Micro-Cracks Detection of Eggshells Based on a Magnetostrictive Transducer

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Abstract: With respect to the problem that it is difficult to pick out eggs with small cracks, a novel vibrating type of eggshell cracks detection system using a magnetostrictive transducer was developed firstly. Then the acoustic signals was recorded while the transducer vibrating with the swept frequency from 1 to 14000 Hz. Thirdly, the wavelet and Burg power spectrum were used for data pretreatment and feature extraction respectively. By comparing the spectrums of intact eggs and hairline cracked eggs, the characteristic frequency of 4500~8000 Hz was found. Moreover, five feature parameters were defined for further analysis. In addition, the Support Vector Machine (SVM) based classifier was applied to build the model for identifying the cracked eggs from intact eggs. The experimental results show that the useful information of the acoustic signals was enhanced significantly and the identification accuracy reaches to 100 % and 98 % for training set and testing set respectively. This paper proposes a novel method for discriminating eggshell cracks using a magnetostrictive transducer in conjunction with the signal power spectrum analysis and LIBSVM methods which results show its feasibility.

Keywords: Magnetostrictive transducer, Power spectrum, SVM, Nondestructive testing, Eggshell crack.

1. Introduction

Egg is one of the most important poultry products because of its rich nutrition [1]. Eggshell crack detection in the egg sorting and packing industry is very important. So several nondestructive testing methods have been proposed such as digital image recognition method [2], acoustic recognition method [3] and dynamic frequency method for replacing the traditional manual method. The technique of computer vision was employed to detect the appearance feature of eggshells and the automatic detection system for eggshell based on machine vision was developed by Jenshin, et al. The identification rates of intact and cracked eggs were not less than 80 % [4]. But for the weakness that it is difficult to differentiate fresh cracks and hairline cracks, many researchers try to improve it by analyzing the dynamical frequency response of eggshells. Wang Jun exited eggs by a pendulum on different directions and collected the signals by flexible piezoelectric film sensors near the knocking side and then analyzed the signal difference between intact and cracked eggs [5]. Jiewen Zhao, et al. detected eggshell cracks based on acoustic response and support vector data description algorithm. Jianrong Cai, et al. developed the on-line system based on acoustic resonance comprises of a roller conveying system, a exciting set, a mini microphone, a signal conditioning circuit, digital signal processing (DSP) and a computer. The identification algorithm was implemented in the DSP chip, but it needs
several times of impact in the certain region of an egg during detection [6]. What’s more, it’s difficult to detect the microcracks such as hairline cracks of the eggs accurately by the existing methods.

In the paper, we firstly introduced the developed eggs cracks detection system using a magnetostrictive transducer. Then several signal processing methods was applied to enhance the useful information and improve the identification precision. In addition, the paper tried to identify the eggshell crack in different regions. The rest of this paper is organized as the following structures: The experimental conditions, experimental facility and the vibration signal acquisition method is shown firstly. Then vibration signals were filtered by wavelet filters to remove the noise and the data was normalized in Section 3. How to extract the useful information from vibration signals is illustrated in Section 4. The identifying method and result are given in Section 5 which show the validity of it. The last section draws the conclusion.

2. Acoustic Vibration Signal Detecting Systems

2.1. Samples Preparation

The experimental eggs were bought from a poultry farm and stored at a refrigerator in the temperature of about 4 °C (Centigrade) for 3 days. The eggs mass ranged from 53 to 68 gram and the diameters at the equator were from 35 to 41 mm. Several irregular eggs were removed from the samples based on the surface color and strength. A total number of 210 intact eggs were used in the experiments. Then each egg was handled manually to be micro cracked such as hairline cracked for further testing. Finally, 210 intact eggs and 210 cracked eggs were used in the experiment. 270 eggs including 150 intact eggs and 120 cracked eggs (40 eggs cracked at the top, 40 eggs cracked at the middle and 40 eggs cracked at the bottom) were employed as training set and 150 ones including 60 intact eggs and 90 cracked eggs (30 eggs cracked at the top, 30 eggs cracked near the equator and 30 eggs cracked at the bottom) as prediction set.

2.2. Experimental System and Procedure

As shown in Fig. 1, we firstly developed a vibrating type of eggshell cracks detection system using a magnetostrictive transducer. The subsequent detection of eggshell cracks was carried out in the vibrating system that mentioned above. Firstly, the swept vibration signal from 1 to 14 kHz was created in the computer by software. Then it was amplified by circuit board to drive the magnetostrictive transducer. The collision between the egg and the magnetostrictive transducer generated sounds. In the meanwhile, the computer recorded the acoustic signals at 44 kHz sampling rate through a microphone. The sampled acoustic signals contain rich information about the egg’s quality. By analyzing the acoustic signals we can identify the egg is intact or not.

![Diagram](image)

(a) The schematic diagram
(b) The experimental system

Fig. 1. The schematic diagram and picture of the experimental system.

3. Acoustic Signals Pretreatment

The original acoustic vibration signals are shown in Fig. 2(a). The frequency range of the acoustic vibration signals is from 1 Hz to 14 kHz, so the signals with the frequency higher than 14 kHz should be removed. The multi-resolution wavelet was used to filter the noises from the acoustic vibration signals. The multi-resolution wavelet analysis is a method to get the signal features at different levels; its nature is to decompose the signals in a serious of different level spaces. The fine information and coarse information of the signals are in the small scale space and big scale space respectively. The signals can be analyzed from low resolution to high resolution along with the change of the scale [7]. The signal $x_n(n)$ can be decomposed by

$$x_k^{(j)} = \sum_n h(n-2k)x_n^{(j-1)} , j \geq 1, j \in \mathbb{Z} ,$$  

$$d_k^{(j)} = \sum_n g(n-2k)x_n^{(j-1)} , j \geq 1, j \in \mathbb{Z} ,$$
where $x_j^{(j)}$ and $d_j^{(j)}$ are the discrete coarse coefficient and fine coefficient respectively under the level $j$ decomposition; $h(n)$ and $g(n)$ are the coefficients of the low-pass filter and high-pass filter respectively. And the signal reconstruction algorithm is

$$x_k^{(j-1)} = \sum_n h(n-2k)x_k^{(j)} + \sum_n g(n-2k)d_k^{(j)},$$

(3)

where $x_k^{(0)}$ is equal to the original signal $x(k)$. The acoustic vibration signals can be handled by the algorithms above. The original acoustic vibration signal in time domain and frequency domain are shown in Fig. 2(a) and Fig. 2(c) respectively. We employed the wavelet function Daubechies 10 to decompose the signals to 5 layers. The acoustic signals were reconstructed after the high frequency coefficients of the wavelet being set to zero. The frequency spectrum of the original acoustic signal compared with that of the processed acoustic signal are shown in Fig. 2(b) and Fig. 2(d) respectively. It’s clear that the processed acoustic signal is smooth enough for further analysis.

![Acoustic signals and the spectrum before and after filtering.](image)

**Fig. 2.** Acoustic signals and the spectrum before and after filtering.

4. Feature Extraction of the Eggshell’s Acoustic Signals

The vibration signals that collected using our experimental system are stationary stochastic signals. It’s difficult to extract the signal features effectively between intact and cracked eggs using traditional methods such as FFT analysis technique, AR model, ARMA model, et al., directly. In order to meet the measuring precision, the paper tried to adopt power spectral estimation method because it is a powerful tool for stationary stochastic signals analysis with the advantages of high resolution and less calculation. The Burg AR is chosen by comparing power spectral estimation methods such as Periodogram, Welch’s, Burge, Yule-Walker, MUSIC power spectrum, et al.

4.1. Burg AR Method

Burg is a regressive spectrum estimation method with the recursive constrain of Levinson-Durbin, which makes the sum energy of forward prediction error and backward prediction error minimum. It can avoid of the calculation of the self-correlation functions and the results estimated so it is very near to the true values by making use of less data. The calculation steps of the algorithm are as follows [8]:

a) Calculate the reflection coefficient $k_j$ by

$$k_j = \frac{-2\sum_{n=m}^{N-1} e_{m}^f(n)e_{m}^b(n-1)}{\sum_{n=m}^{N-1} e_{m}^f(n)^2 + \sum_{n=m}^{N-1} e_{m}^b(n-1)^2},$$

(4)

With the initial conditions $e_0^f = \Delta(n)$.

b) The sum of the forward prediction error and backward prediction error $p_j^n = (1-k_j^1)r_c(0)$ and the parameters of AR model $a_j(1) = k_j$ can be calculated while the model order is $m = 1$ according to the self-correlation function.
\[ r_s(0) = \frac{1}{N} \sum_{n=0}^{N-1} x(n)^2 \]  

(5)

c) According to the Formula (6-7)

\[ e^f_n(n) = e^f_{n-1}(n) + k_n e^f_n(n-1), \]

(6)

\[ e^b_n(n) = e^b_{n-1}(n-1) + k_n e^b_n(n) \]

(7)

The forward prediction error and the backward prediction error are calculated by the formula.

d) When the model order \( m = 2 \) we can calculate the AR model parameter \( a_2(1) \), \( a_2(2) \) and \( \rho_m^b \) according to the recurrence formula of Levinson

\[ a_n(k) = a_{n+1}(k) + k_n a_{n-1}(n-k), \]

(8)

\[ a_n(m) = k_n, \]

(9)

\[ \rho_m^b = (1-k_n^2) \rho_{m-1}^b \]

(10)

All the \( p \) order model parameters are calculated by repeating the process above until the model order \( m = p \).

4.2. Feature Extraction by Applying Burg AR Method

Following the scheme provided above, the Burg method was used in the process of calculating the power spectrums of the acoustic signals. The four order AR model was adopted in the Burg method after many attempts. And the comparative Burg power spectrums of the intact and cracked eggs’ vibration signals are shown in Fig. 3 with the sampling rate is 44 kHz and the samples of FFT is 14000. The power spectrums of the intact and cracked eggs’ acoustic signals which range from 1 to 14000 Hz with the interval of 20 Hz were calculated. The results show remarkable difference between the Burg power spectrums of intact eggs and that of cracked ones. Fig. 3 shows that the former are greater than the latter. So the Burg power spectrum within this frequency band was adopted as the feature vectors because of its sensitivity to distinguish the intact eggs from cracked eggs. An eggshell was segmented by three regions which abbreviations (similarly hereinafter) mean that Cracked at the Top of the Egg (CTE), Cracked near the Equator of the Egg (CEE), Cracked at the Bottom of the Egg (CBE) (Seeing in Fig. 4).

4.3. The Chosen of Feature Parameters

By comparing the spectrums of intact eggs and hairline cracked eggs, it’s clear that there is significantly difference in the frequency band 4500–8000 Hz. So the feature parameters used for further analysis are defined as shown in Table 1, where \( S_i \) means a signal spectrum value.

![Comparative Burg power spectrums of intact and cracked eggs.](image)

Fig. 4. Segmented regions of an eggshell

<table>
<thead>
<tr>
<th>Feat</th>
<th>Description of the features</th>
<th>Calculating formulas</th>
</tr>
</thead>
<tbody>
<tr>
<td>X1</td>
<td>Maximum amplitude of the acoustic signal spectrum ( S_i )</td>
<td>( X_1 = \max(S_i) )</td>
</tr>
<tr>
<td>X2</td>
<td>The frequency of maximum spectrum amplitude ( f_{max} )</td>
<td>( X_2 = f_{max}(S_i) )</td>
</tr>
<tr>
<td>X3</td>
<td>Frequency band from one-tenth spectrum amplitude to the maximum amplitude near ( f_{max} )</td>
<td>( X_3 = f_{max}(S_i) - f_{1/10}(S_i) )</td>
</tr>
<tr>
<td>X4</td>
<td>Mean spectrum amplitude from 5000 to 8000 Hz</td>
<td>( X_4 = \frac{\sum_{5000}^{8000}(S_i)}{3000} )</td>
</tr>
<tr>
<td>X5</td>
<td>Ratio of the maximum spectrum amplitude to the second one</td>
<td>( X_5 = \frac{S_{max}}{S_{2nd}} )</td>
</tr>
</tbody>
</table>
5. Eggshell Cracks Detection by SVM

Five dimensional feature vectors are generated in the frequency uniformly between 5000 to 8000 Hz using Burg power spectrum as mentioned above. Next, we need to select an effective classification method for distinguishing the intact eggs from cracked eggs. The Support Vector Machine was chosen because of its widely used in classification and identification problems in a broad range of domains [9].

5.1. Clustering Support Vector Machine

The Support Vector Machine (SVM) is a machine learning method proposed by Vapnic in the middle nineties of nineteen century, which has been proved to be very effective in the field of Machine Learning. SVM is based on the principal of the structural risk minimization. The SVM assumes that all samples in the training set are identically distributed and independent. It uses an approximate implementation to the structure risk minimization principal in statistical learning theory. A kernel is utilized to map the input data to a higher dimensional feature space so that the problem becomes linearly separated, which plays a very important role [10]. The Lib-SVM is a kind of SVM proposed by Lin Chih-Jen, which is adopted to solve nonlinear classification problems widely. All data-processing algorithms were implemented with the software Matlab7.14 (Mathworks, USA) under Windows7. Lib-SVM Matlab codes were downloaded from http://www.csie.ntu.edu.tw/~cjlin/ free of charge [11].

5.2. Intact and Cracked Eggs Identifying Results by SVM

The feature vectors generated by the Burg power spectrum such as X1, X2, X3, X4 and X5 that mentioned above were taken as the inputs of the two-class classification SVM model after normalization. The label is 1 if the eggs are intact eggs, otherwise it is -1. The training samples of the SVM and the predicting accuracy are shown in Table 2.

Table 2. Predicting accuracy of SVM for known eggs.

<table>
<thead>
<tr>
<th>Category</th>
<th>Number of eggs</th>
<th>Predicting accuracy (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intact eggs</td>
<td>150</td>
<td>100</td>
</tr>
<tr>
<td>Cracked eggs</td>
<td></td>
<td></td>
</tr>
<tr>
<td>CTE</td>
<td>40</td>
<td></td>
</tr>
<tr>
<td>CEE</td>
<td>40</td>
<td></td>
</tr>
<tr>
<td>CBE</td>
<td>40</td>
<td></td>
</tr>
</tbody>
</table>

The radial base functions (RBF) was used in the experiments. The parameters of the SVM such as \( c \) and \( g \) have to be optimized to obtain a good performance. In this study, the procedure of optimization was carried out by changing the value of \( c \) and \( g \) from \( 2^{-10} \) to \( 2^{10} \) respectively. Then the model was built after 30 times cross-validation. The optimal model was achieved when \( c \) was nearly equal to 0.33 and \( g \) equal to 111.43. Identification results of LIBSVM model influenced by values of \( c \) and \( g \) are shown in Fig. 5. Here the identification rates of intact and cracked eggs were both 100 % for the training set. In addition, the testing set was tested by the model that trained above and the results are shown in Table 3 which indicates the high accuracy.

Table 3. Predicting accuracy of SVM for unknown eggs.

<table>
<thead>
<tr>
<th>Category</th>
<th>Number of eggs</th>
<th>Predicting accuracy (%)</th>
<th>Predicting accuracy (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intact eggs</td>
<td>60</td>
<td>98.3</td>
<td>98.3</td>
</tr>
<tr>
<td>Cracked eggs</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CTE</td>
<td>30</td>
<td>93.3</td>
<td></td>
</tr>
<tr>
<td>CEE</td>
<td>30</td>
<td>100</td>
<td></td>
</tr>
<tr>
<td>CBE</td>
<td>30</td>
<td>100</td>
<td></td>
</tr>
</tbody>
</table>

6. Results and Conclusions

Detection of cracks in eggshells based on acoustic vibration signals by magnetostrictive technology for enhancing the useful information was attempted in this work and the experimental facility has been developed. The wavelet was used for data pretreatment and the Burg power spectrum was used for extracting the features. Then the LIBSVM-based classifier was used to build the model for identifying the intact eggs from cracked eggs. The results show that the identification accuracy reaches to 100 % and 98 % for training set and testing set respectively. So the method by combing Burg power spectrum and SVM is a good way to identify whether an egg is intact or not. Some relative ideas would be attempted for further improvement such as on-line estimation of eggshell parameters based on magnetostrictive technology.
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References


