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Full Length Research Paper

The identification of white fertile eggs prior to incubation based on machine vision and least square support vector machine

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The ability to automatically identifying fertile eggs prior to incubation would allow timely removal of the infertile eggs, which could bring high profits to hatcheries with better chick quality and lower pathogen contamination of chicks. A method based on machine vision and least square support vector machine (LS-SVM) for fertile eggs identification prior to incubation was proposed. Digital images were acquired by high-resolution digital cameras with cold light back illumination, and egg shapes (e.g. egg shape index, roundness, elongation, geometric moment) and color mean information of the egg yolk region such as hue (H), intensity (I), saturation (S) from image characters were extracted. LS-SVM algorithm was used to establish fertile egg classification model from infertile eggs. The test results obtained from the 40 testing sets showed that the best classification accuracy was 92.5%. With using a same data set, the performance comparison between LS-SVM classifier with different kernel functions and the other different classifiers was conducted. Compared with other kernels, LS-SVM classifier with radius basis functional (RBF) kernel was found to obtain the best accuracy and provide better accuracy, higher speed compared with support vector machine (SVM) and back-propagation (BP) artificial neural networks classifier.

Key words: Fertile egg, identification, machine vision, least square support vector machine, prior to incubation.

INTRODUCTION

In the egg industry, hatching egg selection is the mainly direct influencing factor of hatching effect. Quality of hatching eggs is directly related to the young birds hatching rate, survival rate and poultry quality. Hatchery statistics show that about 8 to 9% of all incubated eggs do not hatch due to egg infertility (Das and Evans, 1992a). Infertile eggs detection prior to incubation is one of the difficult problems in the hatchery industry, which has no reasonable solution so far. In practical applications, candling eggs at 7 to 12 days of incubation are always used, but the breakout infertile eggs have lost edible value and errors in candling often occur at this time. The automated detection of fertile eggs and infertile eggs prior to incubation can lead to timely removal, optimizing space and labor, avoiding contaminating of other eggs and bringing better profits to hatcheries.

In recent years, many methods of nondestructive detection of fertile egg have been proposed in the technical literature. Das and Evans (1992b) detected fertile embryo with machine vision and neural network, the accuracy is 93% at day 3 and 4 of the incubation, but only 67% at day 2 of the incubation. Yu et al. (2007) detected fertility of hatching eggs automatically by machine vision and improved PSO neural network system. Bamelis et al. (2002) used two light wavelengths to detect embryo development at 4.5 to 5 days of incubation. There were many new methods of detecting egg fertility or monitoring embryo development such as acoustic resonance frequency (Coucke et al., 1997), magnetic resonance imaging (Klein et al., 2002), high frequency ultrasound imaging (Schellpfeffer et al., 2005), and hyperspectral imaging (Lawrence et al., 2006; Smith et al., 2008). Former reports showed that efforts have

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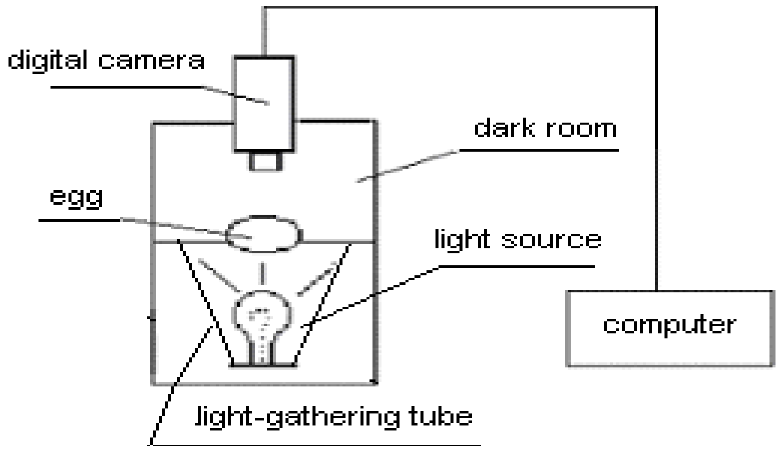

Figure 1. Machine vision imaging system.

been made to detect egg fertility during middle and late stage of incubation. Few reports focused on the period prior to incubation showed poor result in accuracy. In this study, using the machine vision acquired egg images and evaluating egg shapes and hue (H), intensity (I), saturation (S) color information of egg yolk region as characteristic parameters, novel classification model for fertility and infertility was established in order to obtain better accuracy and efficiency.

MATERIALS AND METHODS

Egg samples

One hundred eggs including 60 fertile eggs and 40 infertile eggs were collected from Huazhong Agricultural University Hatchery within one week. These eggs were obtained from 45 week old Single Comb White Leghorn chickens. After numbered and imaged, the eggs were placed into the incubator at 38.5°C and 65% relative humidity. At day 6, the eggs were candled and broken out to assess visually for fertility or infertility. We randomly chose, for each class, 60% of the subset to build the training set (36 fertile eggs and 24 infertile eggs) and the remaining 40% was put aside for testing set (24 fertile eggs and 16 infertile eggs). Three replicates of each treatment were performed; corresponding training set and testing set were obtained. The average of 3 times results was regarded as the final result.

Imaging system

The machine vision imaging system used to acquire egg images was shown in Figure 1. It was consisted of a light source, a light-gathering tube, a dark room, a Canon EOS 550D digital camera, and a computer. The light source provided an illumination of 7700 lux at the point where the egg was placed. A single 150W, 24V-DC tungsten-halogen lamp was served as light source. All images in this study were acquired by using the imaging system.

Image processing

The original egg image obtained by the machine vision system was shown in Figure 2a. In order to obtain whole egg region, considering background of the eggs image was black, image processing (Gonzalez, 2008) was applied as following: to convert the color image into gray scale image (Figure 2b); to use binary method for gray scale image (Figure 2c); to use Gaussian filter to smooth binary image (Figure 2d). Thus, the whole egg region was clearly separated. The pixel area and length of the whole egg region could be easily calculated and measured. According to preliminary research results of Research Group (Wang et al., 2009), the separating method of the egg region from the original picture was processed as follows: firstly, to convert the color image into gray scale image (Figure 2(e)); the yolk region could be more clearly apparent by gray balance processing (Figure 2f). However, there were a lot of noise points and the pixel value was not stable enough after gray balanced image. For this reason, median filter with 3×3 template and Gaussian smoothing were used for denoising and keeping stable (Figure 2g). From Figure 2g, egg yolk was clearly to be seen, but separation of egg yolk image could not be well obtained by threshold method. Here, hybrid of "color reverse" (Figure 2h) and "And" algorithm was applied to obtain egg yolk region. Figure 2i was the result of Figure 2h "And" Figure 2d. Erosion played the role of removing the object boundary points in mathematical morphology. Erosion with 3 × 3 structure elements was applied to the result of "And" (Figure 2j). Then removing the boundary of egg image was conducted (Figure 2k) by Figure 2h "And" Figure 2j. Lastly, the egg yolk region was extracted by auto threshold method (Figure 2l). Therefore, the coordinates of the egg yolk region were obtained by the binary image, and then H, I, S color information of egg yolk region could be calculated in original color space.

Feature extraction

In general, there were minute differences in shapes between fertile eggs and infertile eggs. Infertile eggs may be more circular, whereas fertile eggs may be long and thin (Taniguchi, 2007). Therefore, some shape parameters were extracted as character parameters. And there were differences in color information of transmission between fertile eggs and infertile eggs. Thus, color information of egg yolk was also extracted as character parameters. In the research, perimeter, area, major axis and minor axis of egg images were measured. Calculation of those parameters was explained in detailed by Zhou et al. (2007). To reduce error, some shape parameters were defined as following:

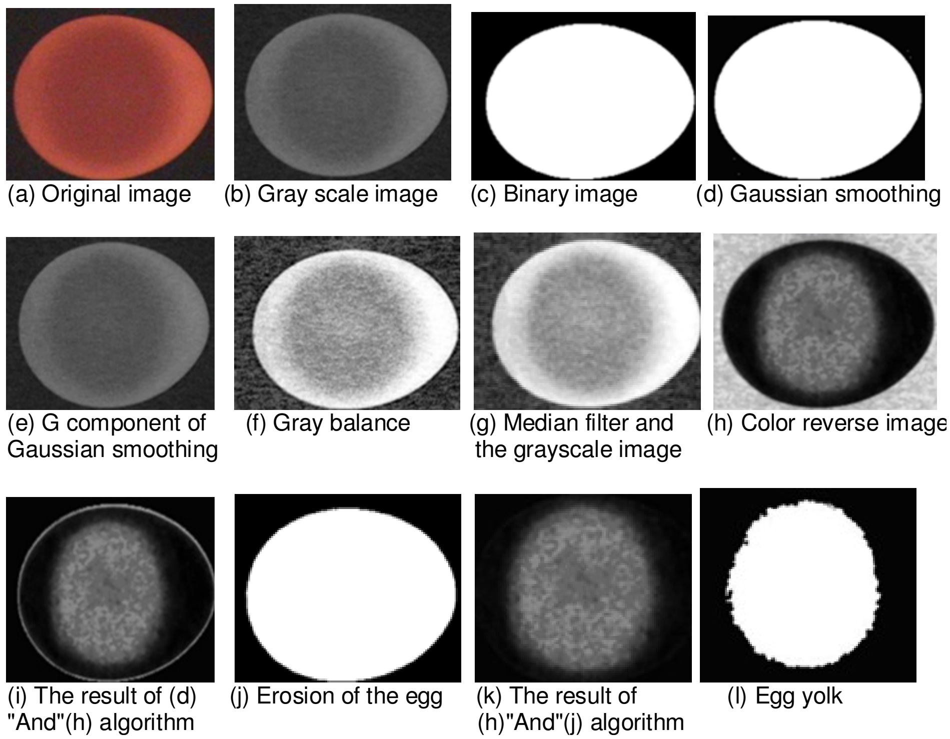

Figure 2. Egg image processing.

Egg shape index (SI): it is defined as:

$$SI = \frac{a}{b} \tag{1}$$

where, a is pixel major axis and b is pixel minor axis.

Roundness (D_R): Roundness is used to characterize the complexity of the object boundary. The closer to round shape of the egg, the greater the degree of its circular. The mathematical expression is as following:

$$D_R = \frac{4\pi A}{P^2} \tag{2}$$

where, A is pixel area and P is pixel perimeter.

Elongation (E): Elongation described the slender nature of the egg. The slender the egg, the smaller the elongation value. Elongation is defined as following:

$$E = \frac{b}{A} \tag{3}$$

where, A is pixel area and b is pixel minor axis.

And, moment features with scale, translation and rotating invariance can be easily expressed and analyzed in the region characteristics of the image (Ramteke, 2010). Invariant moments are selected as character parameters. $(p+q)$th order two-dimensional geometric central moments are denoted by μ_{pq}, which is expressed as:

$$\mu_{pq} = \iint_S (x-x_0)^p (y-y_0)^q f(x,y)\,dxdy \quad p,q=0,1,2,... \tag{4}$$

where, s the region of pixel space in which the image intensity function $f(x,y)$ is defined. (x_0, y_0) is the image intensity centroid. Seven moment invariants are given below:

$$\begin{aligned}
\varphi_1 &= \eta_{20} + \eta_{02} \\
\varphi_2 &= (\eta_{20} - \eta_{02})^2 + 4\eta_{11}{}^2 \\
\varphi_3 &= (\eta_{30} - 3\eta_{12})^2 + (3\eta_{21} - \eta_{03})^2 \\
\varphi_4 &= (\eta_{30} + \eta_{12})^2 + (\eta_{12} + \eta_{03})^2 \\
\varphi_5 &= (\eta_{30} - 3\eta_{12})(\eta_{30} + \eta_{12})\left[(\eta_{30} + \eta_{12})^2 - 3(\eta_{21} + \eta_{03})^2\right] \\
&\quad + (3\eta_{21} - \eta_{03})(\eta_{21} + \eta_{03})\left[3(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2\right] \\
\varphi_6 &= (\eta_{20} - \eta_{02})\left[(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2\right] \\
&\quad + 4\eta_{11}(\eta_{30} + \eta_{12})(\eta_{21} + \eta_{03}) \\
\varphi_7 &= (3\eta_{21} - \eta_{03})(\eta_{30} + \eta_{12})\left[(\eta_{30} + \eta_{12})^2 - 3(\eta_{21} + \eta_{03})^2\right] \\
&\quad + (3\eta_{12} - \eta_{30})(\eta_{21} + \eta_{03})\left[3(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2\right]
\end{aligned} \tag{5}$$

where, $\eta_{pq} = \frac{\mu_{pq}}{\mu^t{}_{00}}$ is standardized central moment. $t = (p+q)/2+1$, $p+q = 2,3,...$

Therefore, there are 13 parameters used to form the feature vector. It is defined as:

$$\mathbf{G}=[SI, D_R, E, \varphi_1, \varphi_2, \varphi_3, \varphi_4, \varphi_5, \varphi_6, \varphi_7, H, S, I]^T \quad (6)$$

Least square support vector machine (LS-SVM) classifier

To improve classification accuracy, an artificial intelligence method was selected as classifier. Support vector machine (SVM) is a new machine learning technique based on the statistical learning theory, which can avoid the problems of over learning, dimension disaster and local minimum in the classical study method (Vapnik,1995). SVM is characterized by a (convex) quadratic programming (QP) problem. LS-SVM, evolved from the SVM, translates the quadratic optimization problem into that of solving linear equation set (Suykens and Vandewalle, 1999). Compared with SVM, LS-SVM is a much simpler algorithm with higher operation speed, which is widely applied to pattern recognition and nonlinear regression. Consequently, LS-SVM was selected as classifier in the paper. A simple binary classification problem is given as follows:

Consider a given training set $\{(x_i, y_i), i = 1,2,...,l\}$ with input data $x_i \in R^n$ and corresponding binary class output labels $y_i \in \{-1,+1\}$, and the classifier takes the following form:

$$y = sign[\omega^T \varphi(x) + b] \quad (7)$$

where nonlinear function $\varphi(\cdot): R^n \to R^{n_h}$ is the mapping the input space to the high dimensional and potentially infinite dimensional feature space. ω is the weight vector and b is a bias term.

In the primal weight space of LS-SVM, the optimization problem can be expressed as following:

$$\min \ \frac{1}{2}\omega^T\omega + \frac{\gamma}{2}\sum_{i=1}^{l} e_i^2 \quad (8)$$

Subject to the equality constraints:

$$y_i[\omega^T \varphi(x_i) + b] = 1 - e_i \quad i = 1,2,...,l \quad (9)$$

where, e_i are slack variables and γ is a positive real constant.

A linear equations can be obtained by introducing the Lagrangian function and the corresponding condition of Karush-Kuhn-Tucker (KKT). The optimum parameters of the model can be found by solving the set of linear equations. Finally, the LS-SVM classifier is constructed as follows:

$$y(x) = sign[\sum_{i=1}^{l} \alpha_i y_i k(x, x_i) + b] \quad (10)$$

where, α_i are Lagrange multipliers. $k(x, x_i)$ is kernel function. There are many forms of kernel functions such as linear kernel, the polynomial kernel, radius basis functional (RBF) kernel. In the paper, we have used RBF kernel function as following:

$$k(x, x_i) = \exp(-\|x - x_i\|^2 / 2\sigma^2) \quad (11)$$

where, σ is a kernel function parameter.

RESULTS AND DISCUSSION

The image samples used in the experiment were consisted of 100 egg images, including 60 fertile egg images and 40 infertile egg images. The above mentioned feature vectors $\mathbf{G}$ were obtained using MATLAB7.0 (the Math Works, Natick, Massachusetts, USA) for each image with 256×256 size to build the feature data set, including fertile egg subset and infertile egg subset. The freely available LS-SVM toolbox (LS-SVM v.1.5, Suykens, Leuven, Belgium) was applied with Matlab to develop the LS-SVM classification models.

The hyperparameter γ and the kernel parameter σ^2 were obtained in condition that the total error was minimum: $\gamma = 2000$ and $\sigma^2 = 0.5$. Thus, the two parameters were used in all experiments. The correct identification accuracy was given by the correct identified numbers including the fertile eggs and the infertile eggs divided by the total sample numbers.

Performance of the binary LS-SVM classifier

In order to analyze the performance of the binary LS-SVM classifier, different kernel functions and different classifiers were applied to same samples set in the research.

Identification with different kernel function

Kernel function plays a decisive role in the performance of the LS-SVM classifier (Vapnik, 1999). Three LS-SVM classifiers respectively based on the linear kernel, the polynomial kernel, and the RBF kernel were proposed. The classification accuracies with linear, polynomial and RBF kernel functions were shown in Table 1. As shown in Table 1, the linear kernel performed worst, the linear kernels performed a bit better, and RBF kernel achieved the best accuracy of 99.1 and 92.5% in training set and testing set respectively. RBF kernel was used to map the original non-linear feature space to high dimension space, which fitted well with the idea of SVM. Therefore, RBF kernel was selected in the paper.

Table 1. Classification results based on LS-SVM classifier with different kernel function.

Kernel function	Training accuracy (%)	Testing accuracy (%)
Linear	95.8	83.3
Polynomial	97.5	88.3
RBF	99.1	92.5

Table 2. Comparison of the classification indices with different classifier.

Classifier	Training time (s)	Testing time (s)	Classification accuracy (%)
LS-SVM	2.0113	0.0435	92.5
SVM	2.2256	0.09982	92.5
BP	3.8557	0.101	87.5

Table 3. Identification accuracy of fertile eggs based on LS-SVM with RBF kernel.

Egg type	Right ratio		Mistake ratio	
Fertile egg	22/24	91.7%	2/24	8.3%
Infertile egg	15/16	93.8%	1/16	6.2%
Total	37/40	92.5%	3/40	7.5%

Comparing classification results using different classifiers

For comparison purposes, classification results using SVM and back-propagation (BP) with the same data set were obtained. The comparing results of the three classifiers were shown in Table 2. The results show the performance of BP classifier was worst, with the lowest correct classification rate of 87.5%, longest training time and testing time, LS-SVM classifier and SVM classifier achieved the best performances, with the same correct classification accuracy of 92.5%, while the computational speed of LS-SVM classifier was higher than that of SVM classifier. In this sense, the proposed LS-SVM classifier performed better than the standard SVM classifier and BP classifier. LS-SVM classifier ensured the accuracy, greatly reduced the computational complexity and sped up the solving speed. The results of identification fertile egg based on LS-SVM with RBF kernel were shown in Table 3. The results showed 15 of the 16 infertile eggs were judged correctly. Only one egg was erroneously judged. The mistake ratio of infertile eggs is lower than that of fertile eggs. It was encouraging, which could reduce taking up space and improve yields.

Conclusions

In this research, an attempt has been made to extract eggs shape parameters and color information of egg yolk and to classify the fertile eggs using LS-SVM with RBF kernel. The results in this study demonstrated the capability of LS-SVM classifier for identifying fertile eggs prior to incubation. LS-SVM classifier provided better accuracy, higher speed compared with SVM and BP classifier. Classification accuracy in this study was 92.5%, which was encouraging. Further research including many more egg samples and brown shell eggs will be carried through and more accurate classification models with other techniques for identification fertile eggs prior to incubation will be obtained.

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