Nondestructive detection of infertile hatching eggs based on spectral and imaging information

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Abstract: In order to quickly distinguish infertile eggs from fertile eggs, the hyperspectral imaging technology consisting of imaging and spectral information was used for detecting the fertile information of eggs. Before hatching eggs were incubated, a hyperspectral imaging system (wavelength between 400 to 1 000 nm) was used to acquire the images one-by-one manually. The characteristic information of ratios of length to short axis, elongation, roundness and the ratios of the yolk area to the whole area was extracted based on the images. The normalization method was used as the spectral data preprocessing, and then 155 spectral characteristic variables were extracted from 520 nm waveband through the correlation coefficient method. Principal component analysis (PCA) method was adopted to reduce the dimensions of image-spectrum fusion information; the top six principal components were extracted. Support vector machine (SVM) method was used to establish classification of fertile and infertile eggs models, which are based on image, spectrum and image-spectrum fusion information respectively. The accuracy rates of the SVM models were 84.00%, 90.00% and 93.00% respectively. The experimental results show that the model based on image-spectrum fusion information technology is superior to the single information model. Hyperspectral transmission imaging technology is effective and feasible to detect the fertile hatching eggs before incubation.

Keywords: hyperspectral image, hatching eggs, information fusion, nondestructive detection

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1 Introduction

It is one of difficult problems in egg hatching industry to identify the fertile information of hatching eggs and eliminate infertile eggs before incubation. The statistics of previous research indicates that the hatch success rate of hatching eggs is 86%-95%[1]. The existing domestic infertile eggs detecting mainly depends on traditional manual candle method[2]. However, this detection method requires high intensity of labor and is time consuming. In addition, the result of detection is subjective and its accuracy cannot be guaranteed[3]. Therefore, the detection of infertile eggs prior to incubation can improve the economic efficiency of incubation and the quality of eggs processing in late period, and it can bring considerable economic benefits[4].

Currently, the detection methods of hatching eggs are machine vision[5,6], optical detection[7], acoustic impulse[8,9] and hyperspectral imaging[10-12]. However, these studies focused more on the detection of hatching egg in early incubation period, but less on the detection in pre-incubation period[12,13]. Ma et al.[14] used the machine vision to analyze fertile eggs and infertile eggs in pre-incubation period, extract shape characteristics and

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build the detecting model with Genetic algorithm neural network to achieve the identification information on fertilization of hatching eggs, that provided for a new method of infertile eggs detection. Zhang et al.[12] conducted spectrum analysis via hyperspectral image technology and detected the embryonic development of hatching eggs in early incubation period. However, these previous hatching eggs identifications were based merely on the model of single image information or single spectral information. Hyperspectral image technology combines the advantages of image and spectrum with the waveband of super-multichannel (hundreds of waveband), high resolution (a few nanometers), narrow waveband ($\leq 10^{-2}\ \lambda$) and wide spectral range (200-2 500 nm). This technology can not only reflect the characteristics of external image information of the analyte, but also reveal their internal quality spectral information. It has become an important trend to detect internal and external quality of agricultural products through hyperspectral image technology. And this technology is also widely used in the detection of the safety of fruit and livestock[15,16]. This paper is aimed to propose the application of hyperspectral image technology combining image and spectrum information to the detection of hatching eggs before incubation and to test the feasibility of this technology.

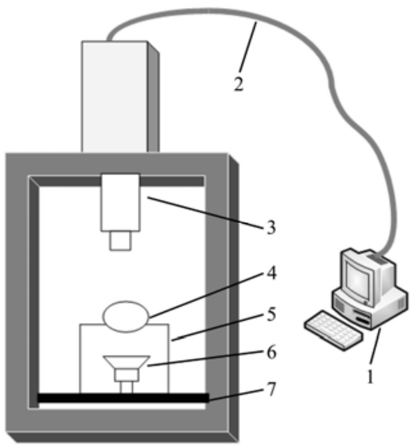
2 Materials and methods

2.1 Materials

The experimental samples of 300 eggs were white shell Jingfen No.1 hatching eggs from Yukou Poultry Industry Co. Ltd in Jingzhou city, Hubei province, and white Leghorn hatching eggs from Huazhong Agricultural University chicken farm. Among these 300 eggs, there were 144 fertile eggs and 156 infertile eggs. According to the sample distribution principle of 2:1, we selected randomly 96 fertile eggs from 144 fertile eggs and 104 infertile eggs from 156 infertile eggs constituting a 200 sample training set. The rest 48 fertile eggs and 52 infertile eggs composed a 100 sample testing set.

2.2 Hyperspectral transmission imaging acquisition system

Hyperspectral transmission imaging acquisition system was shown in Figure 1. The system mainly consists of hyperspectral imager (wavelength range is 400-1 000 nm) transmission acquisition unit, electrically moving platform, computers and light source. Hyperspectral imager is made up of by CCD camera (Andor, Clara, Britain), hyperspectral imager (SPECIM, V10E-CL, Finland) and imaging lens components. In order to avoid the influence of external light source, the entire device is placed in a sealed black box. In order to collect the distortionless hyperspectral image of hatching eggs, it is necessary to adjust the parameters of Hyperspectral instrument, which included light intensity, resolution, exposure time and sample collection speed. Ultimately, through a series of experimental analysis and comparison, the exposure time of the camera was determined as 0.1 s, the resolution of image as 400×400, hatching egg collection speed as 1.7 mm/s.



1. Computer 2. USB line 3. Hyperspectral imager 4. Egg 5. Sealed box 6. Light source 7. Motorized translation platform

Figure 1 Transmission hyperspectral image acquisition system

Due to the existence of invisible electrical current in the camera, and the influence of external factors, there existed some noise information in an image. It is necessary to calibrate hyperspectral image in black and white[17]. Before collecting the image and data of eggs, standard white calibration plate was placed just above the transmission light source, and white image was collected, then all white calibration image W was obtained. The lens was covered with lens cap, black image was collected, and then the all black calibration image D was obtained. The hyperspectral transmission original image I was obtained with scanned sample, then the calibrated image R was calculated according to Equation (1):

$$R = \frac{I - D}{W - D} \quad (1)$$

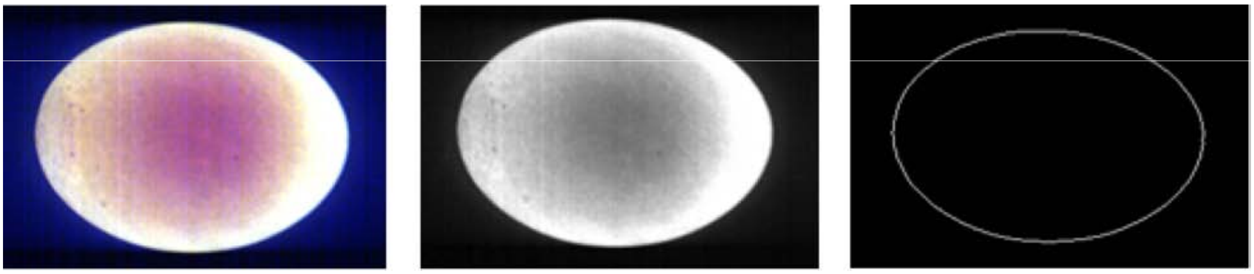
where, I is the hyperspectral transmission original image; W is the all white calibration image; D is the all black calibration image; R is the calibrated image.

The egg was placed horizontally, and its hyperspectral image was collected, and then eggs were put vertically with blunt end upwards into an incubator where temperature is 38.5°C and the relative humidity is 65%. These parameters were set according to the operating manual of incubator. After the eggs were hatched for five days, the fertile eggs and infertile eggs were distinguished from each other manually by Egg-candlers. Those eggs whose fertilization can not be distinguished were opened to check if there was blood streak in eggs.

2.3 Extraction of characteristic parameters

2.3.1 Parameter extraction based on image characteristic

According to the previous research, there was some difference between the shapes of fertile eggs and infertile eggs, typically, unfertilized eggs are short, thick and round, and fertilized eggs are thin and long[14]. Therefore, the methods of graying, median filtering, and Gaussian-Laplacian edge detection were used in this study for the pretreatment of the hyperspectral images as shown in Figure 2. Based the preliminary pretreatment, more methods of G component extraction, median filtering, Gaussian filtering, invert, “and” operation, binary, and corrosion were applied to get the images of yolk[18] as shown in Figure 3.



a. RGB image b. Gray image c. Edge image

Figure 2 Hatching egg image preprocessing

a. G component b. Binary image c. Yolk image

Figure 3 Hatching egg yolk extract

The four characteristics of hatching eggs, namely, the ratios of length to short axis, elongation, roundness and the ratios of the yolk area to the whole area were extracted as image characteristic in this study on the basis of previous researches[14,19].

1) The ratios of length to short axis F: long axis a of hatching eggs divided by short axis b of hatching eggs. The function is defined as:

$$F = a/b \quad (2)$$

2) Elongation E: the higher the value of E is, the more round the hatching egg’s shape is. The function is:

$$E = \min\{W, H\}/\max\{W, H\} \quad (3)$$

where, W and H signify the width and height of the hatching eggs image respectively.

3) Roundness R: the roundness describes the degree of roundness of hatching eggs. The higher R value is, the more close to round the shape of eggs is. The function is:

$$R = 4\pi S/L^2 \quad (4)$$

where, S and L signify the area and perimeter of the whole hatching egg.

4) The ratio of egg yolk area to the whole area of egg (Y), the function is:

$$Y = S_1/S \quad (5)$$

where, S_1 and S signify the egg yolk area and the whole area of egg respectively.

2.3.2 Extraction of characteristic based on spectral information

Spectral image of hatching eggs between 400-1 000 nm were collected by Hyperspectral imager, and ENVI software was used to extract 100×100 pixels average original spectral information on the ellipse area of eggs core. The Figure 4 showed the result.

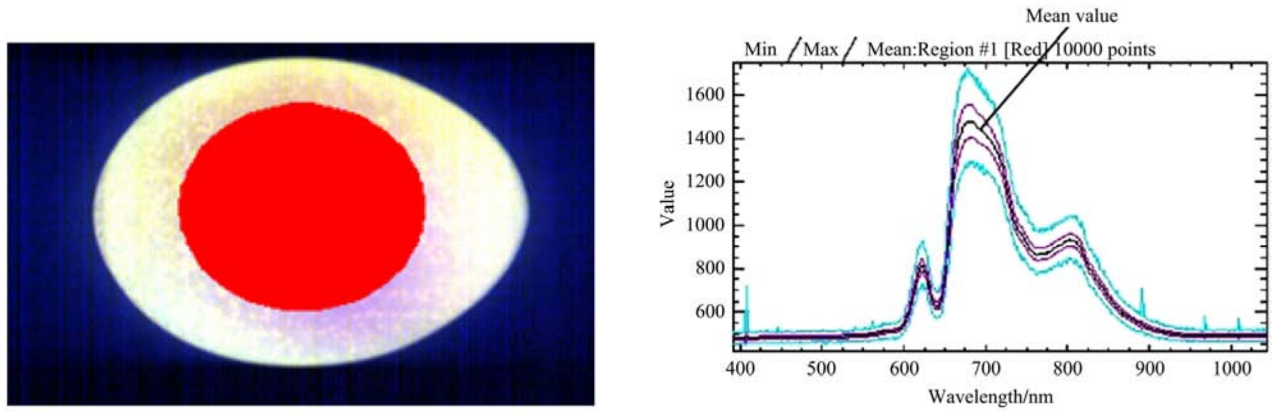


Figure 4 Range of interest

In order to remove the redundant noise information and decrease the dimension spectrum, make an analysis of three different wavelength range including visible light (400-760 nm), near infrared (760-1 000 nm) and full band 400-1 000 nm), all the wavelength range above was abstracted from the full band (400-1 000 nm). At the same time different spectral pretreatment methods were used: multiple scatter correction (MSC), variable normalization (Normalize), standard normal variable transformation (SNV), first derivative (FD), MSC+FD, SNV+FD and Normalize +FD, and then the effective pretreatment method were determined through analysis. In order to increase the accuracy of prediction and robustness of the model, irrelevant or nonlinear variables were eliminated in the correlation coefficient method. Accordingly, the effective spectral variables were determined. In the correlation coefficient method, correlation calculation was conducted between the vector of spectral transmittance rate corresponding to each wavelength in the correction set of spectral matrix and the target vector of components to be tested. This correlation calculation resulted in the wavelength-correlation coefficient r diagram. The larger the correlation coefficient is, the more effective information the corresponding wavelength contained. The formula of correlation coefficient r is as follows:

$$r = \frac{\sum_{i=1}^{N}(x_i - x_j)(y_i - y_j)}{\sqrt{\sum_{i=1}^{N}(x_i - x_j)^2 \sum_{i=1}^{N}(y_i - y_j)^2}} \tag{6}$$

where, $x_j = (\sum_{i=1}^{N} x_i)/N$, $y_j = (\sum_{i=1}^{N} y_i)/N$, x_j and y_j signify spectra vector mean value and components vector mean value, j=1, 2, $\cdots$, M. M is the length of wave, i= 1, 2, $\cdots$, N. N is the number of samples in calibration set.

Spectral variables were determined in correlation coefficient method so that the dimensions of the hyperspectral image were greatly compressed. Therefore, the storage and processing time of hyperspectral data was extremely decreased.

2.3.3 Fusion of image and spectrum characteristic

A model was established by combining image characteristic variables and spectral characteristic variables together. Considering that there may be some correlation between these characteristic variables. The method of principal component analysis was adopted to extract principle component vectors of high contribution rate as the characteristic vectors.

2.4 The establishment of the hatching eggs classification model

Support vector machine (SVM) is a new learning method based on statistical learning theory and structural risk minimum principle. It has obvious advantages in solving such problems as nonlinear, small samples and high-dimensional pattern recognition. So it is widely used in identification classification of texts, handwritings, images, etc[20]. Therefore, in this study SVM is adopted to establish models, and the performance of SVM model is under the influence of kernel function and its parameters. The common kernel functions include linear kernel (Linear), polynomial kernel function (Polynomial), radial basis function (RBF) and Layer neural network kernel function (Sigmoid). The most widely used is the RBF kernel function and its domain of convergence is wide, without dimension and sample size limitation. As a result, RBF kernel function was chosen. The two optimal parameters in kernel function, penalty factor and kernel parameter (C, γ), were determined by using cross-validation method (10-fold cross-validation).

3 Results and analysis

3.1 Classification results based on image characteristic

Four values including the ratios of length to short axis, elongation, roundness and the ratios of the yolk area to the whole area were considered as image characteristics. The SVM method was used to train the training set with the four image characteristics above-mentioned as input. RBF kernel function was chosen, the two optimal parameters in kernel function, penalty factor and kernel parameter (C, γ), were determined by using 10-fold cross-validation method, the value of C and γ is 32 and 1. The 100 testing set with the test results shown in Table 1, the accuracy of training set is 86.50% and the accuracy of testing set is 84.00%.

Table 1 Classification results based on image

Sample	Training set (200)		Testing set (100)	
	Infertile eggs (104)	Fertile eggs (96)	Infertile eggs (52)	Fertile eggs (48)
Wrong number	22	5	12	4
Accuracy/%	78.85	94.79	76.92	91.67
Total accuracy/%	86.50		84.00	

3.2 Classification results based on spectral characteristic

3.2.1 The influence of different waveband regions on the calibration results of model

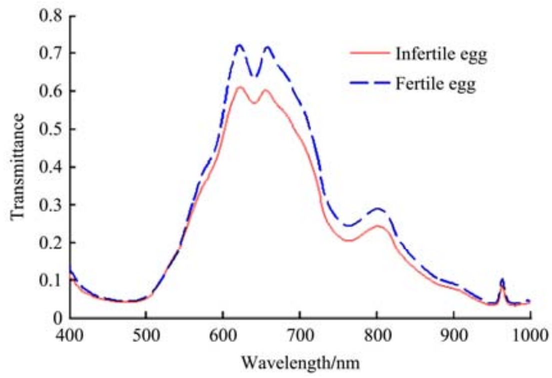
Three different spectral range, that include 400-760, 760-1 000 and 400-1 000 nm, were respectively used to establish SVM model. RBF kernel function was chosen, penalty factor and kernel parameter (C, γ) of the three regions were (13, 1), (11, 1), (16, 1) respectively. The table 2 shows that the accuracy rate of visible light of training set and testing set are higher than that of the near infrared band and full band. Therefore, the band range of 400-760 nm visible light were chosen to classify actual type of hatching eggs.

Table 2 Calibration results of different waveband regions

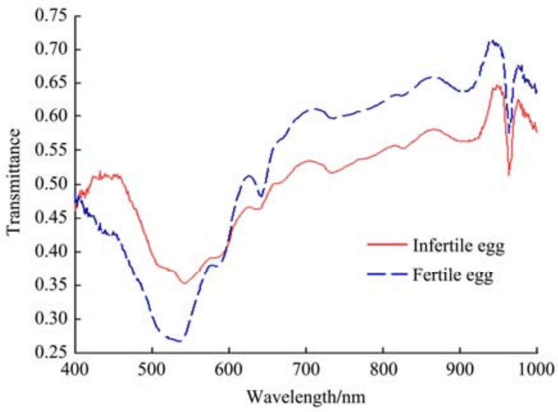
Band regions/nm		400-760	760-1000	400-1000
Accuracy/%	Training set (200)	89.00	85.50	81.00
	Testing set (100)	85.00	78.00	81.00

3.2.2 The influence of different pretreatment methods of calibration model results

When we collected the images of hatching eggs via hyperspectral transmission, instrument and environment factors brought some noise information into the images. Consequently, the accuracy of hatching eggs discriminant model was influenced adversely. Therefore, it is necessary to pretreat the spectra of samples before modeling and predicting unknown samples so as to improve the robustness of the model and the accuracy of the prediction. The main methods of the spectra pretreatment include multiple scatter correction (MSC), variable normalization (Normalize), standard normal variable transformation (SNV), first derivative (FD), MSC+FD, SNV+FD and Normalize +FD. After the spectra went through the six different kinds of pretreatment, data obtained from pretreatment were analyzed based on SVM model with RBF kernel function, penalty factor and kernel parameter (C, γ) (The value C and γ is 512 and 1 respectively). The results of analysis (Table 3) indicated that the best pretreatment method is Normalization. The original spectral curve of fertile eggs and infertile eggs and the spectral curve after Normalized pretreatment are shown in Figure 5 respectively. Normalization can eliminate redundant information and increase the difference between the samples so as to improve the robustness of the model and the accuracy of the prediction[21]. After the Normalized pretreatment, the accuracy of training set reached 93.50% and the accuracy of testing set reached 90.00%. In consequence, the Normalized method was used to spectral preprocessing.



a. Original spectrum of fertile and infertile eggs



b. Normalized pretreatment spectrum of fertile and infertile eggs

Figure 5 Spectrum of fertile eggs and infertile eggs

Table 3 Calibration results from different spectral pretreatment methods

Preprocessing approach		MSC	SNV	Normalize	MSC+FD	SNV+FD	Normalize+FD
Accuracy /%	Training set (200)	89.50	95.00	93.50	80.00	81.00	80.50
	Testing set (100)	86.00	82.00	90.00	79.00	81.00	80.00

3.2.3 Spectral variables selection

Based on correlation calculation, waveband between 400 nm and 760 nm was determined, and effective spectral variables were extracted in the Normalized pretreatment method and correlation coefficient method with the results shown in Figure 6, in which, two horizontal lines respectively represented the upper and lower threshold. The absolute threshold was set as 0.4. The wavelengths between the two parallel lines represented irrelevant waveband and the wavelengths beyond the two horizontal lines represented the optimal ones. r in the range of 0.4-0.6 is regarded as medium correlation. The wavelength corresponding to r>0.4 was used to establish qualitative calibration model and irrelevant spectral variables was eliminated. Accordingly, 155 effective wavebands were extracted from 520 wavebands and used as spectral characteristic variables. The model based on SVM was established. The accuracy of training set reached 97.50% and the accuracy of testing set was still 90.00%, which indicated that the 155 spectral characteristic variables could represent the original information.

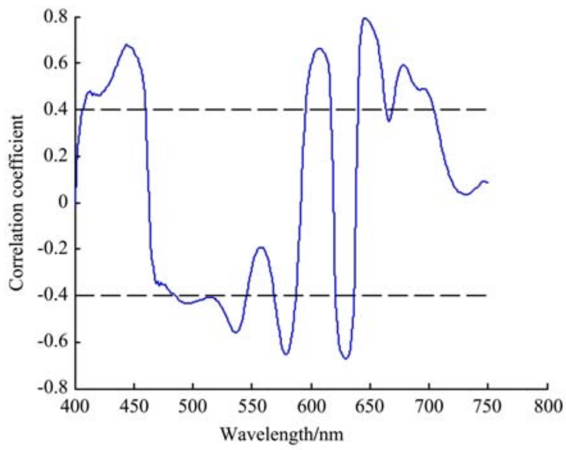


Figure 6 Wavelength-correlation coefficient r diagram

3.3 Establishment of model based on image-spectrum fusion information

In the model established on image information and spectral information, the accuracy of testing set was 84.00% and 90.00% respectively. Both of them need to be improved. So we establish a model by combining four image characteristic variables and 155 spectral characteristic variables together. Considering that there may be a certain correlation between the 159 characteristic variables, we adopted the method of principal component analysis to extract principle component vectors of high contribution rate that representative of characteristic vector. Consequently, the dimensions of image-spectrum fusion information were reduced. As shown in Figure 7, the cumulative contribution rate of top 6 principal components reached 98.85%, which means that extracting top six principle components can almost represent all the information. Finally, hatching eggs classification model has been built by using SVM method with RBF kernel function. The two optimal parameters in kernel function, penalty factor and kernel parameter (C, γ), were determined by using cross-validation method (The value of C and γ is 8 and 8). With the results shown in Table 4, the training set accuracy reached 96.50%, testing set accuracy reached 93.00%, 9% higher than that of single imaging information model, 3% higher than that of single spectral information model. The classification model based on image-spectrum fusion technology is superior to the single imaging information model and the single spectral information model.

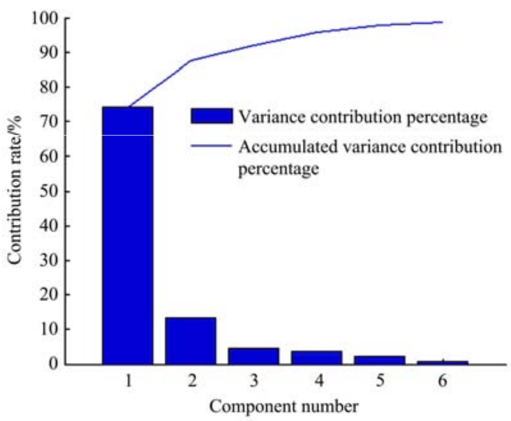


Figure 7 The variance contribution percentage and cumulative distribution line column chart

Table 4 Classification results of image and spectrum

Sample	Training set (200)		Testing set (100)	
	Infertile eggs (104)	fertile eggs (96)	Infertile eggs (52)	fertile eggs (48)
Wrong number	1	6	3	4
Accuracy/%	99.04	93.75	94.23	91.67
Total accuracy/%	96.50		93.00	

4 Conclusions

The hyperspectral imaging technology combining the image and spectrum information has solved the problem of "imaging without spectrum, spectral without imaging". The characteristic information of images was extracted by studying the difference between the fertile and infertile eggs prior to the incubation in both images and spectra. Spectral characteristic variables were extracted in the different pretreatment methods and correlation coefficient method, top six principal components were extracted in PCA method to reduce the dimensions of representative image-spectrum fusion information. The SVM was used to establish classification model of hatching eggs, which is based on images, spectra and image-spectrum fusion information respectively. The research findings illustrate that the classification model based on image-spectrum fusion technology is superior to the single information model and the training set accuracy of the former reached 96.50%, testing set accuracy reached 93.00%. Therefore, it can be concluded that the application of hyperspectral imaging technology based on fused image and spectrum information to the classification of hatching eggs is effective and feasible.

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