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Swine live weight estimation by adaptive neuro-fuzzy inference system

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ABSTRACT

Swine live weight is an important aspect in the production of pork products and also to Stockmen, with reference to market costs, feed conversion, and animal health. The objective of this study was to develop a contactless, stress-free method of swine live weight estimation by machine vision technology. This novel approach was based on image processing for features extraction and Adaptive Neuro-Fuzzy Inference System (ANFIS) for modelling. Firstly, the model determines which input combination holds the highest predictive ability, secondly, used the feature combination with the best predictive power to correlate to live-weight. The test results showed that the average relative error of our proposed system was about 3% and a standard deviation of 0.7%. Thus, development of a practical imaging system for swine live weight estimation by the proposed method is feasible.

Key words: Adaptive Neuro-Fuzzy Inference System, Contactless, Features, Modelling, Predictive Power.

INTRODUCTION

Animal live weight information can be used to estimate the animal growth, feeds conversion efficiency, disease occurrences, body uniformity and market readiness (Wang, *et al.*, 2008; Menesatti, *et al.*, 2014; Li, *et al.*, 2015; Wongsriworaphon, *et al.*, 2015). Methods for assessing the live weight of swine are of great importance from several perspectives and have been widely studied and applied. Animal-predicated food products are customarily related to the ages of the animals that are utilized in their production, e.g., shrimp products (Pathumnakul, Piewthongngam *et al.*, 2009) and pork products (Khamjan, *et al.*, 2013; Plà-Aragonés and Rodríguez-Sánchez 2015).

A 22 weeks old pig is ready for slaughtering for most pork products as the feed-to-live-weight ratio increases rapidly with age, thus, if a group of swine is not slaughtered in a particular week, the conversion of the feeds into weight will be less efficient in the following week. Therefore, matching appropriate size pigs to the feed products during slaughtering and victuals processing stages could amend the production efficiency by reducing the raw material procurement, inventory, shortage and perished costs (D'Souza, *et al.*, 2004; Oliveira, *et al.*, 2009; Apichottanakul, *et al.*, 2012; Agostini, *et al.*, 2013)

One of the widely studied methods has been the body parts quantification approach (Topai and Macit 2004; Tasdemir, *et al.*, 2011; TASDEMIR, *et al.*, 2011; Tscharke and Banhazi 2013; Menesatti, *et al.*, 2014). Self-accessed scales were developed to automated the animal's front or hind leg mass estimation during feeding (Ramaekers, *et al.*, 1995; Zaragoza 2009). However, it required extensive data processing to eliminating redundant data, hence prone to serious estimation errors (Williams, *et al.*, 1996). Walk through scales have also been developed for dairy cows (Cveticanin and Wendl 2004; Alawneh 2011). However, accuracy depended on how the cows proceeded, whether they ambulated at a steady pace or not over the equipment at all. (Cveticanin 2003).

Machine vision techniques have been applied to determine live weights and growth of various animals: (Minagawa and Murakami 2001) chicken (Mollah, *et al.*, 2010), cattle (Tasdemir, *et al.*, 2011; Menesatti, *et al.*, 2014), swine (Pastorelli, *et al.*, 2006; Wang; *et al.*, 2008), and rabbit (Negretti, *et al.*, 2010). Images of animals are mostly used to extract features which are used to correlate to the corresponding live weight, however, digital image-based methods for estimating an animal live weight require the animal be at an appropriate position and quite stationary otherwise the accuracy and computational speed would be compromised hence it is impractical in a real farm scenario (Kashiha, *et al.*, 2014). Precedent studies sought to develop methodologies for quantifying a swine's live weight while it was moving mundanely, in the feeding area, however, this mandated additional low-level illumination setups in the feeding area (White, *et al.*, 2004; Wang, *et al.*, 2008). Albeit the approaches mentioned above provided precise estimation, expeditious operation and were non-stressful to the swine, the quality of the digital images, the efficiency of the image processing technique and background determines the accuracy of the estimated live weight (Wongsriworaphon, *et al.*, 2015).

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In this study, we introduced and developed a computer vision system which applies Adaptive Neuro-Fuzzy Inference System (ANFIS) model for indirect detection of pig live weight, with the objectives of creating a fast image processing algorithm for feature extraction, a rapid and more accurate machine vision system, a versatile system that can be easily integrated and expandable to large farms.

MATERIALS AND METHODS

This research experiment was carried out at Jiangpu farm in Nanjing, Jiangsu Province, China. Two groups of whitish Landrace pig breeds of ages between 18 and 20 weeks were used. First 40 swine were used for modeling, the second 20 swine for model testing. After each swine's top view video recorded, its live weight was measured using a mechanical floor scale of an accuracy of ± 1 kg. The mechanical swine live weights ranged between 100 -149 kg. In all 400 images were selected for modeling (10 images per swine).

Our proposed system for live weight estimation composed of a digital video recorder Turbo HD DVR DS-7200HGH-SH from HIKVISION for image acquisition and Toshiba Satellite i5 laptop computer with Matlab (The MathWorks Inc., Natick, MA) for image processing, features extraction, data analysis, and model representation. For this study, 1080P (highest resolution) was chosen so as to improve on accuracy. The camera was fixed perpendicularly to the ground at a distance of 2.9 meters from the camera lens to the ground. The swine were guided to a mechanical floor scale weight balance one at a time through a passage of 1 meter wide where the video camera was installed above as shown in Fig 1. No illumination sources were used apart from natural light sources as in the previous studies, to keep the experiment environment as close to real farm environment as possible.

Image processing: The video frames were extracted and images selected by visual inspection under the criterion that the whole pig should be within the screen field and not touch any part of the edges as shown in Fig 2. The selected images were processed as described by the Figure 3 according to the following procedure.

Step 1: The images were resized by 0.3 of the original so as to increase the processing speed. The background image canopy was then removed.

Step 2: The images were binarized then smoothened by ` morphologically closing it.

Step 3: Rotated the image, so that's its longitudinal axis was positioned vertically.

Step 4: To obtain a more accurate live weight detection, the head and tail were removed from the image.

Step 5: Verified that the image was almost symmetrical by determining the asymmetrical value $\mathfrak{D}$ according to Equation 1.

$$\mathfrak{D} = \frac{\sum|d_R(t) - d_L(t)|}{\sum[d_R(t) + d_L(t)]}$$

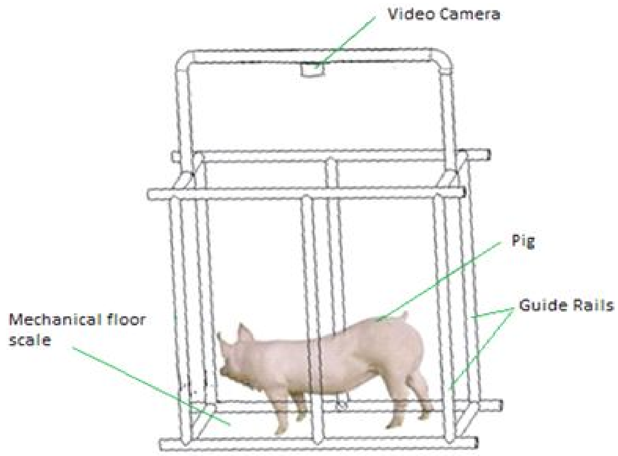

Fig 1: Experimental Set-up

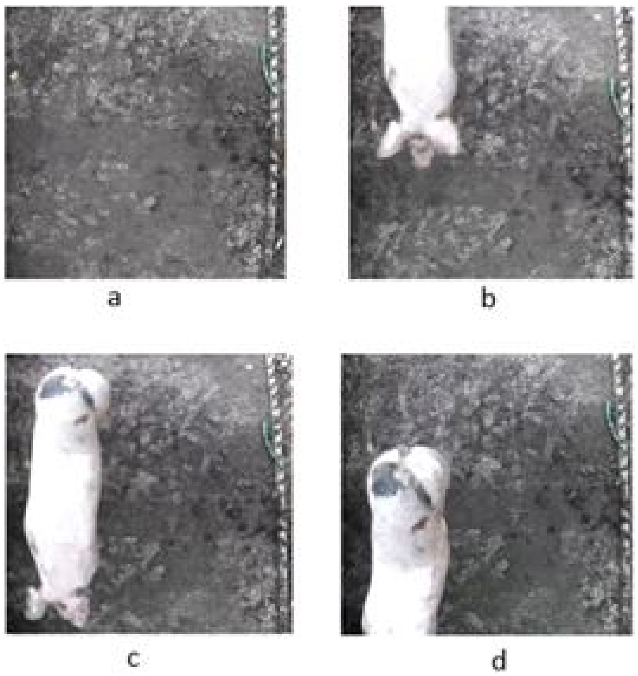

Fig 2: Image of walking pig; (a) background image, (b) pig just entering the image screen field, (c) image used in the study as all parts of the pig are within the image screen field (d) image of pig exiting the image screen field

Where:

$d_R(t)$: right-hand side width at the t^{th} point respectively along the longitudinal direction.

$d_L(t)$: left-hand side width at the t^{th} point respectively along the longitudinal direction.

Feature extraction: The extracted features included the area, convex area, perimeter, eccentricity, major axis length, minor axis length, average boundary distance (distance from the centroid to the boundary) and vector perimeter. The following steps were used to extract the above features.

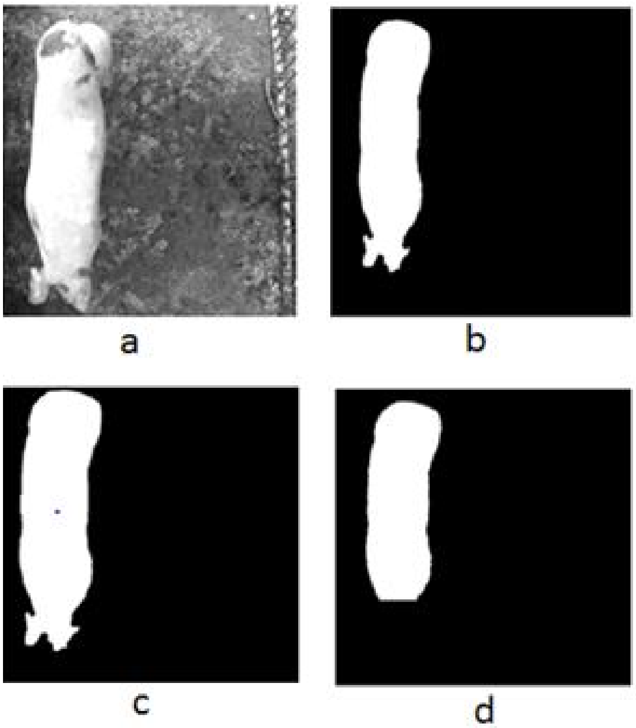

Fig 3: Image processing prodedure; (a) grayscale image, (b) binarized image after background removal, (c) central location identification, (d) removal of head, ears and tail after rotation

Step 1: The binary images mathematical properties were determined to obtain all the features except for the perimeter, average boundary distance, and vector perimeter.

Step 2: Boundary detection of the binary images were performed using The Sobel algorithm.

Previous studies proposed image boundary detection by mouse clicks on the image, but this method is subjective, relies on the operator accuracy and eyesight, hence, prone to errors. This study introduced an automatic boundary detection of a binary image as in Fig 4.

Step 3: The perimeter mathematical property of the boundary images was then extracted.

Step 4: Determined the average boundary distance which is the average of the summation of Euclidean distance between the boundary vector points and the swine's centroid, as defined by Equation 2.

$$\mathfrak{x} = \frac{1}{t}\sum_{1}^{t} ð_c(t)$$

Where:

$\mathfrak{x}$: the average boundary distance

t : the number of boundary vector points

$ð_c(t)$: Euclidean distance between the boundary vector points and the pig's centroid.

Step 5: Determined the boundary vector perimeter which is the summation of Euclidean distance between two successive boundary vector points, as defined by Equation 3.

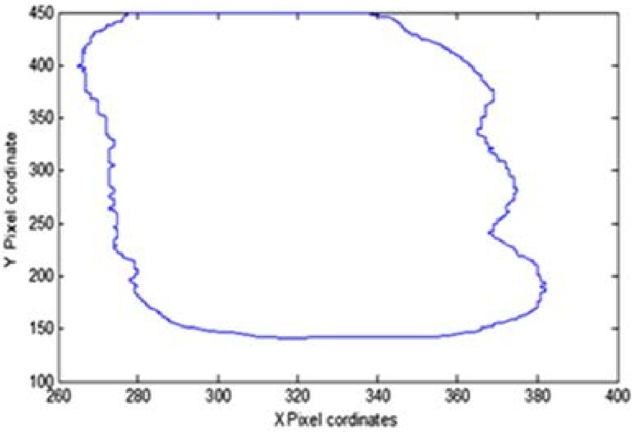

Fig 4: The Cartesian coordinates of the processed pig image

Where:

$\Im$: the boundary vector perimeter

$ð_p(t)$: The Euclidean distance between vector points (t) and (t-1)

t : number of boundary vector points

Adaptive Neuro-Fuzzy Inference System (ANFIS): ANFIS was used as a nonlinear regression model in this study. Training data dimension reduction was achieved by identifying important input variables from the eight extracted features and the output variable as the mechanically measured weight. Our data set of 400 entries with no missing values was used to construct a fuzzy inference system.

RESULTS AND DISCUSSION

In assessing the performance of the proposed model, the best model takes Area and Minor Axis Length as the best predictors. Fig 5 (a) shows 8 trained ANFIS models each with one input, perimeter exhibiting the lowest checking error of 2.7062.

Further training of 28 ANFIS models each with two inputs combination showed that the area and minor axis length had the lowest checking error of 0.9008 in Fig 5 (b). For verification purposes, 56 ANFIS models each with 3 inputs combination was trained, the area, minor axis length and boundary vector distance had the lowest checking error of 0.8022. Hence, no significant change in the minimum checking errors between 3 inputs and a 2 inputs model. Thus, 2 input model was more applicable. 28 fuzzy models were build based on the above heuristic observation, each with a single epoch of ANFIS training as shown in Fig 5 (b). To obtain more reliable results more training epochs were allocated to each of the 28 models but no substantial change in the Root-Mean-Squared Errors (RMSE) was observed as from epoch 2 thus the training was stopped at epoch 2 according to Fig 5 (b). The model with Area and Minor Axis Length as the inputs was selected then its performance was refined by extended training of up to 100 epochs. The lowest checking error occurred at epoch 78, hence, this was our final best model.

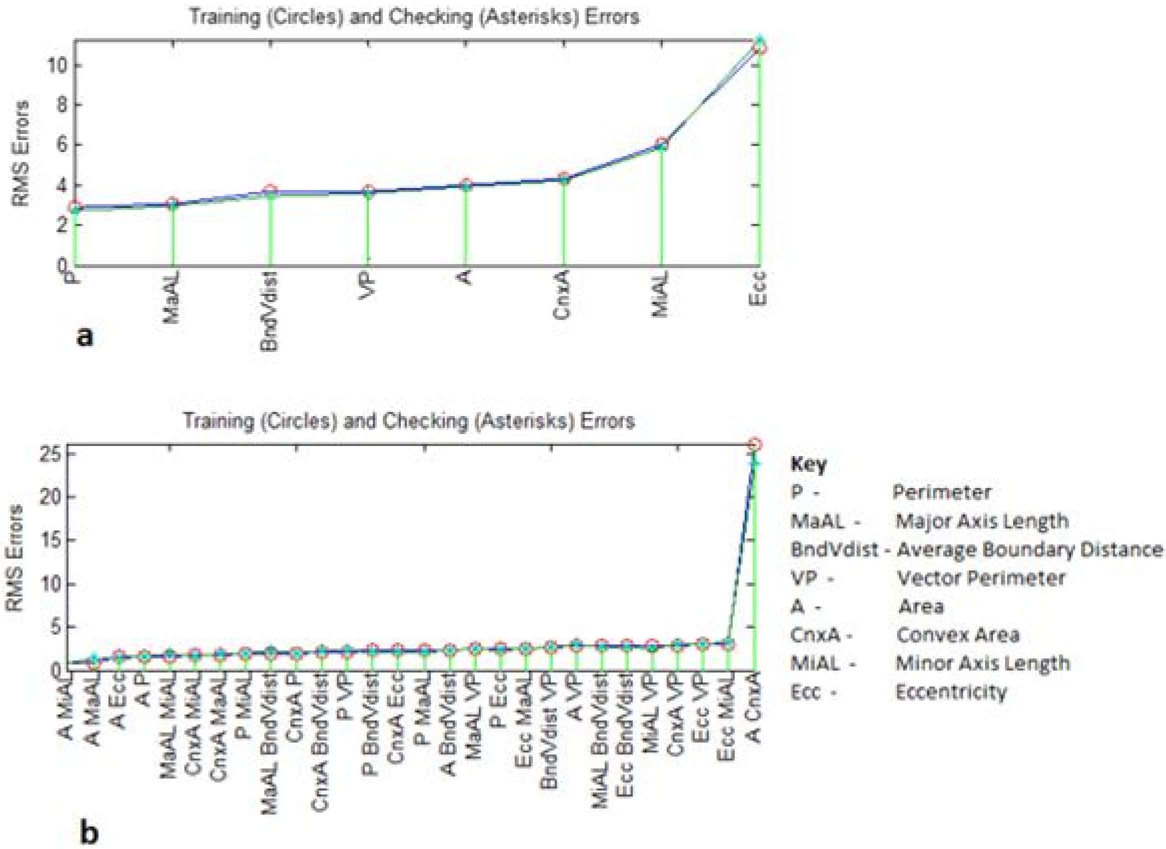

Fig 5: Training and checking errors (a) 8 trained ANFIS model with one input (b) 28 trained ANFIS model with two inputs.

The evaluation of the predictability of area to live weight is presented by Fig 6 by the relationship between live weight (measured and predicted) and Area as an input of our generated ANFIS model.

The data was fitted with a polynomial function of, $y=5.462\chi^5+4.649\chi^4-11.42\chi^3-4.313\chi^2+14.2\chi+121$ for the relationship between Area and mechanical scale measured weight and $y=5.798\chi^5+4.988\chi^4-12.2-4.923\chi^2+14.55\chi+121.2$ for Area against ANFIS estimated weight, the curves were very proximate and obscure each other, thus an indication of successful training of the network model high degree of Area as a predictor. To evaluate the accuracy of the ANFIS model, its RMSE was compared against a linear regression model; ANFIS had an RMSE of 0.895 while Linear Regression had an RMSE of 2.067. Thus, it can be observed that ANFIS model outperformed the linear regression model.

Live weight approximation: The successfully trained ANFIS model was used to approximate the weight of 20 swines. Fig 7 shows the best linear fit curve achieved for the

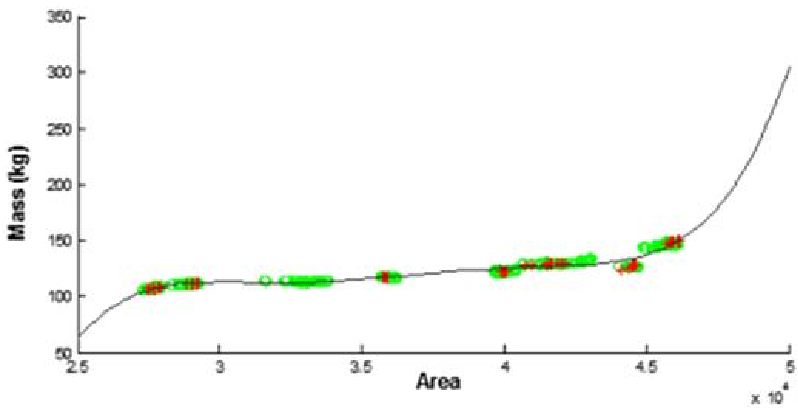

Fig 6: Swine mass against area. Green circle represents mechnical scale measured mass while the red crosses represent predicted masses using the ANFIS model.

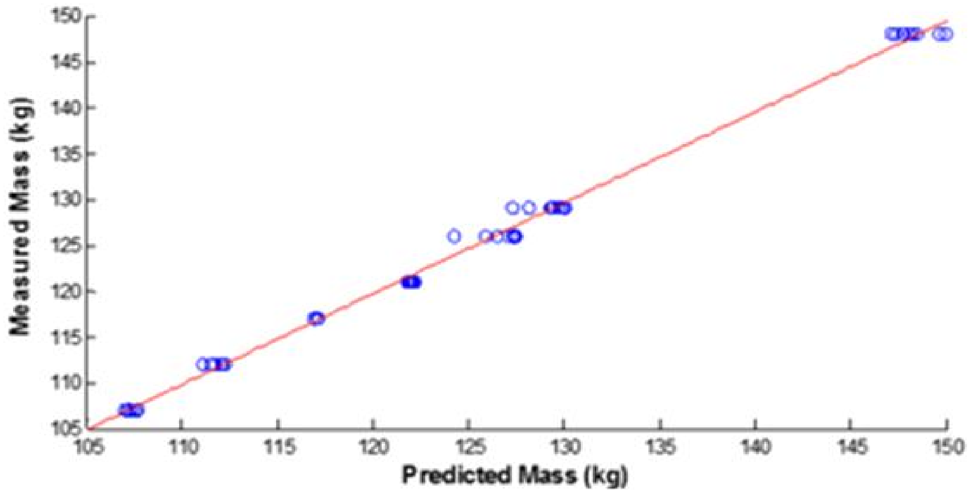

Fig 7: Predicated mass against Scale measured mass

test data $y=0.99\chi-0.085$ with a coefficient of determination $R^2=0.9976$ of the predicted mass against scale measured mass. This is a clear indication that our proposed system falls short of an ideal system of $y=x$ but within acceptable deviation, the highest percentage error being 3.079% and the lowest percentage average error at 0.023%.

With the determination that this system is practical, the two main limitations are image quality as animal movement during imaging significantly reduces the model accuracy and the model fail to extrapolate to data ranges outside its training limit, hence for future studies animal posture, and movements should be factored in and feasible data extrapolation modelling.

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