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Egg Weight Estimation by Machine Vision and Neural Network Techniques (A case study Fresh Egg)

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Abstract

Egg weight measurement is one of the most important parameters in marketing this product. Information regarding egg weight is not only vital for grading systems based merely on weight, but it is also necessary for assessing quality indices such as yolk-albumen ratio, shell thickness and hatchability. In the present study a machine vision system combined with artificial neural network technique was used for estimating egg weight. The system hardware consists of a CCD camera, a capture video, an illumination system and a mirror. As an egg is introduced into the frame, grabber two perpendicular images are grabbed. These images are then processed in MATLAB and pixel data corresponding to each image edge is extracted. Once center of gravity of each image edge is obtained, twelve size features can be calculated for each image. These features are then classified into three categories named as input vectors (1-3). Each input vector along with its real weight data (measured) is exported to three parallel training algorithms of a Multi Layer Perceptron (MLP) Network. The training algorithms are variable learning rate (MLP-GDX), resilient back propagation (MLP-RP) and scaled conjugate gradient (MLP-SCG). These training algorithms were optimized to estimate egg weight. Evaluation results showed that MLP-SCG was superior to other two algorithms in estimating egg weight at high accuracy (R=.96). In other words, MLP-SCG was capable of egg weight estimation at an absolute error of no more than 2.3g for the average egg size of 60 g.

Keywords: Egg weight, image processing, Neural network (ANN), Multi layer perceptron.

INTRODUCTION

Egg is an important and fundamental foodstuff with a high nutritive value. Egg has four major nutritional components: proteins, lipids, vitamins and minerals. This worthy nutritive egg is capable of developing embryo and chicken body [10,11,12,13].

Egg weight is a proper characteristic for nondestructive prediction of shell egg features [1, 9]. Paganelli et al. [14] reported a 0.99 correlation coefficient between egg weight and shell weight. Many other investigations have been directed towards establishing a relationship between egg weight and hatchability [5,17]. They reported that hatchability was at maximum when egg weighed about 50 g, hatchability decreased as the egg weight was increased. Furthermore, egg weight can be considered as a good prediction of chick weight. The correlation between egg weight and chick weight at hatching is shown to be 0.50–0.95 and a best quadratic equation was determined by using three basic parameters: weight, volume and surface area [17].

The above studies show that the measurement of egg weight has many applications and is vital requirement for poultry industry. On the other hand, learning techniques have been applied increasingly for food quality evaluation using computer vision in recent years. Artificial neural networks can be regarded as an extension of image processing techniques which have been developed over several decades. Now combination of machine vision and neural network are commonly found in tasks involving grading and sorting [3,8] and also in bioprocessing operations such as drying [4,7].In the earlier days, machine vision and neural network technique have been applied to nondestructive measurement of egg. Patel et al [16] combined a color computer vision and a neural network system for detection of eggs with defect. They joined three histograms of each egg and formed a histogram with 768 cells. Each cell was considered as inputs to the neural network. The system was capable for dirt stain detection with 97.8% accuracy, 91.1% accuracy for blood spot detection and 96.7% accuracy for crack detection. This type of investigation was done by these authors in 1994 for crack detection of egg [15].

The main objective of this study was to develop a much faster method for estimation egg weight through combining machine vision and neural network technology.

MATERIALS and METHODS

In this study, characteristic parameters firstly defined by the researcher were calculated from the edge information detected from the egg image. These features classify into three group and feed to three training algorithms of ANN. At end, the best characteristic and superior training algorithm was selected.

Egg samples

Ninety fresh eggs (selected immediately after laying) with variety size and variety weight were collected from White Leghorn Line hens at different sites. The samples were weighed using an electronic balance. The maximum and minimum weights were limited to 75.8 and 51.1 g.

Machine vision system

The machine vision system consists of frame grabber, illumination system a mirror and color CCD camera. Egg samples were put in grabber. For each egg by using a flat mirror installed with 45 degree to camera, two perpendicular sights of egg were observed. The images are captured in RGB format, so every pixel in the image is represented by the combination of three values (corresponding to red, green and blue colors) between 0 and 255. The RGB Images were grabber by a canon CCD camera (IXUS 960IS) and have a 1200*1600 pixel resolution. Its external features information was extracted. In this system to get rid of shadows during image acquisition, the front lighting by the halogen had been used. The flowchart of the image processing software is shown in Fig. 1. In the image processing the first step is extraction some qualitative information from the objects to describe the image. This feature can dive into two categories: external features and internal features. External image features describe the boundary information and the features extracted from the properties of pixels inside the object boundary are called internal features [6]. In this paper we apply one of the external feature subcategories (morphological features) for predicts egg weight.

Morphological features describe the shape of an object. Shape features are physical dimensional measures that characterize the appearance of an object. Area, perimeter, major and minor axes lengths are some of the most commonly measured Morphological features. The first step to extract morphological features of image is segmentation, which divides the image into its constituent objects. For this purpose and to generate binary images that distinguish unambiguously between egg and background thresholding is necessary. For this purpose three values was considered as threshold (T1, T2, T3 and T4) and isolation was done based on these.

$$g(x,y) = \begin{cases} 1 \; if \; f(x,y) > T1, T2, T3, T4 \\ 0 \; if \; f(x,y) < T1, T2, T3, T4 \end{cases}$$

According to Table 1, if the color values of the R, G, B and R+G+B for a pixel, respectively is less than 0.294, 0.270, 0.321 and 0.788, that pixel considered as background and a zero value is placed in comes to black and otherwise value of pixel Appears equivalent to one.

Table 1. Color band data for image.

	Egg		Background	
index	minimum	maximum	minimum	maximum
R	0.686	0.945	0.051	0.294
G	0.580	0.882	0.047	0.270
B	0	0.788	0	0.321
R+G+B	1.733	2.611	0.1333	0.788

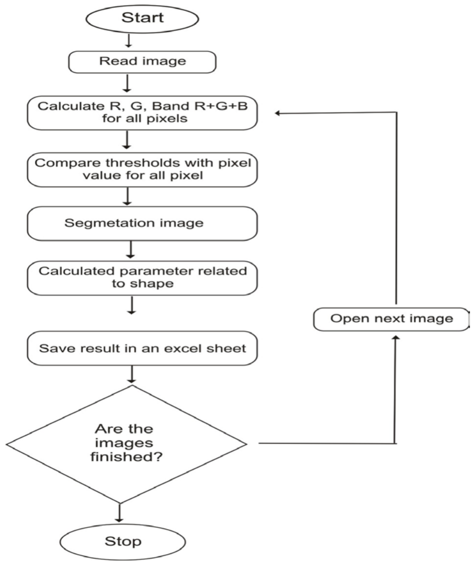

Fig. 1. Flowchart of the image processing software

By this method the images were converted into binary images.

Binary images are then labelled. All objects inside the image were counted. If their number was more than two, a morphological opening operator was used with a disk-shaped structuring element to remove all of them with only two objects remain.

After segmentation in each picture two images of two perpendicular sights for egg were remaining. Then each of them preserve in a new image. In the next step, an edge algorithm was developed to detect corresponding edge pixel in each of two images. Twelve physical features of egg were extracted. These features were including area, maximum radius, minimum radius, effective radius, perimeter and roundness for two sight of egg and thirteen area of egg. In resumption, we survey the methods for extracted these feature. At first we must estimate the center of gravity of two sight egg. Center of gravity was calculated by this formula:

$$\bar{x} = \frac{\sum x.A}{\sum A} \qquad \bar{y} = \frac{\sum y.A}{\sum A} \tag{1}$$

Where: $\bar{x}$, $\bar{y}$ are respectively horizontal and vertical coordinate for egg center of gravity and x, y are horizontal and vertical coordinate of each edge pixel respectively. All edge pixels have a coordinate as (x, y) by use the formula 2 we have a sequel of radius values. The maximum of this value was considered as Rmax and the minimum value of these was considered as Rmin. By using formula 3 the effective radius (Reffect) was calculated.

$$r_i = \left[\left(x_i - \bar{x}\right)^2 + \left(y_i - \bar{y}\right)^2\right]^{\frac{1}{2}}$$

$$r = [r_0, r_1, \ldots, r_{n-1}] \quad (2)$$

$$r_e = (r_0 \times r_1 \times \ldots r_{n-1})^{\frac{1}{n}} \quad (3)$$

Where r_e and r_i are effective and i[th] radius, respectively, and n is the number of radii. Each radius makes an angle θ with horizontal axis. θ This angle can be computed by the following formula. The diameter of objective can be then calculated by summing the radii which make angle with the 180 degree difference. These radii which are positioned in opposed direction make cumulative angle of 180 degree with the horizontal axis.

$$\theta = tg^{-1}\left(\frac{y_i - \bar{y}}{x_i - \bar{x}}\right) \quad (4)$$

Curray [2] suggested the following formula for calculating the roundness of an object:

$$Roundness = \frac{Min(d)}{Max(d)} \quad (5)$$

Where min(d) and max(d) are minimum and maximum diameters respectively.

The area and perimeter was calculated by counting the number of pixels inside and environs of egg image, respectively. All feature corresponding to first sight of egg named by 1 such as area1, , , roundness1, effect R1, and feature corresponding to mirror image named by 2 such as area2, , , roundness2, and effect R2. The unit of features were in pixel.

Neural network training algorithms

Artificial neural networks are a proper technique for estimation and prediction of food properties and process related parameters. The ANN algorithm, including resilient back propagation, variable learning rate and scaled conjugate gradient were trained for estimation egg weight by using extracted features. In this study, before the training of the network both input and output were normalized within the range 0.05 to 0.95 using the following relationship:

$$x_n = 0.05 + 0.9\frac{x_r - x_{min}}{x_{max} - x_{min}} \quad (6)$$

Wherex_n and x_r are the normalized and the original inputs, and x_min , x_max are the minimum and maximum of inputs, respectively. Normalized data were used to train MLP with three different algorithms. All features were classified into three categories as follow:
MLP1: Area1, minR1, maxR1, effectR1, Roundness1
MLP2: Area1, effectR1, Roundness1, Area2, effectR2, Area3,

RESULT and DISCUSSION

After examining many epochs and neuron numbers, the best prediction results were seen for this network architecture for different training algorithms (Table 2). Optimized epoch numbers of the resilient back propagation, variable learning rate, and scaled conjugate gradient Were 1000,100,800, respectively.architecture for different training algorithms (Table 2). Optimized epoch numbers of the resilient back propagation, variable learning rate, and scaled conjugate gradient Were 1000,100,800, respectively.

Table 2. Network architecture data.

	Input	Hidden layer	Output
No. of neuron	12	5	1
Training function	Tansig	Tansig	Purelin

Program codes, including Neural Network Toolbox, were written in the MATLAB for the MLP simulation. A three layered multi layer perceptron was used for training of three different training algorithms. The MLP results were transformed to the original domain and root mean square errors (RMSE) were computed for training and validation data for each MLP. The performance algorithms for three input vectors are shown in Tables 3.

Table 3. Performance MLPs model with three input vector.

Models		Training		Validation	
		R^2	RMSE	R^2	RMSE
RP	MLP1	0.95	1.05	0.9	1.78
	MLP2	0.99	0.39	0.89	1.97
	MLP3	0.99	0.28	0.88	2.48
GDX	MLP1	0.93	1.24	0.92	1.74
	MLP2	0.97	0.84	0.94	1.94
	MLP3	0.97	0.72	0.95	1.68
SCG	MLP1	0.94	1.07	0.91	1.94
	MLP2	0.98	0.59	0.96	1.46
	MLP3	0.98	0.63	0.95	1.46

CONCLUSIONS

The results indicated that a combination of machine vision and neural network was capable for egg weight prediction. The correlation coefficient for modeling at best algorithm was 0.96 and the absolute error was no more than 2.3g. For prediction purposes, it has been presented that scaled conjugate gradient algorithm of MLP network employing back propagation works reasonably well. The values of RMSE for training were approximately more than those for the MLP validation. Other results show that MLP-SCG is slightly superior to MLP-RP and MLP-GDX. Furthermore, the results of MLP2 are more satisfactory than other MLPs. On the other hand, it was concluded that increase in the number of input to model is not always useful.

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