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Walk-through weighing of pigs using machine vision and an artificial neural network

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Machine vision-based weighing of pigs is a non-intrusive, fast and relatively accurate approach that could reduce stress on both the animal and the stockman during the weighing process. An image-based walk-through system was developed in this study for pig liveweight approximation without having to restrain the pig to a certain area for stationary imaging. A protocol was developed to automatically screen and select the images captured for image processing. The artificial neural network technique was used in this study to correlate a multitude of physical features extracted from the walk-through images to pig liveweight in an attempt to improve the accuracy of liveweight approximation. The results showed that the average relative error of the walk-through weighing system was around 3%. The walk-through system has made it even easier for stockmen to obtain the liveweight of pigs using a machine vision-based weighing system.

1. Introduction

The liveweight of pigs is an important indicator of the animal's growth, health and readiness for market. Conventionally, liveweights are taken by driving the animal to a ground scale, which is physically stressful to both the animal and the stockman. In order to reduce the stress, self-accessed scales were developed (Sharp and Turner, 1985; Turner et al., 1985; Slader and Gregory, 1988; Ramaekers et al., 1995; Williams et al., 1996), which automatically estimated the animal's front leg mass (or back leg mass) when the pigs went about their daily activities such as feeding. This technique determines the liveweight of individual pigs without interrupting their normal daily routine. However, it requires a special small electronic weighing platform to be built in front of a single space feeder and requires extensive data processing in order to remove poor data. Examples of poor data include pigs sleeping on the platform, pigs with one or more legs in the trough and several pigs on the platform at once. Also, the stance of the pig during actual measurement must be the same as that when collecting the data and formulating a calibration equation. Otherwise, serious errors in estimating the liveweight would result (Williams et al., 1996).

For dairy cows, walk-through scales were developed (Filby et al., 1979; Long et al., 1991a, b; Ren et al., 1992; Peiper et al., 1993) which automatically measured and recorded the mass while the cows were leaving the milking parlour. This kind of system uses electronic circuits involving a continuous averaging technique and peak hold facilities to obtain the liveweight from a suitably modified, commercially available weigh crate. However, the performance of this weighing equipment depended on how the cows proceeded, for example, whether they walked at a steady pace or not over the equipment. Also, a single mass reading could not be used with any great reliance in isolation from previous readings for that cow. In addition, care is necessary to ensure that the cow

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Nomenclature

b	bias of a neuron
f	transfer function of a neuron
M_{ANN}	mass calculated using an artificial neural network, kg
M_{Scale}	mass measured using ground scale, kg
p_i	ith input of a neuron
q	output of a neuron
r^2	coefficient of determination
$W_L(i)$	left-hand side width of the pig at the ith point along the longitudinal direction, pixel
$W_R(i)$	right-hand side width at the ith point along the longitudinal direction, pixel
w_i	mass of the ith input of a neuron
δ	asymmetry value of the pig's left and right side body
ε	ratio of the head's length to the length of the pig along the longitudinal direction
Δ	relative error

does not exert downward forces, other than its weight, for example, by rubbing its neck or head; otherwise, the peak hold circuit may respond to this and give a high answer (Filby et al., 1979).

There are also indirect methods for liveweight measurements which provide different approaches to minimise any harmful stress. These methods measure the physical features and correlate them to the animal's liveweight. They have been applied to cattle (Manik et al., 1981) and pig (Yeo and Smith, 1977; Pope and Moore, 2002). For example, Pope and Moore (2002) found a linear relation between sow liveweight and heart girth when the mass was in the range of 180–320 kg, with a relative error of 4–5%. The disadvantage of this method is that it still needs physical contact between the operator and the animal, and care must be taken to see that the animal stood squarely with the head parallel to the body on a flat surface at the time of taking the measurements (Manik et al., 1981).

Another way to measure the pig mass indirectly is to use the machine vision technique (Schofield, 1990; Minagawa et al., 1993; Ali and Jørgensen, 1992; Ali, 1993; Schofield, 1993; Schofield and Marchant, 1996; Minagawa, 1997; Schofield et al., 1999; Brandl and Jtirgensen, 1996; Marchant et al., 1999; White et al., 2003; Whittemore, 2004; Wang et al., 2006). The pigs were imaged predominantly from the top, some from the sides as well, using a camera. The images were processed by a computer to correlate the optimal features extracted, e.g., the projected area (Wang et al., 2006), to the pig's liveweight. Stereo photogrammetry has also been used to extract the three-dimensional shape of animals for the liveweight estimation (Minagawa, 1994, 1995; Wu et al., 2004). Some researchers used both the projected area and pig height to estimate the mass (Minagawa et al., 1997; Minagawa and Hosono, 2000; Minagawa and Murakami, 2001). A commercial system for image-based weighing of pigs is currently being marketed by Osborne (Europe) Ltd. (UK) (2006a, b) which measures mass and body dimensions and offers the option of automated height measurement.

Nevertheless, the image-based methods of indirect pig weighing so far reported in the literature require the pig to be in a relatively stationary position. If a pig moves during imaging, both the accuracy and the speed of measurement would suffer. If the current image-based pig weighing system could be improved to allow the mass measurement to be carried out as the pig walks under a camera, then the measuring speed could be substantially increased and more applications would become possible, especially useful for an integrated monitoring system (Frost et al., 1997) or automatic drafting of pigs. The current walk-through weighers, e.g., the Weight Watcher system by Osborne (Europe) Ltd. (UK) (2006b), are based on mechanical scales. No image-based walk-through weighing system has so far been available in the market.

In this study, walk-through weighing of pigs was studied using machine vision and an artificial neural network (ANN) technique. The walk-through system developed in this study has several advantages over the foregoing stationary methods: (1) more accurate—it correlates a multitude of physical features, rather than a single one, to the liveweight, and so it should be more accurate; (2) fast—liveweights can be obtained immediately as the pig walks under the camera; (3) stress free on the pig—the pig is in a relaxed, walking status when the images are taken; and (4) versatile—it can be integrated into existing barns in either small or large operations, so that liveweights can be taken as pigs walk from one pen to another.

The objective of this study was to improve the current machine vision-based pig weighing system by developing a walk-through weighing protocol using ANNs that work with multiple physical features for liveweight approximation.

2. Materials and methods

2.1. Materials

The pigs used in this study were from the Holder Farms in southern Tennessee, USA. The breed was a crossbreed of Yorkshire (50%) and Landrace (50%) with a whitish colour. The colour is important since it determines the required background (in this case dark) to achieve strong contrast.

Two groups of pigs were imaged. The first group consisted of 39 pigs, and the second group 22 pigs. After the pigs were imaged, the liveweight of each pig was measured using a mechanical floor scale which was accurate to ±1 kg. The masses of the pigs in this study were distributed between 14 and 123 kg.

2.2. Experimental set-up

The machine vision-based system for walk-through pig weighing comprised a video camera for image capture and a computer for image acquisition, image processing, feature extraction and data analysis (Fig. 1). The video camera was a

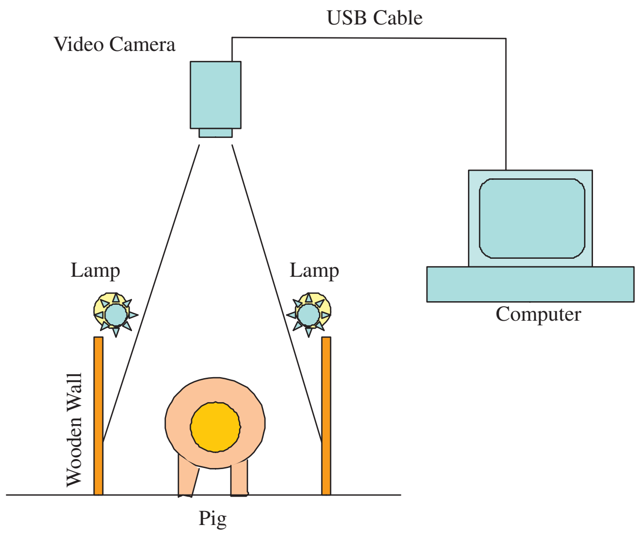

Fig. 1 – Schematic diagram of the experimental set-up used in this study.

digital colour camera model EDC 3000B from the Electrim Corporation, and it was connected to the computer through a USB 2.0 cable. The camera has two resolutions: 640 × 480 and 1280 × 1024. In this study, the lower resolution 640 × 480 was selected for faster data transfer and processing. The frame rate was set to 15 frames per second. The camera was fixed on the ceiling and the distance between the camera lens and the ground was 2.21 m.

A Dell Inspiron 600 m laptop computer, with Matlab 7.0 and its toolboxes (Image Acquisition Toolbox, Image Process Toolbox and Neural Network Toolbox), were employed for image acquisition, image processing and neural network application.

The pigs were guided to walk from one pen to another through a passage about 1 m wide where the video camera was installed on the ceiling. Two fluorescent lamps (40W white fluorescent lamp from General Electric Company, Nela Park, Cleveland, OH) were arranged on each side of the passage, about 1 m above the ground, to provide stable illumination during the experiments. In order to obtain a higher image contrast between the ground and the pig that was whitish, a black sheet of carpet was placed on the ground of the passage.

In this study, the pig had a whitish colour and so a black background was chosen for a great contrast. For breeds with a blackish colour, a white background could be chosen to form a great contrast. For breeds with a grey colour, a background of either black or white or other colours could be chosen, to achieve greatest contrast.

2.3. Image acquisition

Each pig was imaged by the camera from the top down continuously while it was walking through the passage. The camera was connected to the computer by a USB cable and image acquisition was accomplished using the image acquisition toolbox of Matlab. The camera was initially set to "manual" in the Exposure Mode. The aperture was set to be the widest position so that the exposure time for each photo could be minimized at a given light strength to reduce the chance of blurring due to pig movement. The frame rate was set to be 15 frames per second. In the experiments, the Logging Mode was set to "disk" so that the data could be stored on the computer hard disk for later processing.

2.4. Image selection

Selection of images from a series of walk-through photos of the pig is a crucial step for developing an accurate walk-through weighing system. Fig. 2 shows the typical images of a walking-through pig to aid in the description of the way images were selected: (a) the background without a pig on it; (b) the pig just entered the screen field; (c)–(e) all parts of the pig contained inside the screen field; and (f) the pig has left the screen field.

Two ways were employed in this study to select the images: automatic by self-written computer codes and manual by visual inspection. The latter worked as a control with which the weighing results from the former could be compared.

The criteria for manual selection were: (1) the whole body of the pig should be inside the screen field (i.e., no contact with the edges of the photo frame). For instance, Figs. 2c–e were suitable according to this criterion, but Figs. 2b and f were not; (2) its body and head were in line, like in Figs. 2c–e.

The criteria for automatic selection were:

(1) No part of the pig could touch the edge of the screen field;
(2) The asymmetry value δ of the pig's left and right side body could not exceed a certain value, δ defined as

$$\delta = \frac{\sum |(W_L(i) - W_R(i))|}{\sum (W_L(i) + W_R(i))} \tag{1}$$

where W_L (i) and W_R(i) are the left-hand side width and right-hand side width at the ith point along the longitudinal direction. If δ was too large, then the body and head would not be in a straight line. In this study, the critical value of δ was chosen to be 15%.

(3) The ratio of the head's length (L_{Head}) to the length of the pig (L_{Pig}) along the longitudinal direction, ε, should be in a certain range (again to ensure that the body and the head were in line).

$$\varepsilon = \frac{L_{Head}}{L_{Pig}} \tag{2}$$

where L_{Head} and L_{Pig} can be determined using an image processing technique (see Section 2.5). Usually, ε was larger than 10% and smaller than 30%. However, if the pig looked down, then ε could be smaller than 10%. If ε was over 30%, then errors had probably occurred in the selection and the image was dropped. In this study, a photo would be selected if ε was between 10% and 30%.

2.5. Image processing

Fig. 3 describes the way in which images were processed using the Matlab Image Processing Toolbox. A series of

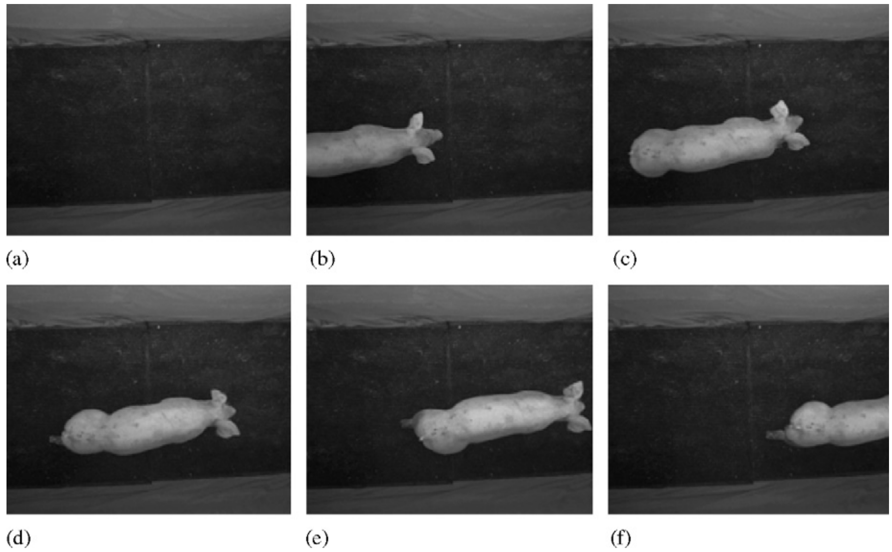

Fig. 2 – Typical images of a walking pig captured in this study: (a) background without a pig on it; (b) pig just entering the screen field; (c–e) all parts of the pig contained inside the screen field; (f) pig left the screen field.

images of the pig, similar to those shown in Fig. 2, were read by the toolbox from the computer hard disk. If the head of the pig was not always positioned straight ahead, e.g., it sometimes turned down, image processing would be adversely affected. For better accuracy in liveweight approximation, the head and ears of the pig on the image were removed by the software following the procedure described below. The procedure for the feature extraction from the images was:

Step 1: Getting rid of the background (a). An image of the background without a pig was taken and used as the baseline for background removal during image processing. Each image was subtracted from the background to obtain a clean image with only the pig in it.

Step 2: Changing the image into grey scale and enhancing the contrast of the grayscale image so that the image looked brighter (b).

Step 3: Binarising the image (c). Since pigs were whitish while the background was darkish, a threshold intensity value was chosen and the computer mapped all values greater than the threshold to one colour and all pixels lower than the threshold to the other colour. The result was an image showing a white blob corresponding to the exact shape of the animal on a black background.

Step 4: Using the functions of Image Erosion and Image Dilation to remove the tail and feet, as well as the tiny background interference (d).

Step 5: Moving the pig to the centre of the field and rotating it so that its longitudinal axis was positioned horizontally (e).

Step 6: Removing the head and ear (f). By calculating the width of the pig at every point along the longitudinal axis, the position of the back of the ear could be found, which was where a sharp peak on the derivative of the width curve occurred (Fig. 4).

Step 7: Extracting the feature parameters including area, convex area, perimeter, eccentricity, major axis length and minor axis length using the Image Process Toolbox. All the physical features involved in this study are defined in the Appendix.

In this study, the pig's ears are used to identify the location of the head. If a breed does not have obvious ears, other parts such as the neck could also be used to identify the location of the head.

In the foregoing procedure, the orientation of the head of the pig was always rotated to face towards the right-hand side for consistency in image processing. To do this, the head of the pig was first sought by drawing a vertical line through the centre of gravity, which divided the pig into two blobs. The roundness, which is a measure of how close a shape was to a perfect circle, of the two blobs was calculated. Since the head of the animal included two ears and a nose, while the end of the animal had only the tail, the roundness of the back was always greater than that of the front of the animal. If the head was found towards the left-hand side, the image was flipped.

2.6. *Artificial neural network*

The ANN used in the study was a 1-hidden layer feed-forward network trained by back propagation. It comprised a number of neurons connected to each other. A neuron has a number of inputs p_i ($i = 1,2,\ldots N$) and one output q:

$$q = f\left(\sum_{i=1}^{N} w_i p_i + b\right) \tag{3}$$

where w_i is the mass of the ith input, b is the bias and f is the transfer function.

The neural network used in this study had three layers: (1) the input layer; (2) the hidden layer; and (3) the output layer. The input layer has six inputs corresponding to six features: area, convex area, perimeter, eccentricity, major axis length and minor axis length (see the Appendix). The number of neurons of the hidden layer was adjustable. The output layer had one neuron, the mass of the pig. A hyperbolic tangent

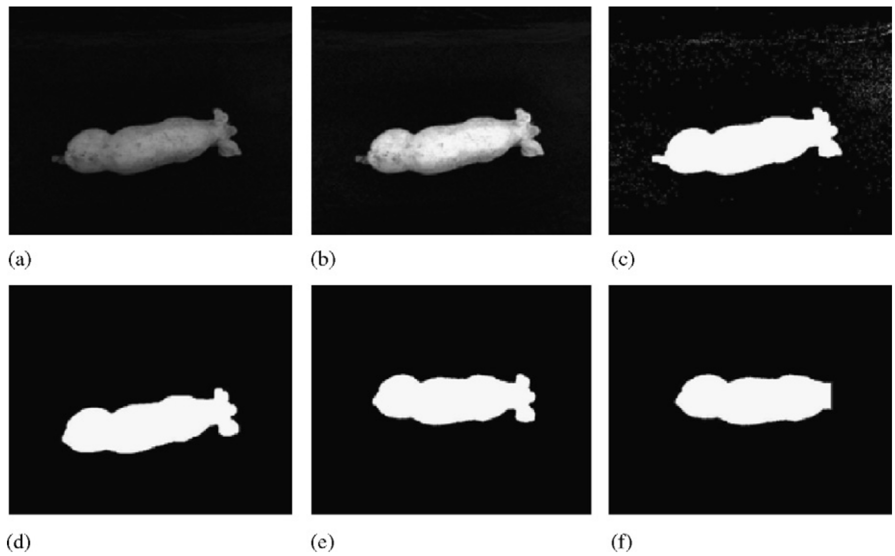

Fig. 3 – Illustrations of the procedure for processing the images of a walking pig: (a) after background removal; (b) enhance the contrast of grey scale image; (c) binarise the image; (d) remove the tail and feet; (e) move the pig to the centre and align horizontally; (f) remove the head and ear.

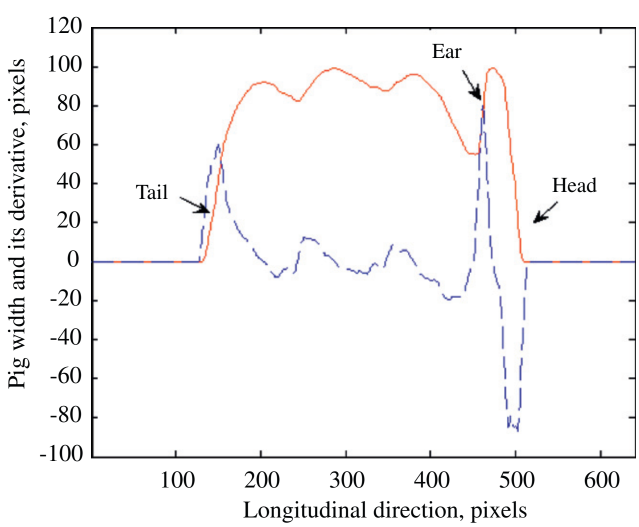

Fig. 4 – The width of the pig (solid line) and its derivative (dashed line). The sharp peak of the dashed line on the right-hand side of the graph, as the arrow "Ear" indicates, denotes the location of the back of the ears.

sigmoid transfer function was used for the hidden layer, and a linear transfer function for the output layer.

The physical feature data extracted from the first group of 39 pigs and the corresponding pig mass were used for the neural network training. The weight w_i and bias b of every neuron were preset before the training process. Then the output of each neuron was calculated using Eq. (2). The output was compared with the scale-measured pig mass and the difference between the two used to adjust the weight w_i and b of each neuron using the Levenberg–Marquardt algorithm (please refer to MATLAB Neural Network Toolbox User's Manual). The process was repeated until the preset goal or the preset iteration number was met.

Each pig walked through the passage several times below the camera, and each time multiple photos were taken. Over 1000 pictures were selected for use in image processing. The obtained feature data were divided into two equal halves: the training set and the verifying set. The first half (training set) was used for training the neural network, and the second half (verifying set) for verifying whether the training was successful and how good the training was. The physical features extracted from the 340 pictures from the second group of 22 pigs (measurement set) were used for an independent test of liveweight approximation.

3. Results and discussion

3.1. *The neural network training and testing*

Wang et al. (2006) showed that a number of physical features, such as area, width, length and perimeter, extracted from pig images, correlated with the pig liveweight, among which the area had the best correlation. Preliminary tests indicated that the best results were obtained when the hidden layer had three nodes.

Fig. 5 shows the result of the trained neural network used in this study. Fig. 5 only depicts, as an example, the relationship between the liveweight of the pig and projected area, since it is impossible to plot the liveweight as a function of all the features tested. The two sets of data were fitted with a power function giving: $y = 7.35x^{1.303}$ for the scale-measured data from the training set, and $y = 7.39x^{1.298}$ for the neural network-calculated data for the verifying set. These two curves were so close that they obscure each other in Fig. 5, which indicated that the neural network had been successfully trained.

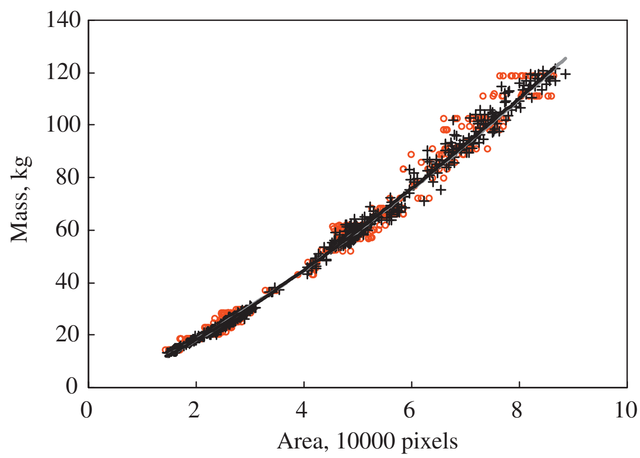

Fig. 5 – Pig masses vs. projected area. The circles represent the mass data measured by a mechanical ground scale for the training set of data and the crosses represent the estimated masses for the verifying set of data using the trained neural networks. The lines indicate power-law fits.

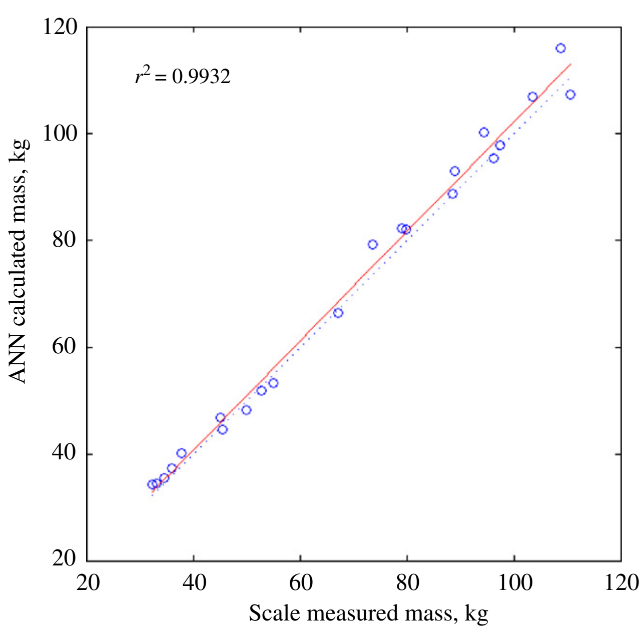

Fig. 6 – ANN-calculated masses (M_{ANN}) vs. scale-measured masses (M_{Scale}) from manually selected good photos. The solid line indicates the best linear fit; the dotted line indicates y = x.

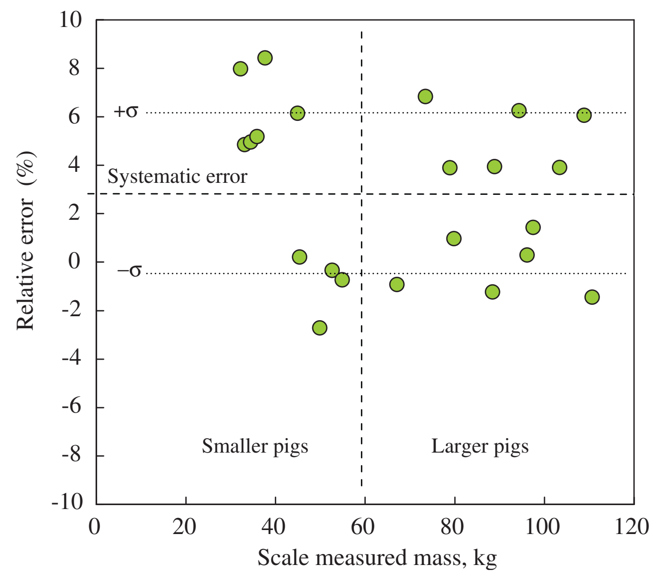

Fig. 7 – Error analysis of machine vision-based pig weighing for manually selected photos.

3.2. *Liveweight approximation from manually selected images*

The successfully trained neural network was then used to approximate the liveweights of the second group of 22 pigs. After the images were processed, the extracted features were input to the neural network for calculation. Since more than one image was taken for each pig, the calculated mass is an average of the calculated masses for that pig, as shown in Fig. 6. The best linear fit was $y = 1.02x - 0.0282$, where y is the ANN-calculated mass in kg and x is the scale-measured mass in kg. The coefficient of determination r^2 was 0.9932.

In order to examine the accuracy of the machine vision-based pig weighing system, the relative error $\Delta = (M_{ANN} - M_{Scale})/M_{Scale}$ was calculated for all the 22 pigs, as shown in Fig. 7. The sign of the relative error was retained to indicate whether the ANN-calculated mass was larger or smaller than the scale mass. Fig. 7 shows more positive than negative values, indicating a systematic error. The errors were randomly scattered around the systematic error line at 2.91% throughout the entire mass range. The standard deviation σ was calculated to be 3.42%.

In order to examine whether there is a difference in measurement error between smaller and larger pigs, the data points were divided into two parts by setting a discriminating criterion of 60 kg (scale measured mass), as shown in Fig. 7. A statistical test showed that the variances of these two populations were not significantly different from each other ($p < 0.05$). Thus, the machine vision-based walk-through weighing method had similar accuracy for smaller and larger pigs in the mass range tested in this study.

The overall accuracy of this system based on manually selected images was 3.58% and decreased to 3.05% when the systematic error was removed.

3.3. *Mass approximation from automatically selected images*

After the images were automatically selected by the computer based on the defined criteria, they were processed and the extracted features were input to the neural network for liveweight calculation. The liveweight was estimated from each of all the automatically selected images of a particular pig and then an average was taken. The relationship between the ANN-estimated and ground scale-measured liveweights was $y = 1.04x - 1.96$, with the coefficient of determination r^2 being 0.9925 (Fig. 8).

Variances of the errors for pigs above and below 60 kg showed no differences between these two populations (Fig. 9), and so the machine vision-based method yielded similar accuracies for both smaller and larger pigs in the mass range tested.

The overall accuracy based on automatically selected images was 3.34% and decreased to 3.07% relative accuracy when the systematic error was removed. The error based on automatic image selection was slightly better than that of manual selection.

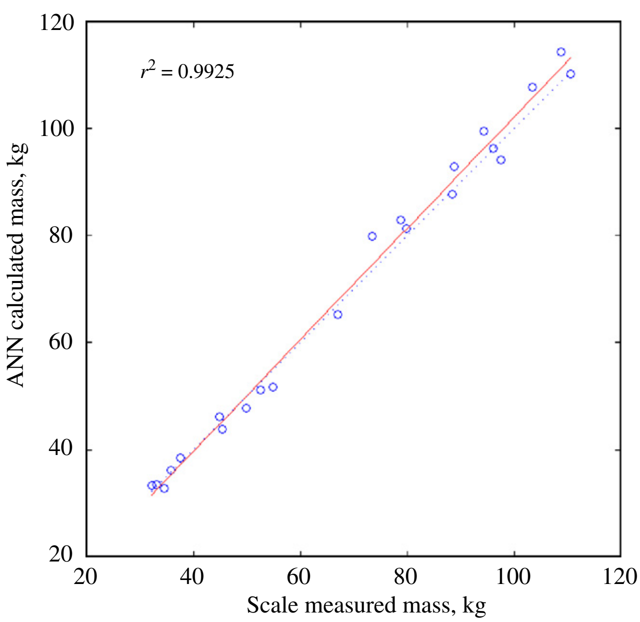

Fig. 8 – Artificial neural network (ANN)-estimated masses based on the computer-selected images vs. scale-measured liveweights. The solid line indicates the best linear fit and the dotted line indicates y = x.

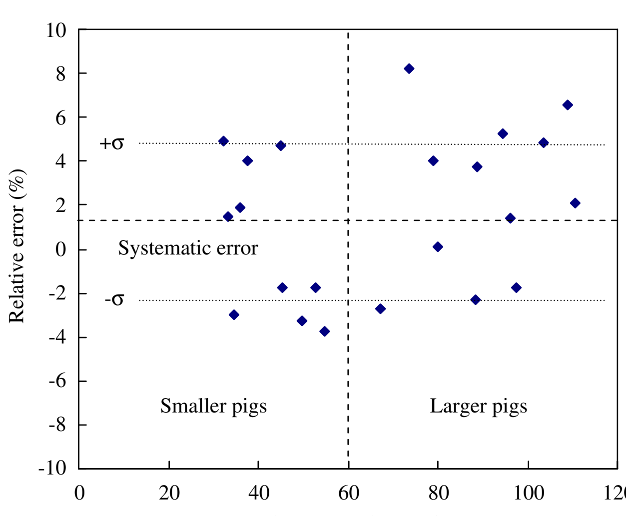

Fig. 9 – Error analysis of a machine vision-based pig weighing system for computer-selected images.

3.4. *Significance of the work*

The major contribution of this study to machine vision-based weighing of pigs has been the development of a protocol which enabled the weighing of a pig while it was walking. Therefore, this walk-through system has made it even easier for the stockman to obtain pig liveweight measurements, because the pig could move around anywhere in the pen or along the passages connecting two pens, where the images will be taken as soon as the pig enters the view of the camera. This has also provided necessary technical innovation for the development of an integrated livestock monitoring system (Frost et al., 1997).

For many pig barns, pigs need to be sold when their liveweights fall into a certain range, say, 109–118 kg (240–260 pounds), according to the specifications of the packer. Outside this range, the price would be considerably reduced. Therefore, a method that enables the stockman to quickly obtain the liveweights of pigs with ease is important to pig producers.

4. Summary and conclusions

A machine vision-based system was developed in this study for approximating the liveweight of pigs as they walked under the camera, without having to restrain the pig in a particular area for stationary imaging. A protocol was developed to automatically screen the images captured and select those suitable for image processing. The results showed that the average relative error of the walk-through weighing system was around 3%. The ANN technique was used to approximate the liveweight in an attempt to improve the accuracy of liveweight approximation, but the results did not show much improvement when compared to other people's work.

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Appendix

Image features are defined as follows:

- Area—the sum of pixels in the whole pig's image; it is also called the projected area;
- Convex area—the area of the smallest convex polygon that contains the pig image;
- Perimeter—the perimeter of the pig image;
- Eccentricity—the eccentricity of the ellipse that has the same second-moments as the pig image. The eccentricity is the ratio of the distance between the foci of the ellipse and its major axis length. The value is between 0 and 1;

- Major axis length—the length of the major axis of the ellipse; and
- Minor axis length—the length of the minor axis of the ellipse.

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