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Estimating Pig Weight with Digital Image Processing using Deep Learning

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***Abstract*—In pig production, food processing and profitability ratios can be assessed by detecting live weight of live pigs in real time. Traditional pig weight detection often requires direct contact with pigs, which is limited by low efficiency and can result in even death. Detecting the weight of non-contact pigs has become a challenge in pig production for decades. The proposed system offers significant features such as color, texture, centroid, major axis length, minor axis length, eccentricity and area. For recognition for estimation weight of pig, we use statistics from the original database with neural network. Analysis of experimental results of contactless pig weight estimation as well.**

Keywords— estimating, digital image, processing, deep learning

I. INTRODUCTION

Weight is an important index for pig farming. The daily weight and nutritional status of pigs can be assessed immediately by increasing the weight of the pigs at the appropriate time. (1) The feed efficiency can be detected in combination with the automatic feeder. (2) Pigs with good or bad food status can be raised separately to meet market standards. In traditional weight measurement, pigs need to be moved to weighing equipment such as mechanical scales and electronic scales. All processes take time and effort, often requiring at least two people to spend three to five minutes with each pig. (3) This process puts a lot of stress on pigs and even leads to sudden death; Feed consumption is reduced on weighing days compared to before and after the day of weighing. (4) Some years ago, some manufacturers added weighing sensors to the automatic feeder to weigh and record weight. Of real-time pigs Most of these devices are expensive and tend to be eroded with wastewater. In addition, they need to remold original piggery.

Since there are many problems in measuring weight, touch-free measurement has attracted attention in measuring or assessing the weight of piglets. At the beginning of the year, 1988. The digital image analysis has suggested that there are about 90 possible uses for stock culture, which can be used to assess the weight of pigs. (5) Numerous researches have proven to be highly correlated. Significant difference between animal size and body weight. By visual analysis and visual vision technology, the size of the back or the back area of the pork. When combined with body size and body weight, the live weight of pigs can be accurately assessed. Measurement techniques based on the vision of the machine offer many virtues, such as non-contact, saving labor and fast. Non-contact measurements have not been widely applied in practical engineering, although research has been taking place for decades. In this article, the use of systematic litter evaluation techniques has been reviewed from two parts of the work of the system framework and the prediction model based on the computer vision.

Yeo and Smith et al (6) presented control feed intake of pigs, there are typically two methods of weight measurement are direct weighting and indirect. Doyle and Leeson et al (7) studied Physical stress on both pigs and breeders occurs when using direct weighting was performed to keep the pigs on the ground, which could have a negative effect on pig farming for Stajnko et al (8) proposed indirect methods by tapes or calipers or analytical systems have been developed to change this situation. Most estimation methods of live pigs are performed with the eyes or hands. Slippers et al (9) proposed live weight estimation. Heinrichs et al. et al (10) correlated the width of the hip. Enevoldsen and Kristensen et al (11) evaluated the live weight of cows by measuring body size, body weight, and body weight. Pope and Moore et al (12) presented circumference measurement is one of the most important indirect methods and is used to weigh pigs. Non-contact measurement methods effectively reduce animal stress. Schwartzkopf-Genswein et al (13) proposed automatic weighting systems, such as radio frequency identification systems. Cveticanin and Wendl et al (14) proposed Fuzzy Logical Weighting System.

At present, the development of computer systems and digital imaging systems is an indirect way of evaluating live animal weights based on image analysis techniques. White et al (15) proposed image analysis to determine the size and shape

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of live pigs to determine live weight. Molly et al. et al (16) conducted a study to estimate the body weight of broiler chickens. Schaefer and Tong et al (17) proposed infrared thermal images of animals are used for predicting body composition. Kashiha et al. (18) presented shape recognition algorithms and algorithms. Kongsro (19) introduced three-dimensional data to evaluate the weight of various pigs according to Microsoft's Kinect system.

II. FRAMEWORK PROPOSED

In this paper, features extraction with 7 features as color, texture, centroid, major axis length, minor axis length, eccentricity and area and for recognition for estimation weight of pig, we use statistics from the original database with neural network.

This paper is structured as follows: section 2 summarizes the previous methodology for segmentation and feature extraction. Section 3 describes estimating pig weight using neural network. Section 4 experimental result and conclusion are listed in Section 5.

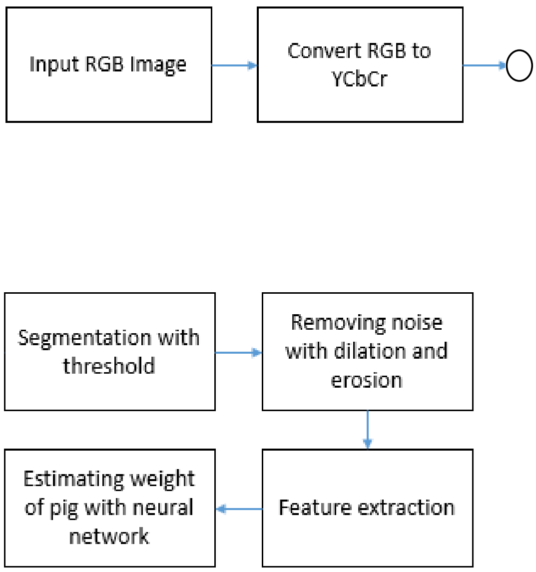

Fig. 1. Framework proposed

Fig. 2. Framework proposed

III. METHODOLOGY

A. 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 YCbcr (Y, Cb, Cr) intensities from pixels known to represent pigs were collected.

In this paper, the background is cut off using the Threshold method with intensity levels between the two groups. Threshold is applied to compare the value of each pixel. If f (x, y) is less than Threshold, the pixel will be black or fractional. And if the value of f (x, y) is greater than or equal to Threshold, the pixel is either white or a part of the background. Can be written as:

$$f_{thr}(x,y) = \begin{cases} 1, f_f(x,y) < Threshold \\ 0, f_f(x,y) \geq Threshold \end{cases} \qquad (1)$$

where:

1 is the black part of the object.

0 is white, which is part of the background.

Fig. 3. Image segmented

B. Removing noise

Segmentation method, we use adaptive threshold algorithm, but there will still be a number of pig pixels that are not detected or detected in other pixel that not a pig. 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 one forms of filtering as morphological filtering. Avoid combining SI and CGS units, such as current in amperes and magnetic field in oersteds. This often leads to confusion because equations do not balance dimensionally. If you must use mixed units, clearly state the units for each quantity that you use in an equation.

Binary mathematical morphology is based on two basic operations, defined in terms of a structuring element, a small window that scans the image and alters the pixels in function of its window content: a dilation of set A with structuring element B enlarges the objects (more 1-pixels will be present in the image), an erosion shrinks objects (the number of 1-pixels in the image decreases). The basic morphological operators on sets A and B are defined as:

$$Dilation:(A \oplus B)(x) = \{x \in X, x = a + b : a \in A, b \in B\} \quad (2)$$

$$Erosion:(A \Theta B)(x) = \{x \in X, x + b \in A : b \in B\} \quad (3)$$

Fig. 4. Image removed noise

C. Feature Extraction

Once the image of the pig was segmented and cleaned up via filtering, features could be extracted. The eight features that were employed in this study were color, texture, centroid, majorAxisLength, minorAxisLength, eccentricity and area.

- Color

The color of the skin pig differs over the various shades of YCbCr. The value of one is assigned on the presence of each color in the pig image.

- Texture

Contrast, correlation and energy of the pixels as texture features. Energy indicates the set of pixels homogeneity.

- Centroid

The center of mass of the region. Centroid has 2 elements as the first element of Centroid is the horizontal coordinate (or x-coordinate) of the center of mass, and the second element is the vertical coordinate (or y-coordinate). All other elements of Centroid are in order of dimension.

$$M_{p,q} = \sum_{i,j \in R} i^p j^q \quad (4)$$

$$\bar{x} = \frac{M_{1,0}}{M_{0,0}} \quad (5)$$

$$\bar{y} = \frac{M_{0,1}}{M_{0,0}} \quad (6)$$

- Minor Axis Length

The length of the line passing through lesion blob centroid and connecting the two nearest boundary points.

- Major Axis Length

The length of the line passing through lesion centroid and connecting the two farthest boundary points. The output of (x_c, y_c) is given by the relation. (7)

$$(x_c, y_c) = \left(\frac{\sum x_i}{n}, \frac{\sum y_i}{n}\right) \quad (7)$$

Where n is the number of pixels inside the lesion, and (x_i, y_i) is the coordinates of the ith lesion pixel.

- Area

The area of a region is defined by the number of pixels in the region (i.e., size). Can be computed using zero order moments (i.e., p=q=0):

$$Area = \sum_{i=1}^{N} \sum_{j=1}^{M} B[i, j] \qquad (8)$$

- Region Eccentricity

A useful measure of a region's circularity is its eccentricity. Can be easily computed using the ratio between the principal axes:

$$eccentricity = \frac{A_{\max}}{A_{\min}} = \sqrt{\frac{\lambda_{\max}}{\lambda_{\min}}} \qquad (9)$$

Eccentricity of the ellipse that has the same second-moments as each pig samples. The value is between 0 and 1. A pig sample with an eccentricity of 0 is actually a circle, while a pig sample whose eccentricity is 1 represents a line segment.

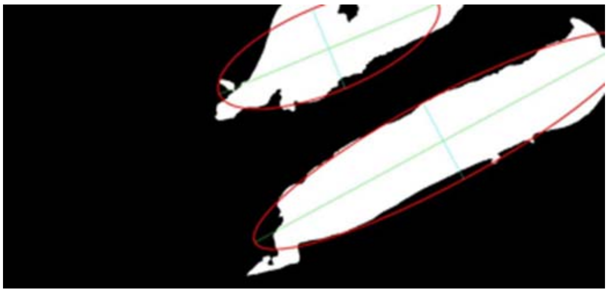

Fig. 5. Plot major axis length, minor axis length on image

Fig. 6. Contoured pig

D. Estimating pig weight using deep learning

In this paper proposed a back-propagation was created to learning rule to multiple-layer. The network is trained by supervised learning method. The network weights are moved along the negative of the gradient of the performance function. Input vectors and the corresponding target vectors are used to train a network until it can approximate a function, associate input vectors with specific output vectors, or classify input vectors in an appropriate way as defined by the user. Networks with biases, a Tansig layer, and a purelin output layer are capable of approximating any function with a finite number of discontinuities. Figure 7 shows the architecture of implemented back propagation network. Back propagation network have more hidden layers of sigmoid neurons followed by an output layer of linear neurons. Multiple layers of neurons with nonlinear transfer functions allow the network to learn nonlinear and linear relationships between input and output vectors.

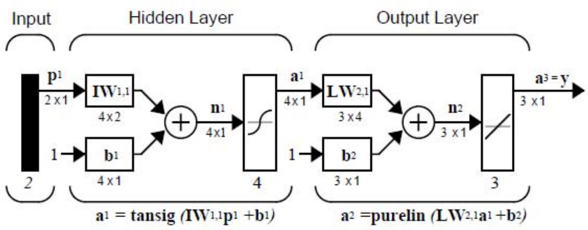

Fig. 7. Architecture of implemented back propagation network

where:

b is biases

w is weight

TABLE I. PARAMETER FOR SETTING UP OF NEURAL NETWORK

Structure	Iterations	Learning rate	Momentum	Transfer function (Input and Hidden layer)	Transfer function (Hidden layer)
8-5-2	1000	0.5	0.5	Tansig	purelin

Fig. 8. Measured weight of pig

IV. Experimental Rerult

In this paper, an automatic method is implemented for pig detection and recognition. Experiments and measurements were performed on a PC with P4-3.2 GHz CPU and 1024 MB RAM. For test data, in this paper applied 100 pig images. For training data, in this paper applied 500 pig images. Fig. 1 shows three original pig images, we applied the image that corrected only from detects processing.

$$Accuracy(\%) = \left(\frac{In - Out}{Total} \right) \times 100 \qquad (10)$$

In table II, shows accuracy of this paper. Detect processing, we use threshold then remove noise with dilation and erosion that it is 87.15%. For accuracy of measuring weight with neural network, it is 82.72%.

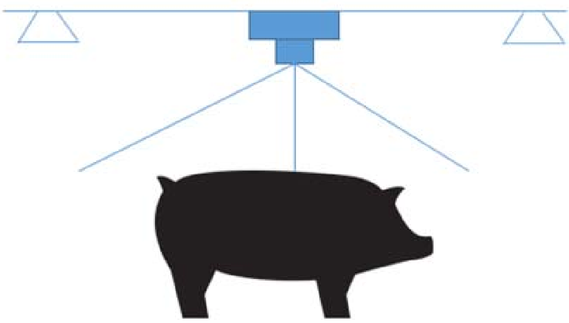

Fig. 9. Camera setup

TABLE II. RESULT OF PIG DETECTION AND RECOGNITION

Processing	Accuracy rate%
Detection	87.15
Measure weight with neural network	82.72

Fig. 10. Show good pig image that detected

Fig. 11. Show failed pig image that detected

V. SUMMARY

In this paper proposed a pig detection and measure weight of pig with neural network. Due to the moving nature of animals, it's a great challenge to snap a straight and head raised pig's image, the location of camera and poor light condition can deal with this challenge. In the first step, detection method is applied for segment image. In the second step, both dilation and erosion are applied for removing noise. In the third step, feature of pig is extracted using 8 methods as color, texture, centroid, major axis length, minor axis length, eccentricity and area. In the five step, bring 7 features to compare with database for measure weight of pig. For experimental result, measure weight with neural network of 82.72 and detection rate of 87.15%.

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