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Automatic weight estimation of individual pigs using image analysis

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ABSTRACT

Health is a key element in pig welfare and steady weight gain is considered an indicator of good health and productivity. However, many diseases such as diarrhoea cause a substantial reduction in food intake and weight gain in pigs. Therefore, continuous weight monitoring is an essential method to ensure pigs are in good health. The purpose of this work was to investigate the feasibility of an automated method to estimate weight of individual pigs by using image processing.

This study comprised measurements on four pens of grower pigs, each consisting of 10 pigs. At the start of the experiments, pigs weighed on average 23 ± 4.4 kg (mean ± SD) while at the end their average weight was 45 ± 6.5 kg. Each pen was monitored by a top-view camera. For validation purposes, the experiment was repeated once.

Individual pigs were automatically identified by their unique painting patterns using shape recognition techniques. The weight estimation process developed as follows: First, to localized pigs in the image, an ellipse fitting algorithm was employed. Second, the area the pig occupying in the ellipse was calculated. Finally, the weight of pigs was estimated using dynamic modelling. The developed model was then validated by comparing the estimated weight against manual twice weekly actual weight measurements of each individual pig. In addition, to monitor the weight of pigs individually, the pigs were marked on their back with basic unique paint patterns and were identified automatically using shape recognition techniques. In this way, the weight of each individual pig could be estimated. This method can replace the regular weight measurements on farms that require repeated handling and thereby causing stress to the pigs.

Overall, video imaging of fattening pigs appeared promising for real-time weight and growth monitoring. In this study pig weight could be estimated with an accuracy of 97.5% at group level (error of 0.82 kg) and 96.2% individually (error of 1.23 kg). This result is significant since the existing automated tools currently have a maximum accuracy of 95% (error of 2 kg) in practical setups and 97% (error of 1 kg) in walk-through systems (when pigs are forced to pass a corridor one by one) on average.

Future work should focus on developing specific algorithms to account for the effect of gender and genotype on body surface area and body weight since these factors affect the model parameters for weight estimation.

1. Introduction

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

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2010). Technologies are presently available that can monitor individual animals automatically 24 h a day. Research reported by (DeShazer et al., 1988) identified over 90 potential applications for image analysis in pig production. Of these, estimation of pig weight was identified as a primary application for the development of image analysis techniques for use in livestock production. Accurate monitoring of weight gain performance and the use of weight data to make effective management decisions is also crucial for efficient pork production. As farms continue to grow in size, even small alterations to production practices can have a large impact on overall profit in grow-finish pig operations (De Lange and Dewey, 2006). Knowledge of daily weight gain would allow producers to optimize nutritional management practices, predict and control shipping weights, and potentially assist in monitoring herd health (Schofield et al., 1999).

Automatic monitoring of animals based on video analysis is a novel approach, which has been applied in various animal species (Burke et al., 2004; Aydin et al., 2010; Venter and Hanekom, 2010; Poursaberi et al., 2010) and which has proven useful to farm managers (DeShazer et al., 1988; Tillett et al., 1997). Individual weight measurement is an important variable in farm management that nonetheless suffers from a number of drawbacks when performed manually. Firstly, utilizing manual scales is labor intensive and requires movement of animals, which can be stressful for both animals and workers. Secondly, mechanical equipment is prone to malfunction as a result of exposure to dirt, dust, moisture and direct contact with animals. Gathering performance data using a manual scale is therefore done sparingly, generally only at the beginning and end of a production period and most often only for a representative subset of animals, and not for every animal (Schofield, 1990). Machine vision-based weighing of pigs is a non-intrusive, fast and accurate approach, which could reduce stress for both the animal and the farmer during the weighing process (Wang et al., 2008). Since slow weight gain can happen for some of the pigs in a pen, it is important to monitor weight for each pig individually. This helps the farmer to check slow-growing pigs and to make appropriate management changes.

Recently, visual image analysis (VIA) has been proposed as a method for real-time and continuous monitoring of pig weight gain performance, thereby allowing quicker detection of problems and more effective management decisions (Marchant et al., 1999). The VIA technique uses aerial-view images of animals provided by cameras to determine body surface dimensions and may be used for real-time monitoring of pig weight. Since video analysis of pigs has numerous other applications (Van der Stuyft et al., 1991; Xin, 1999; Kollis et al., 2007) weight estimation using videos can be an added value for farmers provided they utilize vision technology.

The concepts of relating size and shape to weight are not new to the field of animal science. According to Whittemore and Schofield (2000), Hammond and Brody were already exploring these concepts in the 1930s and 1940s, with Brody making connections between surface area and live body weight (BW). Historically, consideration of size and shape for evaluation of weight was rejected in favor of direct measurement of live BW due to the difficulty in obtaining the required measurements (Whittemore and Schofield, 2000). More recently however, these concepts have been revisited, as advances in technology make it possible to obtain the required size and shape measurements under current pork production practices.

Since 1991, top-view camera imaging has been known as the least disturbing for animals and it produces the most useful data since it is an elegant way to introduce algorithms from research to field implementation (Van der Stuyft et al., 1991). Past research has indicated that the area of the top view of the pig, minus the head and neck is most strongly correlated to BW (Schofield, 1990). Variation in other components has little effect on estimated live BW, and can therefore be inferred based on the size of the animal's body. Camera technology can be used to determine the area of the aerial view of a pig's body. Using information on the relationship between area and BW, VIA systems have been developed and have been found to be accurate enough to estimate live BW within 5% (Schofield, 1990), but to date, this technology has required that pigs were separated from a group for analysis as an individual.

Other researchers previously investigated different approaches to estimate weight of pigs using image analysis. Brandl and Jørgensen (1996) used spline functions to express the relationship between the body area of the pig measured by image analysis and the live weight of the pig. Marchant et al. (1999) developed automated algorithms that could find the plan view outline of pigs in a normal housing situation, measure major body components and predict the weight of the group of pigs at 34 kg with standard errors of 7.3% while using manual weighing to calibrate the system. Schofield et al. (1999) developed prototype imaging systems to record the weight-related areas of pigs by fitting linear regression coefficients. Furthermore, they could log the growth rates of three groups of pigs of three genetic strains to within 5%. Whittemore and Schofield (2000) examined the value of the estimation of size and shape for animal description in relation to nutrient use in breeding sows and growing pigs. Craig and Schinkel (2001) proposed a mixed effects model[1] to estimate pig weight. White et al. (2004) used a VIA system to continuously collect size and shape data of a total of 116 pigs from 25 to 115 kg of weight for three types of pigs and could classify these groups in 64–83% of observations. Wang et al. (2008) developed an image-based walk-through system for pig live weight approximation. They employed an artificial neural network technique to correlate physical features extracted from the walk-through images to pig live weight in order to improve the accuracy of live weight approximation and could estimate pig weight with an average relative error of 3%.

Some suggest that BW and top-view body area have a linear relationship (Marchant et al., 1999; Schofield et al., 1999; White et al., 2004) and use a single linear regression equation to estimate the live BW of animals from the body area based on the interpretation of individual images. Schofield et al. (1999) suggested that different breeds may require different algorithms for BW prediction. Also Fisher et al. (2003) and Green et al. (2003) suggested a need for unique algorithms for specific breeds or lines of pigs. More recently, researchers have been highlighting the benefits of mixed effects models (Schinkel et al., 2009) and justify their argument that mixed effects model is easily adaptable to stochastic modelling. However, despite the advantages of mixed effects models compared to fixed effects models, it is important to note that there is a large amount of variation in the accuracy of different mixed effects models.

In this work, dynamic data based (transfer function: TF) models were used. Such modelling techniques are compact and allow accurate prediction of the time-variant process response, which makes them suitable for model-based predictive monitoring purposes (Aerts et al., 2003).

In this paper, an approach was presented to monitor pig weights in a fully automated way based on continuous image analysis. The hypothesis in this work was that combining TF modelling and top-view pig body area calculation using image processing could lead to a more accurate weight estimation.

[1] Mixed-effects models, like many other types of statistical models, describe a relationship between a response variable and the covariates that have been measured or observed along with the response. For further information reader is referred to Pinheiro and Bates (2000).

2. Materials and methods

2.1. Animals and housing

Two experiments, identical in setup, were carried out in February and June 2011, whereby data from the former were used to develop the model while the latter was a validation experiment. Experiments were carried out at the Agrivet research farm, Merelbeke, Belgium and lasted three weeks each.

Forty gender-balanced pigs, Rattlerow Seghers x Piétrain Plus, were selected and 10 pigs were assigned to each of four fully slatted pens (2.85 m × 3.60 m) after weaning. 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. Pigs had a timer-controlled 12-h light period from 07:00 h to 19:00 h in light intensity with a minimum of 40 and a maximum of 176.1 lux. Using Hotraco IRIS climate control equipment barn temperature was kept on average at 22 centigrade (range 18.6–25.4 centigrade). At the start of the experiments pigs weighed on average 23.0 ± 4.0 kg and 45 kg ± 6.5 at the end.

This study was approved by the Ethical Committee of the Faculty of Veterinary Medicine at Ghent University, Belgium. Fig. 1a shows a floor plan of the experimental pens including the location of the cameras, feeders and water outlets and Fig. 1b indicates position of the camera on top of a pen.

2.2. Equipment and data collection

Top-view video images of the pigs in the four pens were captured by cameras installed in the rafters of the barn. Video images from top view were collected with Panasonic WV-BP330 cameras for all pens during 13 days for 12 h a day (07:00–19:00 h) resulting in 156 h of video recordings per experiment. Videos were recorded in MPEG-1 format, with a frame rate of 25 frames per second, a frame width of 720 pixels, a frame height of 576 pixels and a data rate of 64 kbps. Fig. 2 shows a frame of the videos recorded in the experiments.

Pig body weight was also measured twice a week using MS Schippers MS-100 weighing scale. These measurements served as the gold standard reference to which the estimated weights obtained from image analysis and modelling were compared.

2.3. Image segmentation

The captured video images were subsequently processed offline in the MATLAB 2010A environment to extract the outline of the body area, which consisted of a two-step process. First, pigs were localized and segmented in the image using an ellipse fitting algorithm. Second, head and neck in the image were separated from the body to maximize correlation to BW (Schofield, 1990).

2.3.1. Localizing and segmenting pigs image by ellipse fitting

To localize pigs within the pen, an ellipse fitting algorithm using Generalised Hough Transform as introduced by Davies (1989) was adapted. In the next step, the corpus image was separated from the head by using the same ellipse fitting algorithm. Here, the algorithm gave two ellipses as shown in Fig. 3a. The larger ellipse represents the corpus and the smaller one the head. The corpus area of the pig surrounded by the corpus ellipse, namely “A” in Fig. 3b was calculated once a minute and used for BW estimation. In order to limit processing to standard standing positions of pigs in weight

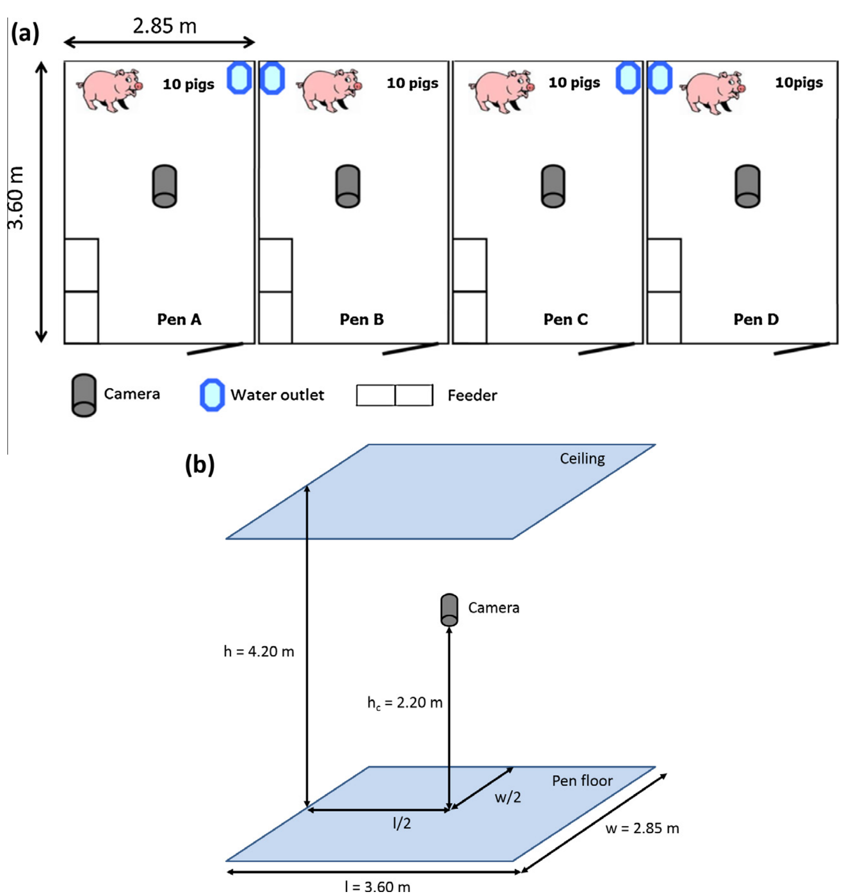

Fig. 1. (a) Ground plan of the 4 pens in the research barn; (b) position of the camera on top of a pen.

Fig. 2. A frame of a video showing a top view of one of the four pig pens in the research barn.

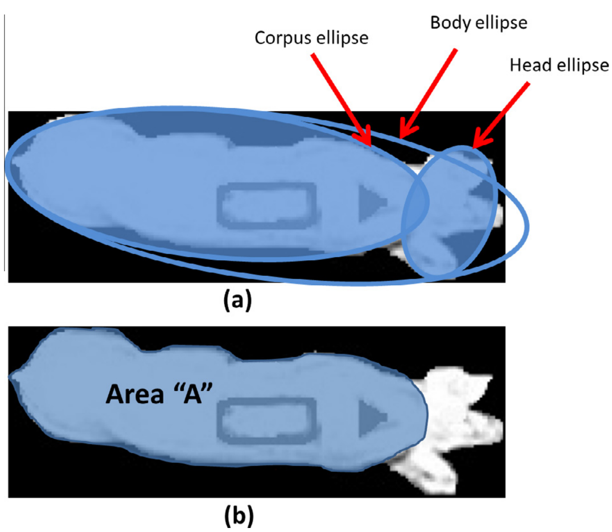

Fig. 3. (a) Extracted pig body using ellipse fitting; corpus and head separation by repeating ellipse fitting algorithm; (b) the resulting body area "A" used for BW estimation.

estimation, 2700 area pixels (for camera height of 2.2 m) were regarded as a minimum of "A".

2.4. Identification of pigs

Since the aim was to estimate individual pig weight as well as at group level, pigs needed to be marked for identification. For this purpose, a specific pattern was stamped on the back of each pig using blue dye (MS Long spray, Belgian MS Schippers). Fig. 4 shows the identification patterns used to identify 10 individual pigs. For further description regarding the identification by using pattern analysis the reader is referred to Kashiha et al. (2012).

2.5. Weight estimation using the TF model

The objective of the next step was to quantify the dynamics of body area (A) and to relate it to the gold standard BW. A single-input, single-output (SISO) TF model was used. The model structure used could be described by Eq. (1) (Young, 2011).

$$\mathrm{BW}(t) = \frac{a(Z^{-1})}{b(Z^{-1})} A(t - nt_T) \tag{1}$$

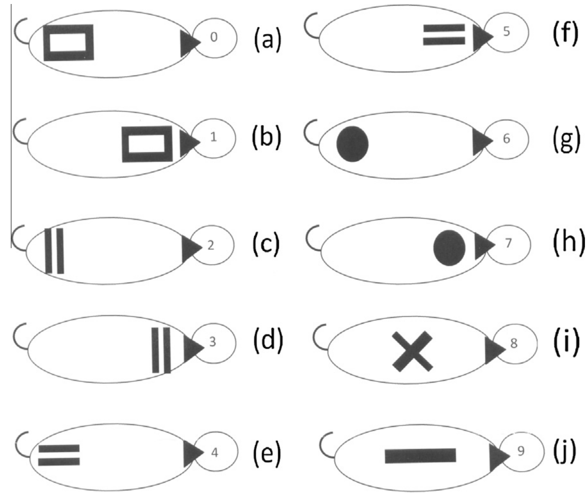

Fig. 4. Patterns applied to identify 10 pigs in a pen.

Table 1
Specification of the TF model developed using BW measurement as the output and body area as input.

YIC	R^2	Parameter estimate
−7.294	0.975	$a_1 = -0.0768$ (0.0061)[a] $a_2 = 0.9609$ (0.0093)[a] $b_d = 0.289$ (0.0014)[a]

[a] The parameter estimates are accompanied by associated standard deviations in parenthesis.

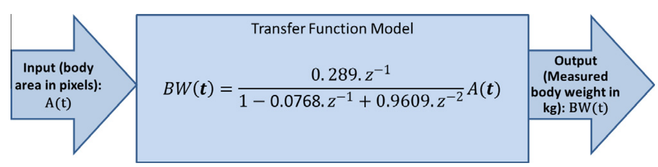

Fig. 5. The TF model adapted to estimate BW (in kg) using body area (in pixels) as input.

In the above equation BW(t) is the body weight, t represents the discrete-time increments for weight estimation and measurement; $A(t)$ represents the input of the model, namely Body Area; nt_i is the number of time delays between each input i and their first effects on the output; $a(z^{-1})$ is the nominator polynomial and equals $1 + a_1z^{-1} + a_2z^{-2} + \cdots + a_{n_a}z^{-n_a}$; $bi(z^{-1})$ is the denominator polynomials linked with the inputs i and is equal to $b_{0i} + b_{1i}z^{-1} + b_{2i}z^{-2} + \cdots + b_{n_{bi}}z^{-n_{bi}}$; a_j, b_i are the model parameters to be estimated; z^{-1} is the backward shift operator, defined as $z^{-1}.y(k) = y(k-1)$; n_a, n_{bi} are the orders of the respective polynomials.

The model parameters were estimated using a refined instrumental variable approach with the Captain toolbox in Matlab (Young, 2011). In order to build the model, different combinations for n_a, n_{bd} and n_{td} were calculated. More specifically, in the SISO model which has only one input, n_a ranged from 1 to 3, n_{bd} from 1 up to 3 and n_{td} from 0 to 2. Therefore, to identify the best fitting TF model parameters of a total of 48 ($4 \times 4 \times 3$) possible models were calculated. The resulting models were evaluated by the coefficient of determination R_T^2 (Young and Lees, 1993) and an identification procedure was used to select the most appropriate model

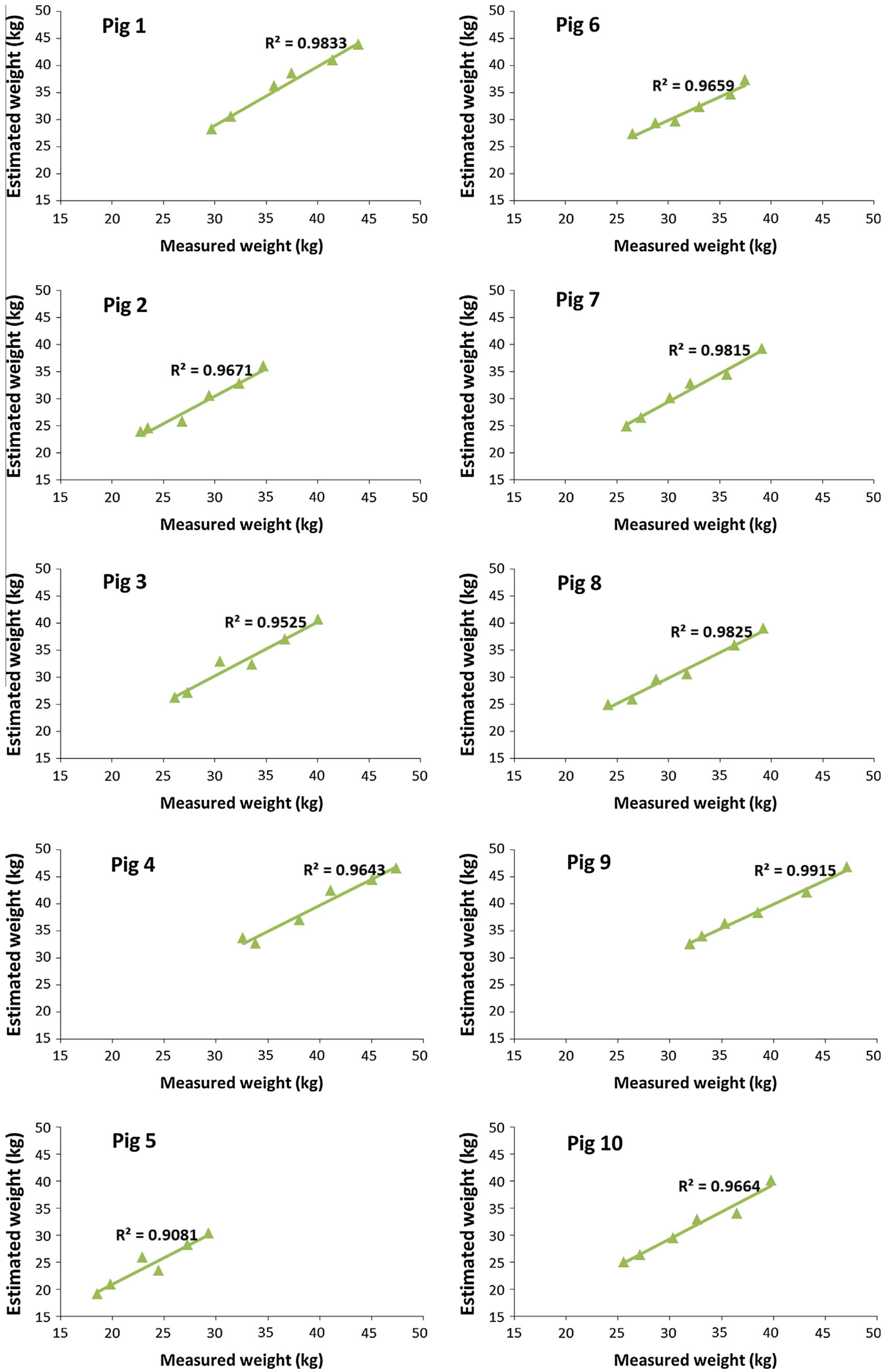

Fig. 6. Weight estimation versus measurements for each pig in pen 1 on six measurement days during the experiment. The average R^2 for weight estimation for this pen was 0.9663.

order based on the minimization of the Young Identification Criterion (YIC) explained by Young and Lees (1993). The smaller the variance of the model residuals in relation to the variance of the measured output, the more negative this term becomes.

Weight measurements in the first and development experiment were used to design the model. The developed model was then used to estimate the BW in the second and validation experiment, which was methodologically identical.

Finally, results of TF modelling were compared against a linear regression model (Schofield et al., 1999) and a non-linear mixed effects model (Schinkel et al., 2009).

3. Results

Using the methods adopted in this paper, pigs were identified and their top-view body area was measured automatically. As a reference, every pig was manually weighed two times a week.

When applying the modelling approach to the data of the whole experiment (240 measurements) the YIC criterion selected models which were predominantly second order (Eq. (2)) and without delay, stable (namely all of the poles within the unit circle) and with the highest R_T^2. The optimal model structure was described by $n_a = 2$, $n_{bi} = 1$ and $n_{td} = 0$ based on parameters demonstrated in Eq. (1).

$$\mathrm{BW}(t) = \frac{b_d \cdot z^{-1}}{1 + a_1 \cdot z^{-1} + a_2 \cdot z^{-2}} A(t) \tag{2}$$

The specific values for the model parameters (a_1, a_2 and b_d) are presented in Table 1. The model described the weight measurement for 240 measurements with R_t^2 of 97.5%. As seen in the table, YIC is optimally low and the standard deviation of the a-parameters and b-parameter is low as well.

Fig. 5 illustrates the adapted model with the optimal parameters shown in above table.

Fig. 6 compares weight estimation results calculated by the model (using average daily body area) shown in Fig. 5 with actual weight measurements on those days for pen 1 in the validation experiment. Fig. 7 shows the measured actual weights versus the estimated weights over six days of measurements for all four pens and ten pigs per pen (240 data points). The ideal case was that all of the data points align with the identity line (R^2 of 100% which means for every data point, estimated weight would equal the measured weight). This means the more erratic the points are, the lower R^2 and accuracy of weight estimation will be.

In total, using TF modelling of top-view pig body area, pigs weight could be estimated with an accuracy of 97.5% and 96.2% at group[2] and individual level, respectively.

4. Discussion

The proposed image processing and modelling method proved the ability to work unattended in an environment with the pigs increasing in weight from a mean of 23–45 kg. The system calculated an average of one area measurement every one minute. Subsequently, the body area calculated by the image processing was used to design a TF model with weight measurements as output. The resulting model was evaluated in a validation experiment in which the body area was the input of the model. The model output, namely the estimated weight, was subsequently compared against conventional weight measurements. This displayed a R^2 of 0.9663 for pen 1 at individual animal level. Average weight of individuals in a group (group level) was also estimated using the developed model. Taking all four pens into account R^2 was as high as 0.975 for group weight estimation and 0.962 for individual pig weight estimation. These results prove that the mean weight of the individual pigs can be estimated with a deviation of 2.5% in a weight range of 23–45 kg.

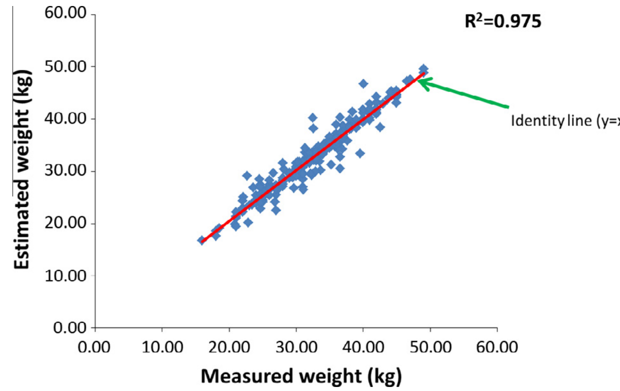

Fig. 7. Measured weights versus estimated weights over six measurement days of all four pens with ten pigs per pen (240 data points) in the validation experiment. Overall R^2 is 0.975 with standard error of 0.0182.

Table 2
Comparison of results of applying "Linear regression", "Mixed effects (non-linear)" and TF models to body area data in group level.

Model	Data points	R^2	SE[a] (%)	SE (kg)
Linear regression	240	0.871	10.04	4.52
Mixed effects (non-linear)	240	0.943	5.95	2.68
TF	240	0.975	1.82	0.82

[a] Standard error.

The results obtained using TF model were compared with previous work on this topic, namely linear regression models (Schofield et al., 1999) and mixed effects (non-linear) models (Schinkel et al., 2009). Table 2 compares the results of these three methods applied to the group level data of the validation experiment while data of the first experiment were used to develop the models.

The data presented in Table 2 indicate that the TF model yields a higher R^2 and a lower SE, which means this method can estimate BW with a higher accuracy and reliability. In addition, the proposed method is capable of estimating BW for individual pigs with an accuracy of 96.2% (SE = 1.23 kg) while the competing methods do not support automatic individual pig weight estimation.

In terms of practical application of this method, problems should be solved as a number of pitfalls have been identified for this study. The first problem is related to individual identification of pigs using a dye marker. The problem arising from faded color patterns and pigs being dirty will need to be addressed if they are to be reliably monitored using image analysis techniques under actual farm conditions. That is, poor results may be caused by dirt on a pig resulting in poor definition of the body edge and area by the measurement algorithm. Another problem lays in the application of paint pattern as such. On the one hand, dirt on the pig or fading paint patterns can cause a low identification rate. On the other hand, application of paint patterns are questionable in terms of convenience for the farmer. These problems need to be considered in the further development of the image illumination and capturing techniques, as well as in the software development for image processing.

A second pitfall is when certain pigs stood on their back feet and therefore presented a reduced area for image capturing and

[2] Group level weight estimation is derived from calculating an average of individuals weight.

analysis. These cases were automatically excluded by thresholding the minimum body area.

The final pitfall was in illumination conditions, which are also important for identification and segmentation of the images. On the one hand, overly bright illumination could prevent accurate identification since contrast of the dark paint patterns on a bright pig skin could decrease. On the other hand, however, a dim illumination could make pig segmentation against dark backgrounds more difficult. In the experiments of this work, it was found that a range of light intensity of 40–150 lux would be optimal.

At the time of conducting this research work, the solution proposed was the cheapest and the best for algorithm development since cameras were used for many other applications as well (Kashiha et al., 2013). For future work, however, a more practical identification method such as electronic tags might be considered. Alternatively, algorithms may be developed for identification of animals deviating from the mean of desired growth without the need for individual tagging. In addition, since weight gain over time is supposed to be closely related to health and behaviors such as feeding in pigs (Hessel et al., 2006), growth patterns and correlation of weight gain with behaviors will be investigated.

5. Conclusion

A technique has been introduced that offers fully automated weight estimation of pigs. By marking pigs, it became possible to estimate their weight individually using top-view video processing. The results show that by measuring the top view body area and adapting a TF model, it is possible to estimate BW with an accuracy of 97.5% (SE = 0.82 kg) on group level and 96.2% (SE = 1.23 kg) on individual level overcoming competing linear and non-linear modelling methods. In conclusion, application of the introduced method can bring important profits for livestock enterprises since continuous information on daily weight would allow producers to optimize nutritional management practices, predict and control shipping weights, and potentially assist in monitoring and improving herd health.

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