Image analysis for pig recognition based on size and weight

A. Wongsriworaphon[1,α], S. Pathumnakul[2,β], B. Arnonkijpanich[3,γ]
[1]Ph.D. Student, Department of Industrial Engineering, Faculty of Engineering, Khon Kaen University, Thailand
[2] Supply Chain and Logistics Systems Research Unit, Department of Industrial Engineering,
Faculty of Engineering, Khon Kaen University, Thailand
[3]Department of Mathematics, Faculty of Science, Khon Kaen University, Thailand
([α] apirachai@kku.ac.th, [β] supa_pat@kku.ac.th, [γ] abanchar@kku.ac.th)

Abstract - **Stockman or farmers always have difficulty recognition of pig mass in their farms. The typical approach is to approximate from age of pigs, daily- given feed, or from experience of human vision. Another practical approach to instantly measure mass of pigs is to use machine vision. The objective of this paper is to use a developed machine vision to analyze pig mass for detection of size and weight of pigs in farm. The pig mass is processed from physical features captured from digital image and their liveweights are approximated from artificial neural network. This neural network model is based on vector-quantized temporal associative memory (VQTAM) and locally linear embedding (LLE). The elementary results showed that the mass approximation of pig weight had acceptable accuracy and it was practical in pig farms.**

Keywords - **Pig weighing system, VQTAM, locally linear embedding.**

I. INTRODUCTION

Thailand is the world's thirteen food producers. Income from food and agriculture industries accounts for 9% of GDP (Office of the National Economic and Social Development Board, Thailand, 2010). The exported products are divided into two types. The first type includes such vegetation as rice, cassava, fruits, etc and the second one covers such livestock products as shrimp, chicken meat, beef and pork etc. In terms of export value in 2008, value generated from animal meat was as high as 2 thousand million dollar. This figure suggests that Thailand is a major food producer and meat products, especially pork-based products, is of high demand from the global market.

In Thailand, development of pig farms including breeding, management, and sanitization is comparable to other countries. The size of farms ranges from small-scale to large-scale farms. Pork production starts from pig farms where pigs are then transferred to fattening farms to be fattened for the required weight. Afterwards, they are slaughtered for further processes and distribution.

In pork–based production process, an important indicator is pig mass, which determines the required pieces of pork. Conventionally, to weight pigs, stockmen carry pigs onto a weighting scale or approximate pig mass from experiencing vision; however, the weight distribution gained from this method is non-uniform. The errors result in a number of negative effects on production process and cost. Furthermore, walking pigs to weight encounters a number of problems and causes pig stress, which affects quality of pork.

Several studies have suggested direct and indirect pig weighing. In [1] self-accessed scale was introduced. The principle is that when a pig is feeding, its front legs are on the scale which is connected to electronic scale to estimate its true mass. Nevertheless, some problems from this method arose when more than one pig are on the installed scale, which causes estimation's errors. In addition, direct weighting experiences several limitations. That is, it is not practical in the real situations. Therefore, this study introduced image processing to capture pig image for analysis of mass approximation [2]. It is one of the indirect weighting based on the width and length of pig body. An advantage of this approach is that weight approximation relies only on physical features, whereas its drawback is that digital image enhancement is a complicated technique. According to [3], weight of pigs were approximated using machine vision and the data were processed by Artificial neural network (ANN). The physical features in this study included area, convex area, perimeter, eccentricity, major axis length, minor axis length and the weight was approximated using ANN and back propagation algorithm. The findings from this study, in which pigs were forced to walk through a walking channel, had average relative error at 3%. However, there were some limitations because forcing pigs to walk through the set channel was a complicated task and not practical. To deal with these limitations, the researchers introduced information technology to cope with the problems by applying digital image processing. The captured digital image was processed and analyzed for the mass of pigs so that pigs were caught at optimal weight for slaughtering. This approach yielded accurate results in production systems and minimize cost.

In this paper, machine vision is used to keep detecting and recognizing mass of pigs when they were in fattening house. The digital image processing and artificial neural network are employed to detect image and process the detected physical features. This approach facilitates pig farmers and could reduce stress on pigs as well as minimize cost from storing and meat loss. This study is conducted on site, so the findings are practical for the real world situation.

II. WEIGHING A PIG WITHOUT A SCALE

Since size and weight of pigs are the key factors to estimate the product value, a method to approximate the weight of pigs is needed. Typically, a number of pigs are randomly chosen from herd and each pig is fed into

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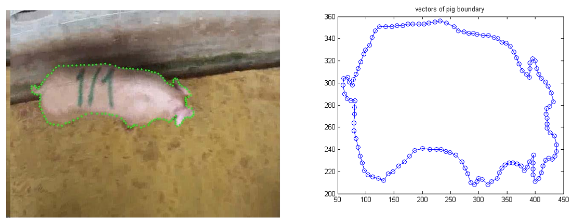
livestock weighing apparatus to record its weight. These weight values are used to predict the total weight of pig herd. Traditional way of measuring weight looks reasonable and easy to implement but still has some limitations. The accuracy depends on pig distribution in which pigs of different sizes should be uniformly distributed on area. Additionally, this way employs skillful stockman to select suitable pigs and cope with messy situations since pigs are more sensitive to any changes in the surroundings. To defeat these problems, in this paper, we propose the new strategy for weighing a pig without a scale. Our technique based on computer vision and artificial neural networks are proposed for determining the size and weight of pigs from digital image. The method consists of three main parts: boundary detection, feature extraction, and pattern recognition. In each of these parts, we demonstrate a practical technique for boundary detection and propose a new supervised learning algorithm based on combination of vector-quantized temporal associative memory (VQTAM) [4] and locally linear embedding (LLE) [5] for pattern recognition. The details of these three parts are the followings.

Fig. 1: Top-view images of each pig that have known weight are chosen to identify boundary pixels.

A. Boundary Detection

Because of using pattern recognition for solving this problem, a supervised learning algorithm is provided with two sets of data, a training set and a test set. These data sets are derived from extracting pig boundary from image sequences and then convert them into 2D vector points in Cartesian coordinate system. From image sequences of the moving pig body, we choose a few images of each pig that have known weight. Figure 1 shows the set of partial images of pigs used in this paper. We merely select top-view images so that we can clearly see the edge of pig body. In addition, top-view images provide easy to identify boundary pixels and assign boundary directions. The GINPUT function in MATLAB is used to get the pixel coordinates of a perimeter/boundary as shown in figure 2(a). Note that pixel coordinate is a location in image, not a numeric data type representing an uncomputable value. Therefore, in practice, it is necessary to convert pixel to 2D vector (x,y) in Cartesian coordinates as shown in figure 2(b). Then these vector-valued functions can be computed using mathematical technique. Our process is different from method of [3] employing image segmentation technique for boundary detection. The main disadvantage of segmentation is that final result is sensitive to changes in the intensity of light energy. In addition, another weakness of segmentation as appeared in [3] is that differences of pig color and background color should be mostly large. However, in practice, the level of illumination in animal housing is quite low. This leads to dimly illuminated test image being difficult to extract the pig body from background. While works of [2] and [3] are experimented on closed environment, i.e. cameras and lamps installed in animal housing should be in fixtures and background is a darkened color, our method is more flexible. The camera position parameters may change slightly. The light direction and intensity of light have no effect on the final result of boundary identification. Moreover, our method allows background to be light color.



(a) (b)

Fig.2: (a) identifying boundary pixels and (b) converting from pixel coordinates to Cartesian coordinates

B. Feature Extraction

In the previous part, the boundary vectors of pig body are extracted from images. In this part, we describe the connection between obtained boundary vectors and set of feature vectors. The important characteristics consisting of average boundary distance and the perimeter of the pig on one side are used as features of interesting object. These main features contain sufficient details of physical characteristics of pigs. From figure 2(b) each point x_i on the boundary is collected into a set of boundary vectors. The algorithm for computing an average boundary distance is as follows.

Algorithm AVG_BOUNDARY_DIST(*boundary_vectors*)
1. **begin**
2. **for** each x_i in *boundary_vectors* **do**
3. let d_i be the Euclidean distance between x_i and a mean value of *boundary_vectors.*
4. compute average distance

$$avg_b = \frac{1}{|boundary\_vectors|}\sum_{j=1}^{|boundary\_vectors|} d_j \ .$$

5. **end**

The values of avg_b are used for defining sizes of pigs as well as the length of perimeter $length_p$. The algorithm for identifying the length of perimeter is explained in the following.

Algorithm LENGTH_OF_PERIMETER(*boundary_vectors*)
1. **begin**
2. **for** each x_i in *boundary_vectors* **do**
3. let d_i be the Euclidean distance between x_i and a previous vector x_{i-1}.
4. compute the length of perimeter of pig
$$length_p = \sum_{j=1}^{|boundary\_vectors|} d_j \ .$$
5. **end**

C. Pattern Recognition

This work uses the concept of machine vision to deal with pig identification. The feature set obtained in previous step is converted proportionally into levels of size and weight. This is useful to the stockman and slaughterhouse in order to obtain pigs with appropriate size and weight for carving. In this part, we introduce an alternative supervised learning algorithm for defining relationship between features and levels of weight. The aim of supervised learning algorithms for system identification is to approximate continuous forward and inverse mapping between input and output data spaces. Artificial neural network (ANN) models have been successfully applied to identifying such mappings [4, 6]. Some of the most popular methods of supervised learning are the multilayer perceptron (MLP) and the radial basis function (RBF) networks. Recently, G. Barreto and A. Araujo have proposed a system identification technique based on the self-organizing map (SOM) [4] for function approximation, instead of MLP and RBF. The SOM is used to approximate input-output mappings for connecting input and output data spaces together [4]. This technique is called vector-quantized temporal associative memory (VQTAM). The SOM is an unsupervised learning algorithm designed to find the topological structure embedded within the multidimensional data space. The neurons in the SOM are arranged on the 2D lateral lattice space. Each neuron i has a corresponding weight vector $w_i \in \mathbb{R}^n$ located among input vectors $x_j \in \mathbb{R}^n; \ j = 1,\ldots,m$. To make the SOM able to convert the feature set consisting of avg_b and $length_p$ into levels of weight, each input vector x_j fed into SOM must be modified as follows.

$$x_j = \begin{bmatrix} x_j^{in} & x_j^{out} \end{bmatrix}^t \tag{1}$$

$$w_i = \begin{bmatrix} w_i^{in} & w_i^{out} \end{bmatrix}^t \tag{2}$$

$$x_j^{in} = \begin{bmatrix} avg_b^j & length_p^j \end{bmatrix}^t \tag{3}$$

$$x_j^{out} = \begin{bmatrix} W^j \end{bmatrix} \tag{4}$$

where x_j^{in} carries data about average boundary distance and the length of perimeter of j^{th} pig as well as the vector x_j^{out} contains the weight of j^{th} pig. During the training stage, the closest neuron weight of the input vector x_j^{in} is selected as winning neuron

$$i^* = \arg\min_{\forall i}\left\{\left\| x_j^{in} - w_i^{in} \right\|\right\}. \tag{5}$$

The recursive formulas for updating each neural weight on both the input and output spaces are as follows:

$$w_i^{in} \Leftarrow w_i^{in} + \alpha(t)h(i^*,i;t)[x_j^{in} - w_i^{in}] \tag{6}$$

$$w_i^{out} \Leftarrow w_i^{out} + \alpha(t)h(i^*,i;t)[x_j^{out} - w_i^{out}]. \tag{7}$$

where the learning rate $\alpha(t)$ is a decreasing function of time and $h(i^*,i;t)$ is a Gaussian neighborhood function defined by

$$h(i^*,i;t) = \exp\left(-\frac{\left\| r_i - r_{i^*} \right\|^2}{2\sigma^2(t)} \right) \tag{8}$$

where r_i and r_{i^*} are the locations of neurons i and i^* on the lateral lattice space, respectively. The function $\sigma(t)$ is an exponentially decreasing function. A trained SOM network can then be used to obtain an approximate weight on each pig using the following equation

$$\hat{W}^j \equiv w_{i^*}^{out} \tag{9}$$

Note that, the estimates produced by (9) have low reliability because of a high error value. To obtain high-accuracy prediction, the number of neurons should be large enough. This leads to time-consuming problem during the training process. A more efficient strategy is to train the SOM with a few neurons in order to get a structural topology of neural weights. Then, after training is finished, a locally linear embedding (LLE) [5] technique is used to improve the quality of estimates as described next.

The LLE algorithm is one of the most widely used nonlinear dimensionality reduction techniques. This method is used to reduce the dimensionality of high-dimensional data while preserving local geometries in a low-dimensional representation of the original data. The outline of LLE applied to our work consists of three steps. The first step, a predetermined number of k nearest neighbors is assigned. Thus, each data vector x_j^{in} can be written as linear combination of its k nearest neural weights

$$x_j^{in} = c_{j1}w_{i_1^*}^{in} + c_{j2}w_{i_2^*}^{in} + \ldots + c_{jk}w_{i_k^*}^{in}. \tag{10}$$

The second step, for each vector x_j^{in} the coefficients of linear combination are computed in order to have the best representation of local geometries on input space. In this step, the LLE wants to reconstruct the k coefficients. This corresponds to minimizing reconstruction error as appeared in the cost function

$$\phi(C) = \sum_{j=1}^{m} \left\| x_j^{in} - \sum_{l=1}^{k} c_{jl} w_{i_l^*}^{in} \right\|^2 . \qquad (11)$$

where c_{jl} is the unknown matrix. This objective function is minimized under two constraints. In the first constraint, each vector x_j^{in} is reconstructed only from its nearest neural weights, or $c_{jl} = 0$ if $w_{i_l^*}^{in}$ is not a neighbor of x_j^{in}. In the second constraint, the coefficients sum to one, or $\sum_{l=1}^{k} c_{jl} = 1, \forall j$. Note that, the optimal matrix c_{jl} can be efficiently computed by solving a constrained least squares problem. The third step, on output space, the estimates of pig weights are improved using the coefficients from previous step

$$x_j^{out} \approx \hat{W}^j \equiv c_{j1} w_{i_1^*}^{out} + c_{j2} w_{i_2^*}^{out} + \ldots + c_{jk} w_{i_k^*}^{out} . \qquad (12)$$

TABLE I
RESULTS of WEIGHT PREDICTION

Real Weight (kg)	Approximated Weight		
	VQTAM	VQTAM+AR [a]	VQTAM+LLE
82.00	86.44	94.16	**86.26**
96.00	97.40	103.09	**96.97**
105.00	103.95	101.75	**105.75**
116.00	109.93	**111.09**	109.95
121.00	124.23	118.04	**122.60**

[a] the improvement of VQTAM using an autoregressive model, see [4].

III. EXPERIMENTAL RESULTS

This study relied on 28 pigs, all of which were from the case study farm. The subjects were drawn by purposive sampling to gain on site information. The average weight of the pigs was 90-120 kg.. These pigs were ready to be slaughtered and processed to be pork products. The pigs were imaged on site in order to be aware of immediate problems and immediately address them. Of 28 pigs, 30 images were taken and used for neural network training and 5 images were used to test the obtained results. The authors selected 28 pigs and divided them into 4 groups, which had been previously grouped by the case study farm. Pigs whose weights were 78-89 kg., 90-102 kg., 103-115 kg. and over 115 kg. were categorized as groups A, B, C, and D, respectively. All of the subjects were weighted from the ground weighting scale and all data were collected to compare with the weight approximated from machine vision. The pigs were imaged by a digital camera (Sony DSC-HX5). The lower resolution of picture was 640x480. The camera was installed on ceiling away from the floor 2.80 meters to acquire top view image. Afterwards, the images in the memory were processed and analyzed to measure physical features using image processing technique, which is explained in the previous section. In table 1, we test the algorithms for 5 testing images and compare the performance of the LLE-based VQTAM with standard approaches, single VQTAM and AR-based VQTAM. Our method always performed better than classical VQTAM. As can be seen, our algorithm produces smaller prediction errors in almost all tests because the LLE provides nonlinear input-output mapping superior to linear projection obtained from AR model.

IV. CONCLUSION

We have proposed the new approach for estimating the size and weight of pigs from an image of pig herds using techniques of computer vision and artificial neural networks. Pig identification consists of three modules: boundary detection, feature extraction, and pattern recognition. Each pig image is used to get the pixel locations of pig outlier and convert from pixel coordinates into 2D vectors. The resulting boundary vectors can be interpreted as the essential features such as boundary, perimeter, and shape. Using ideas of input-output mapping, SOM based supervised learning can be directly used for converting features to levels of size and weight. This is a very useful method for farm management and food processing industries.

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REFERENCES

[1] M. Turner, J. Sharp, J. Benson, and M. Hanley, "Automatic weight monitoring of pigs", Divisional note, National Institute of Agricultural Engineering, vol. 1266-1267, 1985.

[2] N. Brandl and E. Jorgensen, "Determination of live weight of pigs from dimensions measured using image analysis", Journal of Computers and Electronics in Agriculture, vol. 15, pp. 57-72, 1996.

[3] Y. Wanga, W. Yang, P. Winter, and L. Walker, "Walk-through weighing of pigs using machine vision and an artificial neural network", Journal of Biosystem Engineering, vol. 100, pp. 117–125, 2008.

[4] G. Barreto and A. Araujo, "Identification and control of dynamical systems using the self-organizing map", IEEE Transactions on Neural Networks, vol. 15, no. 5, pp. 1244-1259, 2004.

[5] S. Roweis and L. Saul, "Nonlinear dimensionality reduction by locally linear embedding", Science, vol. 290, no. 5500, pp. 2323-2326, 2000.

[6] K. Narendra and K. Parthasarathy, "Identification and control of dynamical systems using neural networks", IEEE Transactions on Neural Networks, vol. 1, no. 1, pp. 4-27, 1990.