Enhancing the accuracy of area extraction in machine vision-based pig weighing through edge detection

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Abstract: The accuracy of extracting projected pig area is critical to the accuracy of the weight measurement of pigs by machine vision. The capability of both the conventional and the edge detection methods for extracting pig area was examined using the images of 47 pigs of different weights. Relationship between the threshold value and the extracted area was numerically analyzed for both methods. It was found that the accuracy of the conventional method depended heavily on the threshold value, while choice of threshold value in the edge detection approach had no influence on the extracted area over a wide range. In normal lighting conditions, both methods yielded comparable values of predicted weight; however, under variable light intensities, the edge detection method was superior to the conventional method, because the former was proven to be independent of light intensities. This makes edge detection an ideal method for area extraction during the walk-through weighing process where pigs are allowed to move around.

Keywords: Area extraction, edge detection, threshold value, pig weighing, machine vision, image processing
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1 Introduction

The weight of a pig is an important indicator of its growth, health and readiness to go to market. The weight provides a valuable reference for the manager in maintaining nutrition and environment at a suitable level for the growing animals. There are typically two ways to measure the weight, i.e., direct weighing and indirect weighing. Direct weighing involves putting a pig on a ground scale, which is physically stressful to both the animal and operator.

Indirect weighing does not use a ground scale. Instead, the pig weight is obtained by analyzing its physical features. One such indirect method is the girth measurement which correlates the circumference with the live weight. For example, Yeo and Smith (1977)[1] used girth measurement to determine the weight of sows in order to control their feed intake. Pope and Moore (2002)[2] also estimated sow live weights using girth measurement. The disadvantage of this method is that it needs physical contact between the operator and the animal.

A more promising indirect way of measuring the pig weight is by machine vision and image processing. The pig is imaged using a camera, and the physical features, such as the projected area extracted from the images, are correlated to the pig weight. For example, Schofield (1990)[3] found a linear relation between the pig weight and the top-view area. Minagawa et al. (1993)[4] found a power relation between the top-view area and the weight of pig. Many other researchers have also conducted experiments on the indirect weighing based on machine vision. Ali and Jørgensen (1992)[5] and Ali (1993)[6] estimated the live weights of pigs from the dimensions obtained by image analysis. Schofield (1993)[7], Schofield and Marchant (1996)[8], and Schofield et al. (1999)[9] also reported imaging systems to monitor pig growth. Brandl and Jørgensen (1996)[10] obtained the live weights of pigs from dimensions measured using an image analysis system. They 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)[11] used image analysis to monitor the pig growth and conformation. White et al. (2003)[12] found the coefficients of the linear equations of weight vs.

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area differed for different pig types. Minagawa et al. (1997)[13], Minagawa and Hosono (2000)[14], and Minagawa and Murakami (2001)[15] found that the correlation coefficient between pig weight and its volume, calculated by multiplying projected image area by pig height, was higher than that between the pig weight and projected image area. Whittemore (2004)[16] used the visual image analysis to estimate the pig weights and sort pigs according to their types. Schofield et al.(1999)[9] developed a prototype on-farm pig weighing system in UK which measured the plan view areas of pigs under production conditions, and analyzed the video images of each pig to obtain the daily growth rate of pigs. This enabled the stockman to monitor the pigs' performance and health, and predict and control their market weight and date. Wang et al. (2006)[17] studied the correlation of measurable features extracted by image processing to animal weights, from which the most outstanding feature that correlated to animal weight was identified. A commercial system for image-based weighing of pigs has been marketed by Osborne (Europe) Ltd (UK) (2004, 2006)[18,19] which measures weight and body dimensions, and offers an option for automated height measurement as well. Wang et al. (2008)[20] has developed a walk-through pig weighing system based on machine vision, which enables the live weight of a pig to be taken while it is walking, rather than requiring the pig to be still for imaging.

Area extraction is crucial to machine vision based indirect weighing, since this method is based largely on the correlation of area with animal weight, although some other features are also used in some cases. Conventionally researchers extracted the area by converting the grayscale image to binary image based on a threshold value. However, the accuracy of area extraction depends highly on the selection of threshold values, as well as the environmental lighting at time of image acquisition. It is ideal that the light intensity is consistent during the image acquisition process, however, in reality, it is hard to maintain a constant lighting environment. This is especially true when the walk-through imaging method is concerned, because in this method pigs are allowed to move to different spots of inconsistent lighting. If a method could be developed that is independent of threshold values and immune to environmental lighting variations, it would greatly enhance the accuracy of area extraction, especially in terms of walk-through weighing. Through literature search, an edge detection method turned up to be promising to achieve the foregoing purposes.

Therefore, the objective of this study was to examine the capability of an edge detection method in pig area extraction that is independent of threshold values and environmental light intensities. The effect of threshold values on area extraction in the conventional method was analyzed. The accuracy of measurement by the edge detection method was also tested in this study using multiple pig images and scale weight data measured in a pig barn.

2 Materials and methods

2.1 Pigs and pig images

Forty-seven pigs from the Holder Farms in southern Tennessee, USA were imaged from the top and weighed using a mechanical floor scale which was accurate to ± 1 kg. The breed was a crossbreed of Yorkshire (50%) and Landrace (50%) with a whitish color. The pigs were divided into two groups: the first group had 24 pigs which were for model establishment and calibration; the second group had 23 pigs which were for testing the accuracy of the image weighing system. The masses of the pigs were between 14 kg and 119 kg.

2.2 Machine vision system

The machine vision system comprising a video camera and a computer, as shown in Figure 1, was used for image acquisition, image processing, feature extraction, and data analysis [20]. The pigs were guided to walk through a passage about 1 m wide where the video camera was installed on the ceiling. In order to obtain a higher image contrast between the ground and the pig originally whitish in color, a black sheet of carpet was placed on the ground of the passage[20].

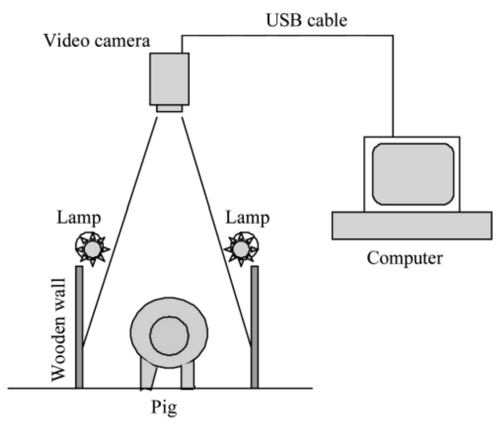

Figure 1 Schematic diagram of the experimental setup used in this study.

2.3 Procedure for weighing accuracy comparisons

Two comparisons were conducted in weighing accuracies between the conventional method and the Canny edge detection method (Canny, 1986)[21]. One was to compare the best possible weighing accuracies between these two methods, given the same pig and light intensity. The other was to compare the weighing accuracies between these two methods when light intensities were changed.

For the first comparison, the images of the first 24 pigs were subject to image processing following the conventional method, and the extracted images were curve fit in the Excel spreadsheet against the scale weight data to yield a best-fit model representing their relationship, following a similar procedure to Wang et al. (2006)[17]. The model was then applied to the rest 23 pigs to predict their weights. Prediction errors were calculated by taking the absolute values of the difference between the predicted weight and the scale measured weight of the 23 pigs. Average relative errors were further calculated by taking the algebraic mean of the prediction errors. In a similar way, average relative errors were also obtained for the edge detection method.

For the second comparison, the light intensities of the images of the 23 pigs were manually adjusted to simulate the possible lighting changes in a practical environment. Suppose I_0 be the initial light intensity when the original images were taken, I_0 would be the same for both the first and the second groups of pigs. The intensities of the images of the 23 pigs were changed by multiplying 0.5, 0.6, 0.7, 0.8, 0.9, 1.0, 1.2, 1.4, 1.6, 1.8 and 2.0, respectively, to simulate the lighting decrease or increase of the environment. At each light intensity, the images were subjected to both conventional and edge detection processing to yield the average relative errors of prediction, which would then be plotted against the relative light intensity I/I_0.

3 Results and discussion

3.1 How do threshold values affect conventional area extraction

In image processing, the conventional method for extracting area is to convert the grayscale image to binary image by setting a threshold value. With pixel values greater than the threshold value separated from those lower than it, the result would be an image showing a white blob corresponding to the shape of the animal on a black background. However, the selection of the threshold value is critical in determining the area of the pig area. If the threshold value is too high, some darker parts of the pig will be missing, so the calculated pig area will be smaller than the actual area. If the threshold value is too low, some brighter parts of the environment could be counted as part of the pig, causing the calculated pig area to be larger than the actual area. Figure 2 shows the binary images of a pig (with a weight of 52.3 kg) corresponding to different threshold values.

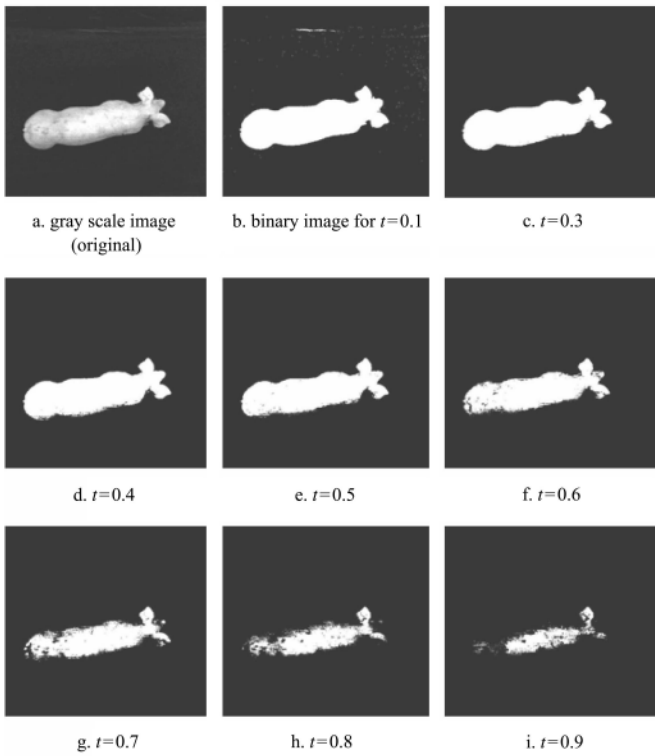

Figure 2 Pig binary images as a function of threshold value t

Pig areas at different threshold values were calculated and plotted in Figure 3. It shows that the area decreased monotonically with the increase of the threshold value. In order to obtain a relatively accurate extraction of the area, threshold values were often determined manually through human observation. However, the limit of human eye's resolution will possibly bring in errors during the measurement. For example, in Figure 2, both (b) and (c) appeared to be a full image of the pig, which was difficult for human eyes to distinguish, but the areas were calculated to be 0.230 m^2 (b) and 0.221 m^2 (c),

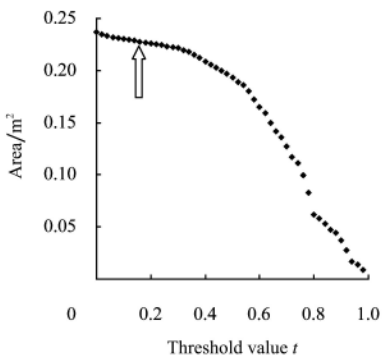

Figure 3 Pig area extracted by converting grayscale image to binary image as a function of the threshold value. The arrow in the figure indicates the corresponding threshold value in the edge detection method

difference of the two areas was about 4%. Using the equation: W = 0.0438 × (A_3) – 35.65 by Schofield (1990)[3], where W is the pig's weight in kg, A_3 is the area in cm^2, the relative difference in the pig weight was calculated to be about 6.3%.

3.2 Area extraction by edge detection method

As mentioned above, the threshold value is critical to the accuracy of the pig area extraction in the conventional method. One way to improve the area extraction accuracy is to use the edge-detection technique. This technique finds the edge of the pig by detecting the rapid change in the intensity of the grayscale image. The two-dimensional derivative of the intensity at point (j, k) is defined as:

$$G(j,k)=[(\frac{\partial F}{\partial j})^2+(\frac{\partial F}{\partial k})^2]^{1/2} \quad (1)$$

Where $F(j, k)$ is the intensity value of the grayscale image at point (j, k). The process of the pig area extraction based on the edge-detection technique is illustrated in Figure 4. Figure 4a shows the grayscale image. Figure 4b shows the edge image obtained using the Canny edge-detection method (Image Processing Toolbox – User's Guide, The MathWorks, Inc.) with a high threshold value t_H = 0.6 ($0<t_H<1$) while the low threshold value t_L is set to be 0.4*t_H. Figure 4c shows the binary image by filling the edge image. The area of the pig in Figure 4c was calculated to be 0.226 m^2, which is indicated by an arrow in Figure 3.

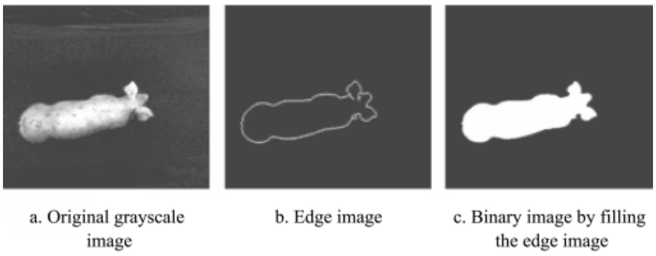

Figure 4 Illustration of pig area extraction based on the edge-detection technique.

It was found that the edge image changed with the high threshold value t_H, as shown in Figure 5. When t_H was small, more edges showed up. When t_H was large, fewer edges showed up. When t_H >0.78, a complete pig edge could not be obtained, as shown in (h) and (i), where the pig area was almost zero.

The relationship between the pig area obtained using the Canny edge detection method and the high threshold value t_H is plotted in Figure 6. When t_H < 0.78, the extracted pig area almost did not depend on the threshold values. This was because the threshold values in the edge detection method only determined the relative intensity of the edges. They did not change the location of the edges. Thus, they did not change the pig area. When t_H ≥0.78, the extracted pig area was almost zero, because a complete pig edge could not be obtained. Thus, the edge detection method was independent of threshold values. As long as any t_H value lower than 0.78 was chosen and used in the edge detection method, the extracted area remained constant, as evident from Figure 6.

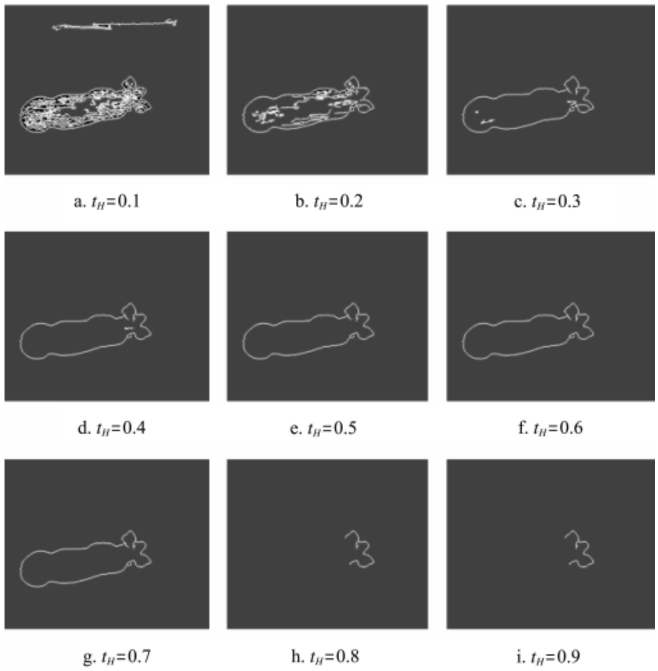

Figure 5 Pig edge images changed with the threshold value t_H

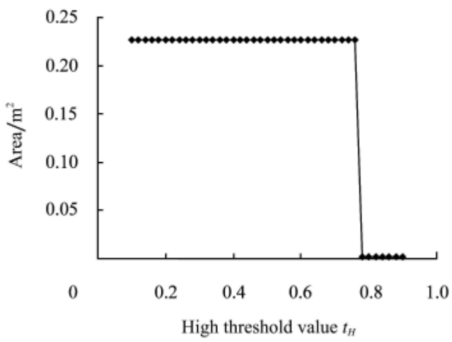

Figure 6 Pig area extracted using Canny edge-detection method as a function of the high threshold value in the edge-detection The low threshold value t_L was set to be 0.4*t_H

3.3 Weighing accuracy comparison: conventional vs. edge detection

As a result of calibration using the first 24 pigs, two best-fit power-law models resulted.

For the conventional method:

$$W = 360.44 \times A^{1.3006} \quad (R^2 = 0.99) \quad (2)$$

For the edge detection method:

$$W = 368.10 \times A^{1.3499} \quad (R^2 = 0.99) \quad (3)$$

Where W is the calculated pig weight in kg; A is the top-down projected pig area in m^2.

Equations (2) and (3) were then applied to the second group of 23 pigs for weight predictions in both scenarios: original light intensity and modified light intensities, and the average relative errors were calculated and plotted against relative light intensity I/I_0 on Figure 7.

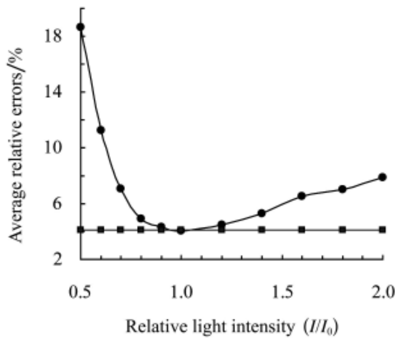

Figure 7 Average relative errors of pig weight estimation vs. simulated relative light intensity of the environment by the conventional method (circle) and the edge detection method (square).

From Figure 7, it can be seen that the average relative errors for the conventional method were large at both lower and higher lighting levels. This signified that the conventional method was strongly dependent on light intensity. The best average relative error in this case was 4.05% at the original lighting level (i.e., I/I_0 = 1). However, for the edge detection method, the average relative error stayed constant at 4.10%, independent of light intensities.

Results showed that under a constant lighting environment where the light intensity did not skew towards either high or low, both the conventional and edge detection methods were capable of yielding similar average relative error (4.05% vs. 4.10% in this study). However, results also showed that in a variable light intensity environment, such as the case when pigs are allowed to walk around, the edge detection method was superior to the conventional method.

4 Conclusions

The conventional image processing method for pig area extraction is strongly dependent on the threshold values, while as long as the threshold value is set to be below 0.78, the Canny edge detection method can yield constant pig area. Comparisons were made between accuracies of the conventional and the edge detection methods in extracting pig area using the images of 47 pigs of different weights. It was found that in normal lighting conditions, both the conventional and the edge detection methods were capable of extracting satisfactorily the pig areas, with average relative error being around 4% in this case. However, for variable light intensities, edge detection method was superior to the conventional method in extracting pig areas. It has been proven in this study that the edge detection method is independent of threshold values and environmental light intensities.

The significance of this study lies in the fact that with the edge detection method, the projected area could be satisfactorily extracted without the need to manually set threshold values, and the area extraction could be conducted automatically by computer with considerable accuracy, making it easier to automate the machine vision-based pig weighing process. This technique would enable an accurate extraction of pig areas for a walk-through imaging approach where pigs are allowed to move around under different light intensities.

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