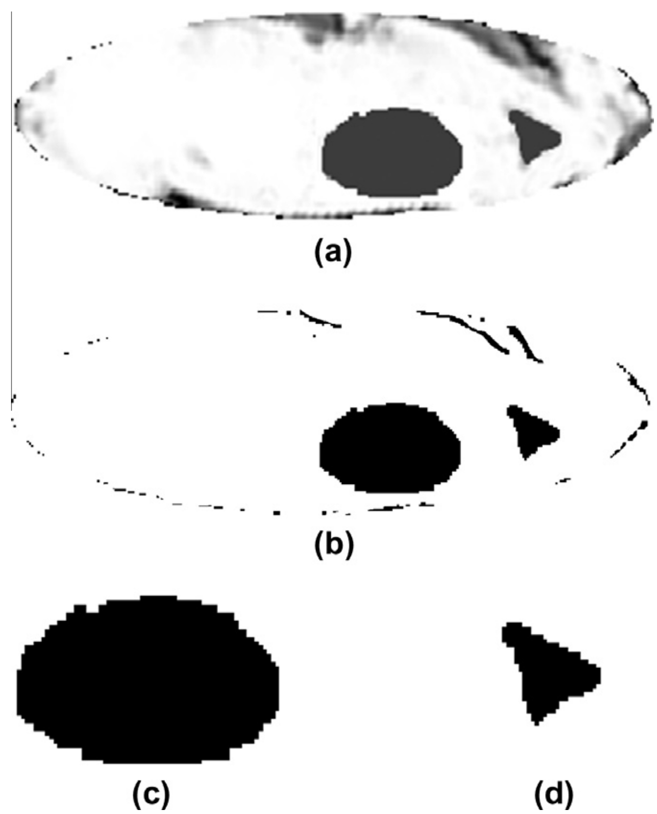

Fig. 10. (a) Pig's body extracted in an ellipse; (b) binarised image of part a; (c) extracted paint pattern; and (d) triangle for distinguishing repeated patterns.

with the highest contrast and the pen image's histogram was already equalised. The process of extracting the pattern was as follows: First, similar to localisation of pigs as explained above, a 2-D Gaussian low-pass filter was used and a global threshold was calculated using Otsu's method. Image (Fig. 10a) was binsarised using that threshold resulting in Fig. 10b. Thereafter using the following process, the paint pattern (Fig. 10c) and the triangle (Fig. 10d) were extracted:

(1) Connected regions in binary image were identified.
(2) Coordinates of connected regions were obtained.

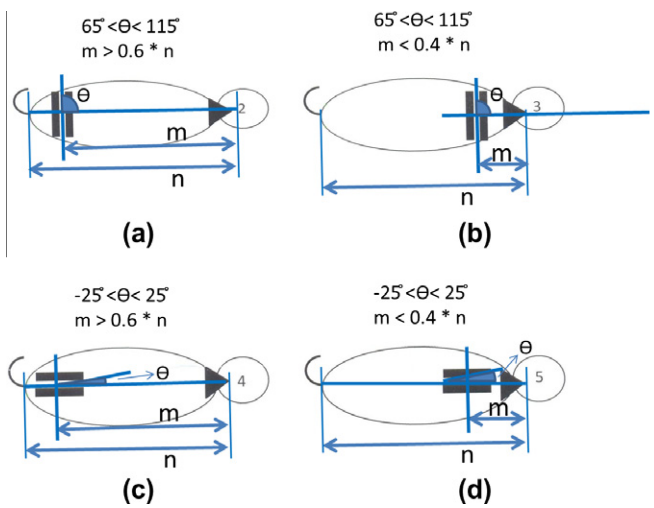

Fig. 11. Distinction of IDs 2–5 (a–d) based on direction and distance of the paint patterns from neck triangle.

(3) The biggest connected region was discovered.

(4) A black background image was generated.

(5) The region discovered in step 3 was reconstructed on the image generated in step 4.

As soon as paint patterns on pigs were located, Fourier transform was applied on the contours of these regions to produce Fourier descriptions (Kunttu et al., 2005). To attain the contour of these patterns, 2D boundary tracing using the Moore neighbourhood method was applied (Pradhan et al., 2010). In this way, successive coordinates of boundary of paint patterns were obtained.

Since IDs 2–5 (Fig. 2) consisted of two split patterns, the boundary tracing algorithm was run twice. In the second run another pattern was sought, ignoring the boundary traced in the first run. The fact that there were two split patterns existing for these IDs, distinguished them from the rest of patterns. Furthermore, based on Fig. 11, depending on the angle between the body direction and patterns (θ) and ratio of m to n (Fig. 9) a unique ID could be detected.

When the identification pattern coordinates in the image were obtained, Fourier Description (FD) was used to describe features in the pattern (Zhang, 2002). To achieve a translation and rotation invariance transform, phase information of Fourier coefficients were ignored and only the magnitudes were used. In addition, scale invariance was achieved by dividing the magnitudes by the DC component (Zhang and Lu, 2004).

The similarity between a query pattern P and a target pattern Q was measured by the Euclidean distance (Schwager et al., 2007) between their normalized FD representations derived from equation 1.

$$D(p,q) = \sqrt{\sum_{i=1}^{n}(q_i - p_i)} \tag{1}$$

In above equation, p and q are FD coefficients of patterns P and Q respectively and n is the number of coefficients considered (here $n = 6$). In fact, to maximize $D(p,q)$ for different patterns in Eq. (1), many patterns were tested and those with highest Euclidean distance of their FD, namely patterns shown in Fig. 2, were selected. Table 1 shows average and standard deviation of Euclidean distance of reference and query patterns.

3. Results

Tables 2–5 show the results of automatic identification of pigs in the experiment carried out for this work. Not all the data were used for validation since manual labelling of the whole experiment data would take a long time.

In total, in 42 h data of four pens, 13,833 out of 15,600 identifications were correctly identified and 159 false positive identifications (1.0%) were recorded. So, with current number of 10 pigs in each pen, automatic identification of pigs could be carried out with an average accuracy of 88.7% while 11.3% were not identified and 1.0% were misidentified. There were a few reasons behind false identifications: (1) Paint patterns were partially faded out over time; (2) Pigs were not always standing in a standard position resulting in unclear paint patterns; Based on data presented in Table 1, patterns 8 and 0 had the highest (the best) and lowest (the worst) total distance from the other patterns respectively. Therefore, pattern 0 was the least identifiable. In addition, cross identification between patterns 2 and 4 occurred more than between other patterns.

Table 1
Average Euclidean distance of Fourier description of paint patterns for 15,600 samples (390 sample per pig per pen); values are shown in this format: Average (standard deviation); For IDs 1, 3, 5 and 7 (repeated patterns) Euclidean distances are the same with IDs 2, 4, 6 and 8 respectively.

Query pattern		Reference pattern					
	Pattern ID	0	2	4	6	8	9
	0	0.0018 (0.0002)	0.1218 (0.0081)	0.1003 (0.0062)	0.0825 (0.0034)	0.0951 (0.0041)	0.1676 (0.0090)
	2	0.1218 (0.0081)	0.0049 (0.0008)	0.0307 (0.0011)	0.1681 (0.0035)	0.2129 (0.0077)	0.0483 (0.0014)
	4	0.1003 (0.0062)	0.0307 (0.0011)	0.0052 (0.0006)	0.1385 (0.0024)	0.1942 (0.0062)	0.1942 (0.0062)
	6	0.0825 (0.0034)	0.1681 (0.0035)	0.1385 (0.0024)	0.0021 (0.0003)	0.1262 (0.0084)	0.2153 (0.0091)
	8	0.0951 (0.0041)	0.2129 (0.0077)	0.1942 (0.0062)	0.1262 (0.0084)	0.0014 (0.0001)	0.2565 (0.0064)
	9	0.1676 (0.0090)	0.0483 (0.0014)	0.0768 (0.0089)	0.2153 (0.0091)	0.2565 (0.0064)	0.0024 (0.0004)

Table 2
Identification of pigs in pen A.

Pig ID	Number of samples	Successful identification (samples)	Successful identification (%)	False positive identification (samples)	False positive identification (%)
0	390	318	81.54	3	0.8
1	390	342	87.69	6	1.5
2	390	329	84.36	8	2.1
3	390	341	87.44	10	2.6
4	390	316	81.03	3	0.8
5	390	325	83.33	2	0.5
6	390	351	90.00	5	1.3
7	390	326	83.59	0	0.0
8	390	374	95.90	1	0.3
9	390	309	79.23	14	3.6
Total	3900	3331	85.4	52	1.3

Table 3
Identification of pigs in pen B.

Pig ID	Number of samples	Successful identification (samples)	Successful identification (%)	False positive identification (samples)	False positive identification (%)
0	390	361	87.78	1	0.3
1	390	331	95.56	7	1.8
2	390	326	92.22	4	1.0
3	390	375	85.56	2	0.5
4	390	368	91.11	3	0.8
5	390	381	95.56	1	0.3
6	390	340	91.11	2	0.5
7	390	344	90.00	1	0.3
8	390	329	81.11	6	1.5
9	390	359	93.33	8	2.1
Total	3900	3514	90.1	35	0.9

Table 4
Identification of pigs in pen C.

Pig ID	Number of samples	Successful identification (samples)	Successful identification (%)	False positive identification (samples)	False positive identification (%)
0	390	351	92.2	1	0.3
1	390	342	96.7	2	0.5
2	390	349	91.1	8	2.1
3	390	365	82.2	4	1.0
4	390	364	84.4	6	1.5
5	390	352	97.8	2	0.5
6	390	333	86.7	0	0.0
7	390	372	93.3	5	1.3
8	390	321	85.6	3	0.8
9	390	351	95.6	12	3.1
Total	3900	3500	89.7	43	1.1

After validating the introduced method, the whole data of the experiment, namely 13 days of recording, 12 h a day and for four pens, individual identification was carried out. In this way they could be tracked and their location in the pen could be determined. To make the tracking results representable, pens were divided to zones as shown in Fig. 12. Attendance of pigs in these zones were monitored and reported in per cent of the total time (156 h) for each pen. Each of these zones relates to a specific behaviour in pigs (Casanovas, 2009). For instance, pigs like to huddle in a corner to sleep. In winter they choose the warmest and in the summer the coolest (Casanovas, 2009). In our experiment the resting zone was at opposite of the feeder zone (Fig. 12). Fig. 13 shows the individual zone appearance for pen A during the experiment. From this

Table 5
Identification of pigs in pen D.

Pig ID	Number of samples	Successful identification (samples)	Successful identification (%)	False positive identification (samples)	False positive identification (%)
0	390	381	97.7	6	1.5
1	390	308	79.0	4	1.0
2	390	361	92.6	2	0.5
3	390	354	90.8	0	0.0
4	390	344	88.2	2	0.5
5	390	372	95.4	3	0.8
6	390	349	89.5	1	0.3
7	390	361	92.6	2	0.5
8	390	340	87.2	0	0.0
9	390	318	81.5	9	2.3
Total	3900	3488	89.4	29	0.7

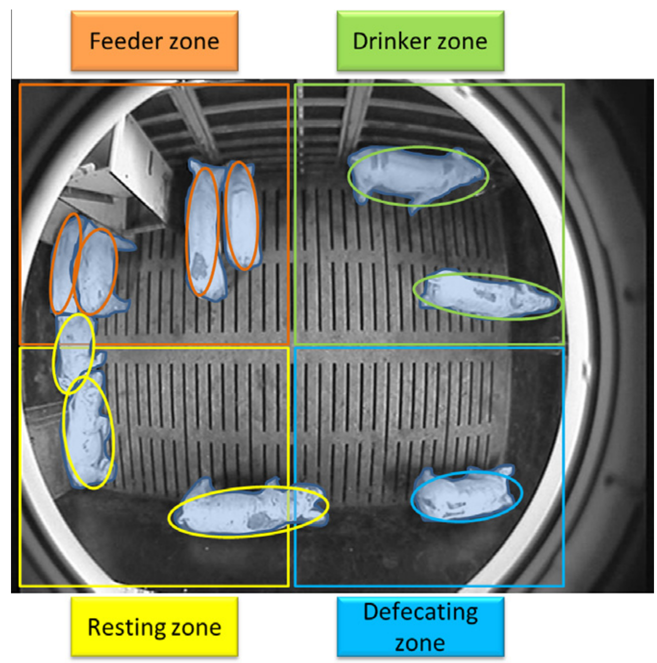

Fig. 12. Defined zones in a pig pen; pen area was divided to four equal square zones depending on the feeder and drinker location.

figure one can conclude that in this pen pig No. 2 rested more than others. It should be noted that as soon as pigs lay down their paint pattern will not be visible by the camera anymore and the identification algorithm assumes that the pig is lying in the same spot in which the last time a successful identification was carried out.

4. Discussion and conclusion

Automatic monitoring of animals is a novel approach and has been applied on many animals (Aydin et al., 2010; Venter and Hanekom, 2010; Poursaberi et al., 2010). In addition, employing technology in this area has proved useful to farm managers. This is mainly due to the broad applications of automated animal monitoring. Specifically, camera technology can be used to monitor every second of animal behaviour. This technology has been mainly practiced to study groups of pigs' behaviours (Lind et al., 2005). However, observing individual pigs' behaviours is of particular importance since it distinguishes pigs regarding health, aggression and agonistic behaviour (Düpjan, 2009).

Identification of pigs is a necessary step towards analysing the different behaviours of pigs individually. Some of the possible

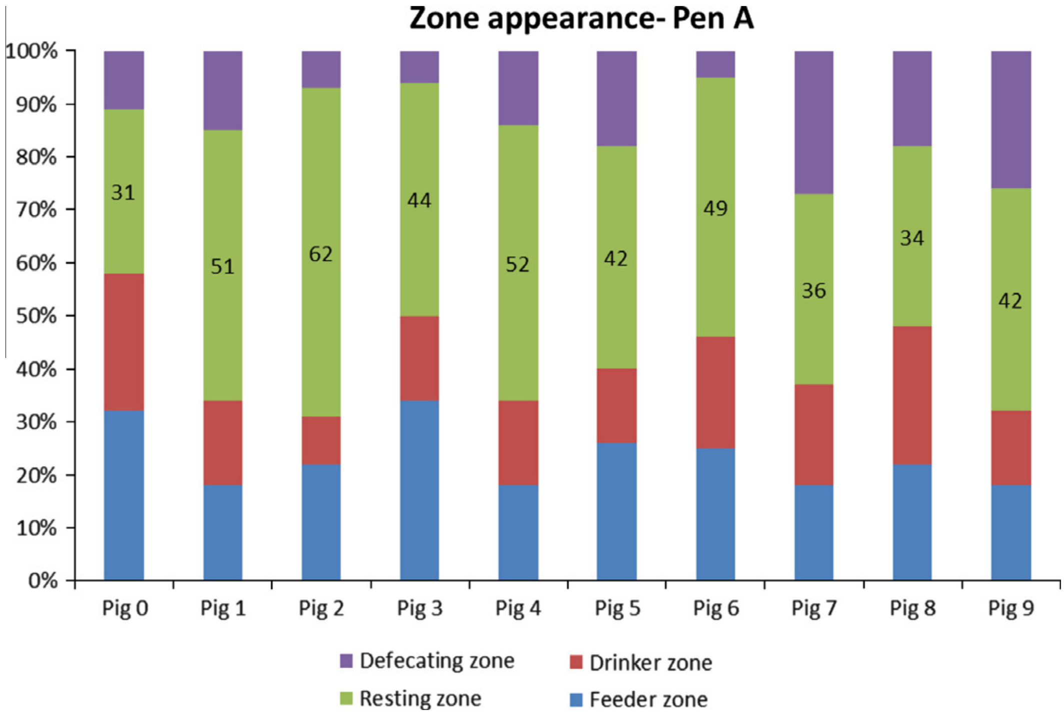

Fig. 13. Zone appearance of pigs in a pen over 13 days; percentage of appearance in resting zone is indicated.

applications are calculating the number of times each pig drinks or feeds, how long each pig stays at the drinker or the feeder, how frequent each pig visits the feeder or the drinker, monitoring the trajectory of pigs movement in a pen or analysing individual agonistic behaviours of pigs. In one application, Kashiha et al. (2013) could estimate water use of pigs using image analysis. Using the method introduced in this paper drinking behaviour of each individual pig can be analysed. Moreover, this can be helpful in monitoring many welfare measures of animals (Botreau et al., 2007) including "body condition" through weight estimation, "functioning of drinkers" through analysing drinking behaviour, "huddling" through analysing resting behaviour, "space allowance" through occupation analysis and "social behaviour" through monitoring global exploring and group playing. Furthermore, monitoring variables such as individual activity and growth can be automated. For instance, this method can detect unbalanced growth of pigs in a pen that can be due to high competition for food (EFSA, 2007). Therefore, there are many possible applications that can make the use of this technique attractive.

Although methods such as ear tags have been used for identification of pigs (Caja et al., 2005; Kitagaki and Shibuya, 2004), automatic identification of marked pigs in a group by image processing in a pig barn has never been reported in the literature. In this work, an innovative approach using calculating Fourier description of patterns painted on pigs and Euclidean distance of these patterns was chosen to investigate the opportunities of automated identification of marked fattening pigs by vision technology. It was shown that identification of marked pigs in a pen is possible by painting basic patterns on their back and using automated image processing to discern these patterns. This was quite suitable for the purpose of this work since there were dramatic variations in pattern and level of illumination caused by animals' movements and light or angle of view changes. While this method is dependent on contrast between, first, floor and pig skin and second, between pig skin and paint pattern it could still identify pigs in a light intensity range of 11.7 and 176.1 lux with an accuracy of 88.7%.

The paint patterns used in this work were chosen based on Euclidean distance of their Fourier description. Although patterns chosen yielded satisfactory results, these are not the only possible patterns to be used. Authors would suggest (1) to use unified patterns since these can be translated to Fourier description in one single step which makes the pattern recognition process faster; (2) to use paint patterns that are easy to be stamped.

Table 6
Angle of view (θ), height and pen length limits for identification rate of 85%.

Lens	Parameter		
	Angle of view, θ (°)	Height, h (cm)	
		Min	Max
Lens 1	52	220	280
Lens 2	100	220	280

To ensure our proposed image processing system works in different setups we tried different lenses with different angles of view and camera height. Table 6 shows the specifications of these setups. In all cases a minimum accuracy of 88.7% was achieved.

Although it is known that farmers will not paint their pigs for monitoring purposes, this method has been employed to do behavioural analysis and to produce proof of concept. The method allows to do behavioural research on group as well as individual animal level without the need of additional sensors and software. It saves costs and the researchers were able to add functionality to the sensor available (camera). It is certainly a valuable tool for research purposes but we are aware that nowadays this method will be replaced or complemented with a more practical technology.

This can help to save many man-hours needed to track pigs manually (Frost et al., 2004) and facilitates detection of behaviours and diseases. For example, it is known that if piglets contract influenza they make 30% less visits to the drink nipple (Bernick, 2007). Using this method it is possible to calculate the number of times each pig visits the drink nipple (Kashiha et al., 2013) and thus automatically detect a drop in visits. As such, this method offers many potential applications to improve animal husbandry management.

Monitoring behaviours of pigs in a pen is possible both in group and at individual level. Individual level data analysis, however, has more advantages. Individual data analysis allows to assess welfare and health of each animal and this could help to avoid outbreak of diseases or abnormal behaviour of a few pigs affecting the rest of the pen-mates. Therefore, monitoring of individual pigs can give earlier alarms raised by a certain problem.

It is worth mentioning that false positive identification of pigs is unavoidable since they do not always stand in a position in which their patterns are clearly visible. Nevertheless, in the analysis carried out, false positive identification was as low as 1.0% in total while true positive identification was carried out with an accuracy of 88.7% and only 11.3% of IDs could not be identified (false negative).

Finally, behaviours of pigs based on the zone they choose to attend in a pen could also be analysed using the introduced method. One analysis provided in this paper was the resting behaviour. Although pigs can rest in any zone within a pen, from manual observations it is known that they rest in more than 96% of cases in the resting zone. Therefore, in this work it was assumed that resting behaviour can be analysed by calculating appearance in resting zone. By combining individual activity and occupation it would be possible to analyse resting behaviour in other zones as well. This will be investigated in future works. Currently, this method could detect the pigs that rested more than the others. Moreover, there are numerous applications for identification, tracking and locomotion monitoring such as detection of tail biting and aggressive behaviour and analysing posture, activity, drinking, feeding, playing and manipulation behaviour that are possible to be implemented (at least for research purposes) using the presented technique. These possibilities will be investigated in our future work.

In conclusion, the introduced method might contribute in future as an important and economically relevant tool in livestock husbandry since feed intake, health, welfare and performance are all variables that are important to be monitored on animal individual level.

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