Weight Estimation Using Image Analysis and Statistical Modelling: A Preliminary Study

Article *in* Applied engineering in agriculture · January 2007

DOI: 10.13031/2013.22332

Thomas M. Banhazi
University of Southern Queensland

WEIGHT ESTIMATION USING IMAGE ANALYSIS AND STATISTICAL MODELLING: A PRELIMINARY STUDY

K. Kollis, C. S. Phang, T. M. Banhazi, S. J. Searle

ABSTRACT. *The weighing of pigs on a farm is traditionally performed manually, making the process time-consuming and laborious. An automated weighing system could thus greatly improve the efficiency of the weighing process. Former studies have demonstrated that an animal's weight may be estimated via analysis of an image of that animal. A recent study conducted at the University of Adelaide aimed to implement an automatic weight estimation system for pigs, and use this system to confirm the results of previous studies while investigating new features, such as additional statistical modelling. A system was designed and implemented using off-the-shelf hardware. It was found that the system was able to estimate a pig's weight with an acceptable error.*

Keywords. *Precision livestock farming, Image processing, Weight estimation, Pigs.*

The aim of this project was to develop a system capable of estimating a pig's weight based on an image of the pig. Previous research into this topics demonstrated that a correlation exists between the weight of a pig and physical features such as the pig's length or two-dimensional area when viewed from above (Brandl and Jorgensen, 1996; Schofield et al., 1999). The main task was to verify these findings and to investigate if improved correlation can be established between certain features of a pig's image and its weight using additional statistical modelling.

To confirm a correlation between a pig's weight and some physical features, the necessary data had to be collected, such as the images of pigs and their corresponding weights. A system for data collection and image processing was designed to function in an automated fashion. The tasks were automated to ensure that components of the system could be reused when the fully developed non-invasive weighing system is commercialized.

BACKGROUND

Within the agricultural industry, weighing of livestock is a necessity. It is used to monitor the growth and health of the animals and to determine their market value (Schofield, 1990; Schofield et al., 1999). When delivering animals to the market their weight must fall within a specified range, and this range is progressively becoming smaller. Marketing animals that fall outside of this weight range can lead to penalties for the farmer and significant deductions from market price (Doeschl-Wilson et al., 2005).

Traditionally, weighing is performed manually and this method is very laborious and time consuming. It would generally involve having to physically move the pig to a set of scales, and for a large pig it could take two stockmen 3 to 5 min to complete the job (Brandl and Jorgensen, 1996). This method is stressful to the animal and impractical, as well as potentially dangerous from an ergonomic point of view.

Research has previously been undertaken on image processing systems used to estimate the weight of various animals (Cross et al., 1983; Ruff et al., 1995; Chao et al., 2000). Promising results have been obtained with pigs (Whittemore and Schofield, 2000; Doeschl-Wilson et al., 2005). A recent study showed that a linear relationship existed between the area of a pig's image and its weight, and by analyzing images of pigs their weight could be estimated with an error of only 5% (Schofield et al., 1999).

By determining the weight of livestock via an image processing system, the amount of time, the cost, and manual labor required for weighing could be greatly reduced. Weighing could occur more often; giving the farmers the ability to monitor their herd more closely. It can provide useful information about the growth of the animals and assist the farmer in choosing an improved feeding regime (Schofield, 1990; Banhazi et al., 2003). It could also give early warning on potential disease outbreak in the herd, which will be an essential component of any futuristic Precision Livestock Farming (PLF) system (Schofield et al., 1999; Banhazi et al., 2002).

MEASUREMENT SYSTEM

To perform this study a number of equipment, including (1) a weighing system, (2) an image capture device, (3) an

Submitted for review in December 2005 as manuscript number SE 6070; approved for publication by the Structures & Environment Division of ASABE in September 2006.

The authors are **Kristina Kollis,** Research Student, **Phang Chee Shiong,** Research Student, University of Adelaide, Department of Electrical Engineering, North Terrace Campus, SA; **Thomas M. Banhazi, PhD, ASABE Member Engineer,** Research Scientist, Livestock System Alliance, University of Adelaide, Roseworthy Campus, Roseworthy, SA; and **Stephen J. Searle,** Research Scientist, University of Adelaide, Department of Electrical Engineering, North Terrace Campus, SA. **Corresponding author:** Thomas M. Banhazi, Research Scientist, Livestock System Alliance, University of Adelaide, Roseworthy Campus, Roseworthy, SA; phone: 618-8303 7781 fax: 618-8303 7975; e-mail: banhazi.thomas@saugov.sa.gov.au.

enclosure to positions the pigs with lighting, and (4) a frame to mount the camera was required.

The weighing system (ACCU-ARM Survey Scale, Osborne Inc. USA, Osborne, Kans.) was set up on a commercial farm and used to collect the necessary weight data.

A Logitech QuickCam Messenger webcam was used to capture images of the pigs. This camera has a 640 × 480 resolution and a frame rate of up to 30 frames per second. It is a cost-effective instrument, can be easily connected to a computer via a Universal Serial Bus (USB) port and can be effectively controlled.

A rectangular enclosure (900 × 1350 × 364 mm) was constructed. The enclosure was only wide enough to fit one pig. Doors on spring hinges were attached to the enclosure to prevent more than one pig entering at the same time.

An extendible frame with a maximum height of 3 m was constructed to mount the webcam on. This was the necessary height to ensure that the entire enclosure was in the field of view of the webcam.

The whole system was in a fully enclosed piggery building with fluorescent lighting. Extra lighting was still required for the webcam to capture quality images. Two 50-W downlights (MR-16C halogen, Etlin-Daniels Ltd., Toronto, ON, Canada) were used and mounted on the webcam frame. A diagram of the setup is shown in figure 1.

Software

Three different computing languages (MATLAB, Java and DELPHI) were used in this study.

MATLAB V6.5.1 (R13) with the Image Processing Toolbox V4.1 (the MathWorks, Inc., Natick, Mass.) was used to perform all image processing algorithms. Custom Java software was used to control the webcam, capture and store the images of the pigs.

Direct communication with the scale was to be established to automatically capture the weight of the animals as soon as they entered the enclosure. Unfortunately due to some technical problems this was not achieved during this study. Therefore, the weights were recorded manually and associated with the images offline.

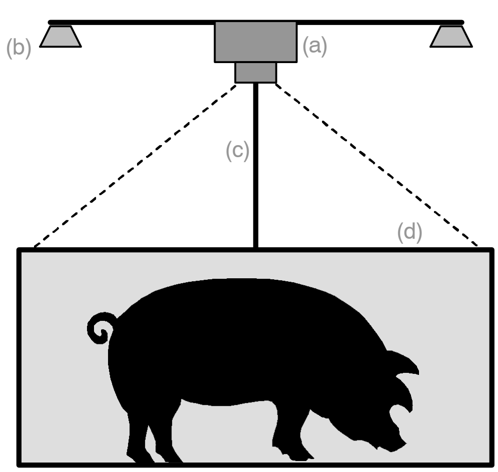

Figure 1. Camera and lighting setup (a) webcam, (b) down lights, (c) webcam frame, (d) enclosure. (The figure is not to scale.)

Building and Pigs

The experiment was conducted in a fully slatted grower/finisher building constructed using sandwich panels and situated in the Wakefield Regional Council area within South Australia. The building, typically housing approximately 1,000 grower pigs, was equipped with tunnel ventilation and a liquid feeding system. All animals used in this preliminary experiment were male Large White pigs.

Image Processing

Requirements

An automated weight estimation system requires some means of extracting information from an image of a pig. This information is a measure of the pig's apparent size, and is the end product of a sequence of image processing steps used during this study. These steps comprised (1) object detection, (2) segmentation, (3) filtering, and (4) feature extraction. Object detection is the determination of whether or not an object of interest (a pig in this case) is in the camera's field of view. Should such an object be present, it is then isolated from the background imagery (segmentation). Filtering is performed on a segmented image in order to remove spurious segmented pixels and to fill in poorly segmented regions of the target object. Finally dimensional features of the segmented region, such as area and length, are computed. Statistical analysis yields a correlation between these features and animal weight. This relationship can then be used to predict pig weight based upon feature values.

Object Detection

A fixed threshold method was used to determine the presence of a pig in the camera's field of view. This threshold was determined by an offline calibration step.

Two images were captured from the fixed camera rig; one image containing a pig and the other image empty, i.e. just the background. These two images were then compared to locate the largest region of significant difference. The brightness of each pixel in the pig image was compared with the corresponding pixel in the background image. A binary image was formed based on the result of this comparison, in the manner depicted in figure 2.

Typically the output binary image, c, would have consisted of a large region of ones and smaller regions of ones scattered throughout the image. The largest contiguous region of one-valued pixels was found. This region was taken to be the silhouette of the pig in the image. A rectangular detection region, with the same center as the silhouette but approximately half the dimensions, was defined. The average brightness of that region in both photos was computed. The midpoint between these two average brightness values was chosen as the detection threshold. This completed the calibration process.

Pig detection could then be performed by sampling an image and comparing the measured brightness from the pixels in the defined detection region with the detection threshold. If a large percentage of pixels passed the test, then a pig was declared to be present and the image saved for further analysis.

Note that in practice, calibration was performed wholly with a relatively clean white pig, despite a small number of non-white or patterned pigs existing in the herd. Calibration

1	3	2	1	1
2	1	1	3	1
2	1	3	3	2
3	2	3	3	2
1	1	2	1	1

Image (a)

1	3	2	1	1
2	8	9	3	1
2	8	9	3	2
3	9	9	3	3
1	2	2	1	1

Image (b)

0	0	0	0	0
0	1	1	0	0
0	1	1	0	0
0	1	1	0	0
0	0	0	0	0

Output (c)

$$c(i,j) = \begin{cases} 0, \left|b(i,j) - a(i,j)\right| < T \\ 1, \left|b(i,j) - a(i,j)\right| \geq T \end{cases}$$

Figure 2. Detecting regions of difference. The elements of the two input images, a and b represent pixel intensities. The output c is a binary image. T is a scalar, its value is greater than zero to account for minor errors between the two images. In this example T is set to two.

depends mostly on the background being consistent across the two frames. The effect of variation in pig appearance on the calibration process is small in our experience and has not been given more than cursory consideration. In Australia the main breed of pig is large white and there is not expected to be significant variation within a herd.

Segmentation

The aim of segmentation was to isolate the object from the rest of the image. The output of this step is a binary image in which 1-valued (white) pixels represent an object pixel, and 0-valued (black) pixels represent the background.

Several methods of segmentation were investigated for this study. The fixed threshold method was used due to its simplicity. Although this method was not entirely effective for segmentation on its own, when combined with post-filtering it could effectively isolate the object from the rest of the image.

The value of the threshold was determined from a set of test data. Several images of pigs were gathered and the RGB (red, green, blue) intensities from pixels known to represent pigs were collected. It was assumed that the intensities of each color would be distributed in a Gaussian manner. Therefore the sample means and standard deviations of each of the three color intensities were computed and taken as estimates of the population statistics. A threshold for a particular color channel was defined as three standard deviations less than the sample mean of that color intensity. Thus one would expect over 99% of all pig pixels to have an intensity greater than the threshold.

It was found that the blue channel yielded the best performance of the three colors in terms of minimizing the number of falsely segmented background pixels. The likely reason is that the background was brown in color and thus had a relatively large red component. Therefore blue intensity was used exclusively for segmentation with the data set of this study. The process is displayed in figure 3. For simplicity the threshold was set to 5.

1	3	2	6	8
2	1	7	8	9
2	1	6	8	9
3	2	7	8	9
1	1	2	6	8

Image (a)

0	0	0	1	1
0	0	1	1	1
0	0	1	1	1
0	0	1	1	1
0	0	0	1	1

Output (b)

$$b(i,j) = \begin{cases} 0, a(i,j) < T \\ 1, a(i,j) \geq T \end{cases}$$

Figure 3. Segmentation based on a fixed threshold. This figure displays the process of segmentation based on a fixed threshold. The elements of the input image represent pixel intensities. The output b is a binary image. T is a scalar, for simplicity of the figure the value of T is set to 5.

Filtering

Segmenting at three standard deviations below the sample mean will segment most of the pig pixels, but there will still be a number of pig pixels that are not detected. Furthermore, any number of background pixels may have intensity above threshold and thus be falsely segmented. It is therefore necessary to perform post-processing to clean up the segmented image. The post-processing involves two forms of filtering; median filtering and morphological filtering.

In a binary image, the median filter replaces each pixel with the value (1 or 0) which is in majority in a neighborhood about that pixel. This process is displayed in figure 4 for a 3-× 3-neighborhood. A median filter is able to correct isolated segmentation errors, thereby "filling in" missed detections without causing great distortion to the image. It was also used to prevent the next process, image opening, from having a detrimental effect.

Image opening is the process of erosion followed by dilation. Erosion is the process of removing all 1-valued pixels that are close to an edge, as constrained by a specified structuring element. Dilation is the operation by which 0-valued pixels near the edge of a region of 1-values are set to 1, thus increasing the size of a segmented region. These processes are illustrated in figure 5.

Opening (erosion followed by dilation) has the effect of removing clusters of 1-valued pixels which are smaller than the specified structuring element. This removes any back

1	0	0
1	**1**	0
0	0	0

Image (a)

1	0	0
1	**0**	0
0	0	0

Output (b)

$$b(2,2) = \begin{cases} 0, \Sigma\, a(i,j) < 5 \\ 1, \Sigma\, a(i,j) \geq 5 \end{cases}$$

Figure 4. Median filter with a 3-× 3-neighborhood applied to a binary image. The pixel that the filter is being applied to is a (2,2) highlighted in bold. As the majority of the neighboring pixels are zeros, this pixel was converted to a zero as shown in bold in the output image b.

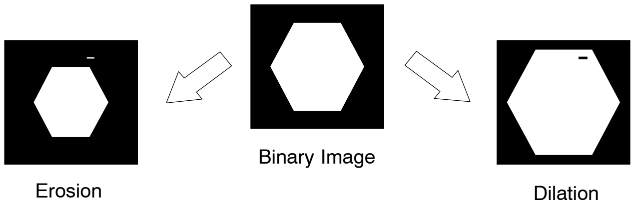

Figure 5. Erosion and dilation performed on a binary image.

ground objects which were erroneously segmented, while preserving the main object (the pig). In this study a disk-shaped structuring element of size 7 was used. The operation was performed trivially in Matlab via the imopen command:

```
im2 = imopen(im1,strel('disk',7));
```

An example of median filtering followed by opening is given in figure 6.

Feature Extraction

Once the image of the pig was segmented and cleaned up via filtering, features could be extracted. The three features that were employed in this study were area, length, and spine length.

The area of the object in pixels is trivially defined to be the sum of the binary pixel values over the whole image. This assumes that by this stage there will be only one contiguous region in the image.

The spine length feature refers not to the pig's actual spine, but to the major branch of the tree structure which is found by performing skeletonization on the binary image. Skeletonization is a process that reduces all objects in an image to lines without changing the essential structure of the image. In this case the skeleton is not a representation of the animal's actual skeleton, but a connected set of lines which represent the centres of the animal's visible protuberances. The skeleton thus is a representation of the topology of the object or animal under scrutiny. (Davies 1997; Heneghan et al., 2002). The process is often used for tasks such as text recognition since the essential shape of letters and glyphs remains the same regardless of handwriting. Skeletonization is trivially performed in Matlab via the command im2 = bwmorph(im1,'skel'). An example of this is shown in figure 7. The skeleton has been superimposed on the negative of its corresponding segmented image to better display the skeletonization process.

Figure 7. Skeletonization performed on a segmented image.

This spine length is the number of pixels which comprise the main (longest) branch of the skeleton. This feature is expected to be robust to the animal's posture, because the distance along the animal's spine remains relatively constant regardless of curvature, and the main junction points of the skeleton remain relatively constant when the animal moves its head.

The spine length was computed by isolating the largest branch in the skeleton and counting the number of pixels. The main branch was located by determining the location of junctions via a zero-crossing method (Mehrotra and Zhan, 1996).

The length feature refers to the distance from the center of the pig's neck to its tail. The position of the pig's neck proved to be difficult to detect due to the unknown orientation of the pig's head. It was decided to estimate the pig's neck position as the point at which the main segment (referred to as the spine above) of the pig's skeleton terminated. After skeletonization as above, the two endpoints of the spine were found. The "head" endpoint was deemed to be the one which gave rise to the most sub-branches, as the head was more topologically complex than the rump and usually produced a more structured sub-skeleton. The tail was assumed to be the most extreme pixel of the segmented image at the opposite end from the head. With these two data points the Euclidean distance could then be found, giving a close approximation of the length of the pig. Euclidean distance was appropriate since the pixel dimension ratio was one-to-one. If this were not the case, a weighted metric (e.g. Mahalanobis distance) would have been appropriate. However since the animals were constrained to been oriented in the same direction as the image X axis, the effect of uneven scaling on the X and Y axes would likely be minimal and the Euclidean distance would be a good approximation to actual distance in this particular study.

Figure 6. Image filtering and opening performed on the image of pig.

Table 1. Statistical results.

	Weight vs. Log (Area)	Log (Weight) vs. Length	Weight vs. Log (Spine Length)
Correlation coefficient	0.7787	0.7751	0.5793
P-value	4.55×10^{-6}	6.91×10^{-9}	1.11×10^{-4}
Average error	3.24 kg (5.33%)	3.53 kg (5.78%)	4.13 kg (6.76%)
68% Confidence Interval	7.56 kg (12.42%)	7.80 kg (5.78%)	9.22 kg (15.10%)
95% Confidence Interval	11.70 kg (19.23%)	11.91 kg (19.51%)	14.10 kg (23.11%)
99% Confidence Interval	14.38 kg (23.63%)	14.56 kg (23.86%)	17.26 kg (28.28%)

Analysis of Results

The full set of data contained 84 image weight pairs. Many of these images were duplicate images of the same animal. 38 unique animals were identified and these formed the base data set. Some of these images were of poor quality, in that the head of the animal did not fall within the field of view, or the outline of the animal was blurry. In these cases the area computation was found to suffer. There were 14 such cases in the data set. These area-weight pairs were excluded from analysis. However, the algorithms for neck detection and length computation were found to be acceptably robust in the case of blurring or partial head obscuration. Therefore the full 38 data points were used for these analyses. It would have been preferable to have a much larger dataset, especially for the area analysis, however promising results were still obtained and are summarized in table 1.

The best results were obtained when using the neck-to-tail distance versus log weight (correlation coefficient 0.5640) and area versus weight (correlation coefficient 0.5295) to determine the weight. These correlation coefficients were both significant, having a probability of occurrence less than 1%. The resulting linear weight prediction formulas achieve an average absolute error just under 5% in either case, confirming the results found in the literature (Schofield et al., 1999). A scatter plot of weight versus log(area) with a fitted regression line is shown in figure 8, and a scatter plot of log weight versus length with regression line in figure 9. The results obtained with the spine length feature were less conclusive, having a correlation coefficient of 0.3300, or a probability of 4.3%. However the absolute error predicted by the corresponding linear prediction equation was 5.94%, only slightly higher than for the other two methods.

A further statistical analysis based on the weight, area and length data (using the 24 "good" samples) resulted in a R^2 value of 0.7154, which corresponds to a correlation coefficient of 0.8458. Using the area and length variables gave rise to the following results:

Average error: 2.83 kg (4.65%)

68% confidence interval: 3.67 kg (6.03%)

95% confidence interval: 7.19 kg (11.82%)

99% confidence interval: 9.47 kg (15.56%)

Initial results indicated that predictive precision of the equations might be improved if combined area and length data were used.

The regression equations of all the weight feature relationships are shown below, where y, x_1, x_2, x_3 and correspond to weight, area, length, and spine length, respectively. No equations incorporating $x_2 x_3$ or $x_1 x_3$ terms are reported because there was no significant interaction between the corresponding features.

$$y = 35.05\log(x_1) - 262.4$$

$$\log(y) = 5.966 \times 10^{-3} x_2 + 3.040$$

$$y = 22.10\log(x_3) - 50.14$$

$$y = 3.470 \times 10^{-2} x_1 + 1.716 x_2 - 1.690 \times 10^{-4} x_1 x_2 - 291.4$$

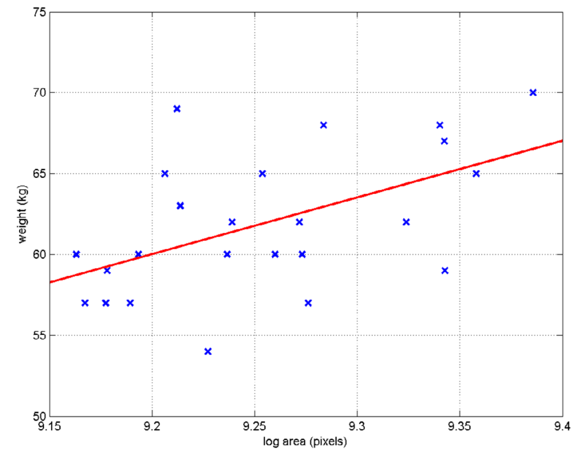

Figure 8. Scatter plot of weight vs. log(area) with fitted regression line.

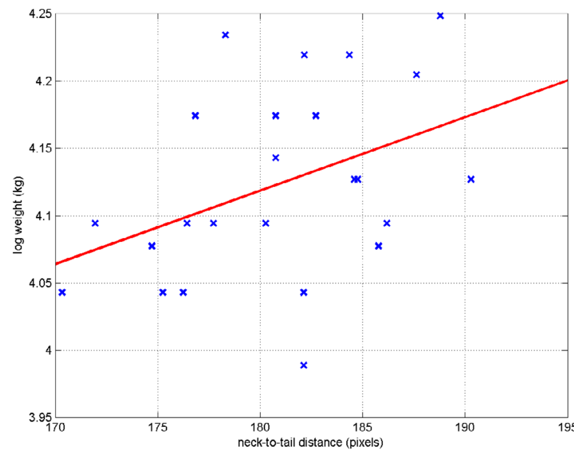

Figure 9. Scatter plot of log weight vs. neck-to-tail length with fitted regression line.

Conclusion and Summary

This study verified that the weight of a pig could be estimated from a top-view image with an average error of around 5%. Of the features investigated, area and neck-to-tail length had high correlation with a pig's weight. The study has demonstrated a weaker relationship between the spine length feature and weight.

This study suffers from the limitation of a small sample of pigs, all of which occupy a small weight range. Nevertheless the study has demonstrated the existence of definite linear or log-linear relationships between features and weight for this range. This study has laid the foundations for further work, in terms of suggesting a new feature (spine length) and suggesting a novel way of measuring a previously used feature (neck position), and demonstrating the efficacy of these methods through application to real imagery. Results have been promising and invite further investigation with a large sample of animals across a broader weight range.

Improvements and Future Work

Due to time constraints and technical problems an automated system that could capture images of pigs and estimate their weights in real time was not developed. However due to the success of the individual components of this project, such a system would be relatively easy to produce. With this study Java was used to capture images for the data collection stage and MATLAB was used to process them, by combining these two programs; a fully functioning system could be designed. Alternatively, to avoid the need to combine the two programming languages, the entire program could be written in either Java or MATLAB.

One important ability of an automated system would be the need to automatically adjust to the particular environment in which it was installed. This aspect falls outside the scope of the current study, but bears mention here. The appearance of the pig in an image will depend upon factors such as camera location (height, orientation), camera intrinsic parameters (focal length, aperture, pixel resolution), and lighting. It will therefore be necessary to perform some calibration of an installed system. However if the equations specifying the linear relationship between pig and weight could be expressed in terms of an objective measurement unit (e.g. meters) instead of a subjective unit which depends upon camera parameters (i.e. pixels), then it would be possible to supply an installation with hard-wired linear relationships. The task of calibrating the camera to determine the relationship between pixels and metres would remain, but the pig-weight equation would not have to be learned by the system. As it stands, the current approach is adaptable to other situations only by performing data analysis to determine the weight-feature relationship once the camera is installed.

Before a fully automated system is put into place, it would be useful to revise the segmentation algorithm. With improved segmentation it may be possible to achieve a higher correlation and lower error.

In addition, there are other features that could be investigated. In this study the calculation of the area of the pig included the pigs head. This has been shown previously to be a possible source of error (Schofield, 1990). Therefore, if the pig's body area was calculated, without including its head, this would lead to a large decrease in the error. Other features that could be investigated are the width of the hips or shoulders, or a combination of the length, hip and shoulder width.

Different equations relating a pig's weight to one of these features may exist for the different breeds or the sex of the pig. Detecting these factors via image processing would not be plausible, but if a farmer were to have only one breed then the equation could be calibrated to suit individual circumstances. In addition if the pigs had new generation RF ID (Radio Frequency Identification) tags which store more than identification, then breed/gender information could be stored on the tag and the appropriate equation applied to the pig.

Another possible extension for this project would be to calculate features in real units i.e. meters or square meters, not pixels as done in this study. Once again this aspect was not looked into due to project restrictions, but if the images contained some markers of known distance then the real measurements of the pig's features could be extrapolated. This would be beneficial because if the equipment was to be relocated, or maintenance was performed, it would not matter if the height or position of the camera were to change.

If multiple cameras were used, there are more features that could be extracted from the images, such as the pig's height, or width from its stomach to its back. As demonstrated by previous research, it is also possible to create a three dimensional image of the pig (Wu et al., 2004). Although these options would most likely give better results, they also involve more equipment and more sophisticated image processing techniques, which in turn would lead to a greater cost. The extra precision gained from these techniques may not be worth the extra cost involved.

Acknowledgements

The authors wish to acknowledge the technical assistance of Mr. Ian Linke and Mr. Alban O'Brien (University of Adelaide) with the setup of the instrumentation, Mr. Greg Ludvigsen (Ludvigsen Family Farms) for providing assess to the experimental facilities, Gerald Johnson (Osborne Industries) for providing assistance with programming and Mr. David Rutley (University of Adelaide) for assisting with the statistical analysis.

References

Banhazi, T., J. L. Black, M. Durack, C. Cargill, A. King, P. Hughes. 2002. Precision livestock farming. In *Australian Association of Pig Veterinarians Proceedings 2002.* Adelaide, Australia: Australian Association of Pig Veterinarians.

Banhazi, T., J. L. Black, and M. Durack. 2003. Australian precision livestock farming workshops. In *Joint Conference of ECPA-ECPLF,* eds. A. Werner and A. Jarfe, 675-684. Berlin, Germany:Wageningen Academic Publisher.

Brandl, N., and E. Jorgensen. 1996. Determination of live weight of pigs from dimensions measured using image analysis. *Computers and Electronics in Agriculture* 15(1): 57-72.

Chao, K., B. Park, Y. R. Chen, W. R. Hruschka, and F. W. Wheaton. 2000. Design of a dual-camera system for poultry carcasses inspection. *Applied Engineering in Agriculture* 16(5): 581-587.

Cross, H. R., D. A. Gilliland, P. R. Durland, and S. Seideman. 1983. Beef carcass evaluation by use of a video image analysis system. *J. of Animal Science* 57(4): 908-917.

Davies, E. R. 1997. *Machine Vision: Theory Algorithms Practices*, 2nd ed. San Diego, Calif.: Academic Press.

Doeschl-Wilson, A.B., D. M. Green, A. V. Fisher, S. M. Carroll, C. P. Schofield, and C. T. Whittemore. 2005. The relationship between body dimensions of living pigs and their carcass composition. *Meat Science* 70(2): 229-240.

Heneghan, C., J. Flynn, M. O'Keefe, and M. Cahill. 2002. Characterization of changes in blood vessel width and tortuosity in retinopathy of prematurity using image analysis. *Medical Image Analysis* 6(4): 407-429.

Mehrotra, R., and S. Zhan. 1996. A computational approach to zero-crossing-based two-dimensional edge detection. *Graphical Models and Image Processing* 58(1): 1-17.

Ruff, B. P., J. A. Marchant, and A. R. Frost. 1995. Fish sizing and monitoring using a stereo image analysis system applied to fish farming. *Aquacultural Engineering* 14(2): 155-173.

Schofield, C. P. 1990. Evaluation of image analysis as a means of estimating the weight of pigs. *J. of Agricultural Engineering Research* 47(): 287-296.

Schofield, C. P., J. A. Marchant, R. P. White, N. Brandl, M. Wilson. 1999. Monitoring pig growth using a prototype imaging system. *J. of Agricultural Engineering Research* 72(3): 205-210.

Whittemore, C. T., and C. P. Schofield. 2000. A case for size and shape scaling for understanding nutrient use in breeding sows and growing pigs. *Livestock Production Science* 65(3): 203-208.

Wu, J., R. Tillett, N. McFarland, X. Ju, J. P. Siebert, and P. Schofield. 2004. Extracting the three-dimensional shape of live pigs using stereo photogrammetry. *Computers and Electronics in Agriculture* 44(3): 203-222.