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Full Length Research Paper

Eggshell crack detection by acoustic impulse response and support vector machine

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This paper investigates the effect of support vector machine (SVM) for the classification of intact and cracked eggs. The four frequency features of the sound impulse resonance of an egg excited with a light mechanical impact on the equator of the eggshell are extracted, including the normali-zation average of the frequency domain, the first dominant frequency, and the average x - and y – coordinates of the centroid for the frequency domain. These features and also the various combina-tions of them are used to construct SVM classifiers. It is shown that the SVM-PFXY classifier based on all the four frequency features gives the best classification effect with 98% testing accuracy, 98.18% crack detection and 2.11% false reject, and that the SVM -P, SVM-PF and SVM -PFY are res-pectively the best single-feature, binary -feature and three-feature SVM classifiers. It is also revealed that the SVM classifier associated with more features generally gives a better classification effect. For evaluating the effects of SVM classifiers for actual crack detection, this paper proposes a detec-tion scheme of eggshell cracks based on four measurements, and the experimental example achieves the highest crack detection of 98.77% and the smallest false reject of 1.87%.

Key words: Eggshell crack, detection, acoustic impulse response, frequency feature, support vector machine.

INTRODUCTION

The detection of eggshell cracks, usually done manually in the poultry industry, has become a bottleneck for the automation of egg sorting and packaging due to the increasing throughput of modern egg grading machines and considerable effort has therefore gone into the deve-lopment of methods of replacing the manual inspection with a highly effective and automatic detection, which has important significance both in economy and food safety to those involved in the production and marketing of eggs, including producers and consumers(DE Ketelaere et al., 2004; Hunton ,1995).

Recent researches on the detection of eggshell cracks are mainly focused on the vibration-based response ana-lysis. It has been shown that vibration- based methods have better accuracies of detection than machine vision methods, especially for those hairline and invisible cracks (Cho et al., 1996, 2000). In the vibration-based detec-tions, a variety of comparisons are broadly used to find crack-sensitive indicators. For instance, De Ketelaere et al. (2000) found that for intact eggs, the impulse response was very similar on every point on the equator, whereas eggs with a damaged shell show a different response on different locations of the equator, and authors therefore, proposed a crack detection algorithm (90% crack detection and 1% false rejects) based on the correlations between repeated measurements taken on the same egg (4 measurements) . Wang and Jiang (2005) found that for the cracked eggs, the magnitudes of the same peak fre-quencies were similar and its first dominant resonance frequency value is lower than that of intact eggs and the authors reported 96% detection accuracy. Jindal and Sritham (2003) used artificial neural network techniques to classify eggs based on the vibration after impact and 8 measurements for each egg and the authors gave a crack detection level of almost 99%, but allowed for more than 10% false rejects (Coucke, 1999; Wang, 2003; Kemps, 2003 and Sinha, 1992).

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In the literature, the existing researches are mostly focused on finding the most effective crack indicator by the frequency analysis of vibration signal. It is worth emphasizing that the crack indicators used in the literature are all single-feature indicators, and a valuable issue is whether some better classification indicators could be constructed by the optimal combination of crack-sensitive features. The objective of the presented paper is to explore more effective multi-feature crack indicators by the use of the support vector machine (SVM) (Vapnik, 1995).

Support vector machines were originally designed for binary classification with the aim of finding a decision surface that has a maximum distance (margin) from the closest training points. Many researches from the different application areas have shown that the SVM is one of the most powerful classification methods (Trebar and Steele, 2008; Karimi et al., 2006; Ma and Huang, 2000). It is known that the egg crack detection is a typical binary classification problem: intact or cracked, this leads this study to construct new detection models by use of the excellent classification power of SVM technique. In this paper, the SVM classifiers based on the different feature selections (from single feature to four features) are set up and their effects for crack detection are dis-cussed and compared. These SVM classifiers are expec-ted to show a robust and efficient correlation to the detec-tion of eggshell cracks.

MATERIALS AND METHODS

Egg samples

Large fresh eggs were collected when one-day old from a commercial farm in Wuhan. The mass of eggs ranged from 58.6 to 71.1 g with an average of about 66.4 g. All cracked eggs were separated from intact eggs, in which some cracks were artificially inflicted on eggshells for the experiment. A micrometer and calipers were used to measure the cracks, and some cracked eggs were detected with hairline cracks and offshoots ranging from 14 to 80 mm.

Experimental system

The experimental equipment consisted of an egg-bed with condenser microphones installed, a roller for rotating the eggs, a mechanical impulse device, a signal amplifier, a personal computer (PC) and software to control the experimental setup and to analyze the results. The experimental equipment also consisted of a mechanical impulse device that was composed of a pendulum at an angle of 0 - 90° and an 8 g wooden ball on an extremely thin nylon string. As a result of the preliminary tests, in the mechanical impulse device, an angle of 45° was selected for all further tests. A sche-matic diagram of the system is presented in Figure 1.

In the above experimental system, the sound emitting from the egg surface after excitation was picked and converted to electrical voltage signal by the microphone and then the signal was amplified and passed through A/D converter into the computer for further processing.

EXPERIMENTAL PROCEDURE

The sample signals were recorded by exciting each egg one time on the equator. For each cracked egg, the tested egg was artificially placed in an egg-bed such that the crack was located in the right half surface of the eggshell (Figure 1) and the various positions of the crack relative to the impact point were considered. All the obtained signals were divided into two groups; the first group consisting of 100 cracked eggs and 100 intact eggs and the second group consisting of 55 cracked eggs and 95 intact eggs. The two groups of signals were used to extract frequency features as the training data and testing data of SVM classification, respectively.

In this paper, the Matlab7.6 computer program was used to transform the response from the time domain to the frequency domain by FFT with the sampling frequency 22050 Hz and 1024 - points, as demonstrated in Figures 3 and 4. The SVM was performed using LIBSVM software package libsvm-mat-2.86 -1 (Chen and Lin, 2001).

SVM technique

The support vector machine is a kind of learning machine based on statistical learning theory. Its main principles of classification are as follows: First, map the input vectors to a feature space (possibly of a higher dimension) either linearly or non-linearly, which is relevant to the selection of the kernel function. Then within the feature space, seek an optimized linear division, that is, construct a hyper-plane that can separate two classes with the least error and maximum margin. In Figure 2 the given data sets consists of two classes of samples (circles and squares); SVM attempts to find an optimal separating hyper-plane with maximum margin from the hyper-plane to the closest point. The best decision surface is determined by only a small set of points called the support vectors.

Given the labeled training data of the form $\{(x_i, y_i)\}_{i=1}^{n}$, each training sample $x_i \in R^N$ belongs to either of two the classes; n is the number of training samples and $y_i \in \{-1,1\}$ is the class label. Then the separating surface generated by SVM is given by

$$f(x) = sign \sum_{i=1}^{n} \alpha_i y_i K(x_i, x) + b, \qquad (1)$$

where K is the kernel function that defines the feature space, b is the bias value, α_i is the number obtained by solving the following quadratic programming (QP) problem:

$$\min \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{n} \xi_i,$$

subject to $y_i(w \cdot x_i + b) \geq 1 - \xi_i, \xi_i \geq 0 i = 1,2,..., n,$

where C is a regularization parameter that controls the trade-off between maximizing the margin and minimizing the training error. The solution of this problem can be obtained by solving its dual formulation:

$$\max W(\alpha) = \sum_{i=1}^{n} \alpha_i - \frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n} \alpha_i \alpha_j y_i y_j K(x_i, x_j),$$

subject to $\sum_{i=1}^{n} \alpha_i y_i = 0, 0 \leq \alpha_i \leq C, i = 1,2,..., n.$

The performances of SVM classifiers depend on the combination of several parameters; capacity parameter C, kernel type K and its corresponding parameters. The kernel function can be linear,

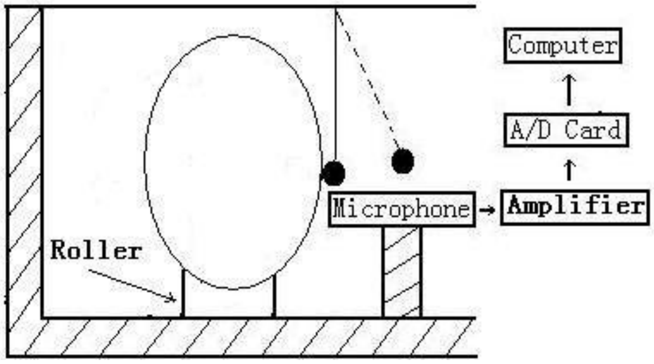

Figure 1. Schematic diagram of detection system.

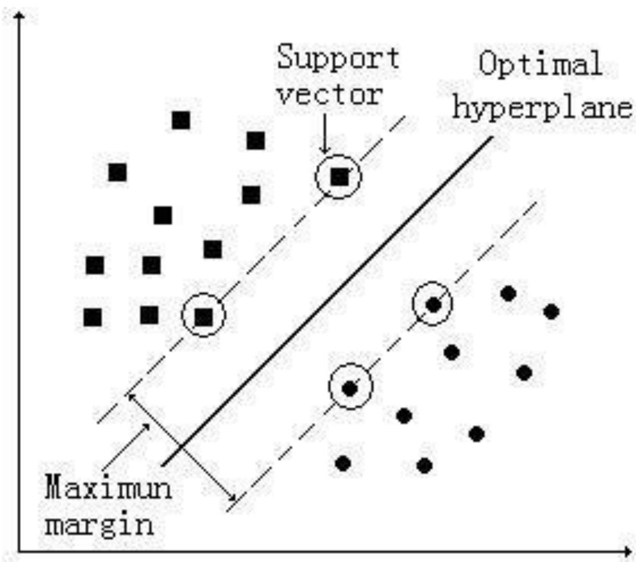

Figure 2. Maximum-margin hyper-plane for a SVM trained with samples from two classes.

polynomial or Gaussian. In this study, the radial basis function (RBF) kernel is chosen because of its good general performance and the few parameters (that is only two: C and γ). The RBF kernel is defined as:

$$K(x, y) = \exp\left(-\gamma \| x - y \|^2\right) \qquad (2)$$

Where γ is the parameter of the kernel function and x and y are the two independent variables.

Evaluation criteria for egg classification

It is expected that some intact eggs will be classified as cracked and some cracked eggs as intact. Therefore, the respective percentages of cracked egg detection and false reject were used for performance evaluation similar to the study of (De Ketelaere et al., 2004). Let N_1 and N_2 be the total number of cracked and intact eggs respectively, M_1 the number of cracked eggs correctly classified, M_2 the number of intact eggs falsely classified, then the percent crack detection (denote by PCD) and the percent false reject (denoted by PFJ) are defined as follows:

$$PCD = \frac{M_1}{N_1},\ PFJ = \frac{M_2}{N_2} \qquad (3)$$

Generally, the percent crack detection will rise when allowing for more false rejects. A good practice is to set the false reject to a level that is acceptable for practical purposes, and to report the percent crack detection achieved at that specific false reject level.

RESULTS AND DISCUSSION

Frequency feature selection

Typical time - and frequency - domain signals from cracked and intact eggs are shown in Figures 3 and 4, respecttively. This study will restrict its analysis to the frequency range (86, 5512 Hz), which reveals the main frequency differrence of cracked and intact eggs. Moreover, this allows the elimination of the nature frequencies of the experimental system, which happens to be very low in comparison to that of eggs.

To implement SVM technique, some frequency features of most relevance to the classification task should be firstly extracted and used as the input vector for a SVM classifier. The frequency analysis technique of the acoustic impulse resonance had been broadly used for eggshell crack detection, in which the relationships between the main frequency features and eggshell cracks were discussed in detail (DE Ketelaere, 2000; Cho, 2004; DE Ketelaere, 2004 and Wang, 2005). In this paper, four frequency features are included: the normalization average of the frequency domain (defined by (4)), the first dominant frequency that is the frequency of the highest peak (defined by (5)), the average x- and y- coordinates of the centroid for the frequency domain (defined by (6) and (7), respectively).

$$\bar{P} = \frac{P}{n \cdot \max\{P_i\}}, \qquad (4)$$

$$Fr = f(P_{i,\max}), \qquad (5)$$

$$D_x = \frac{1}{F}\sum_{i=1}^{n} P_i f_i, \qquad (6)$$

$$D_y = \frac{1}{P}\sum_{i=1}^{n} P_i f_i, \qquad (7)$$

where P_i is the magnitude at the i^{th} frequency point f_i, F and P are respectively the sums of frequency values and magnitudes of the frequency domain, defined as follows:

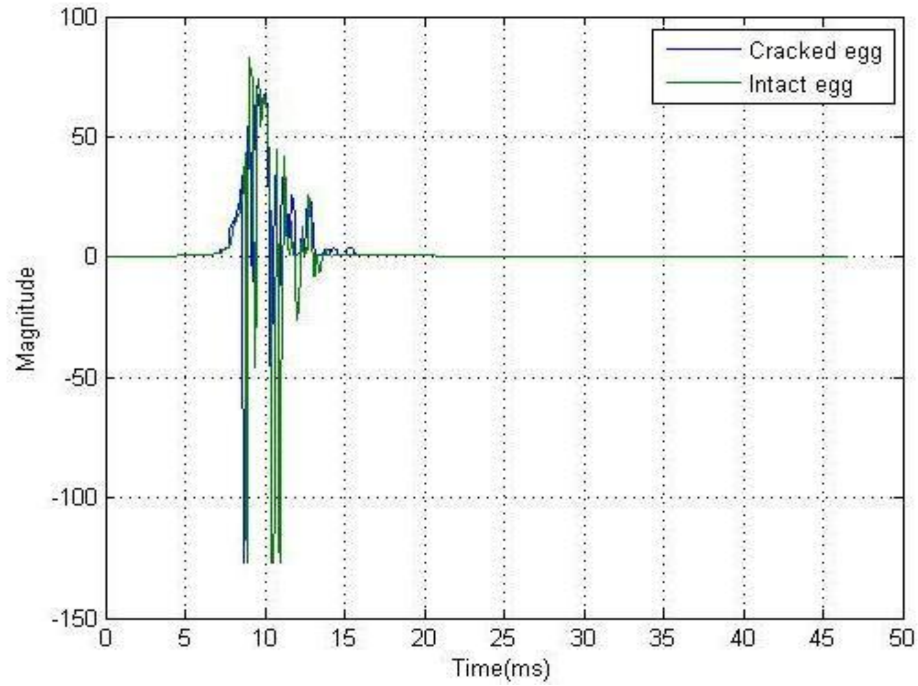

Figure 3. Typical time signal of the response of eggs.

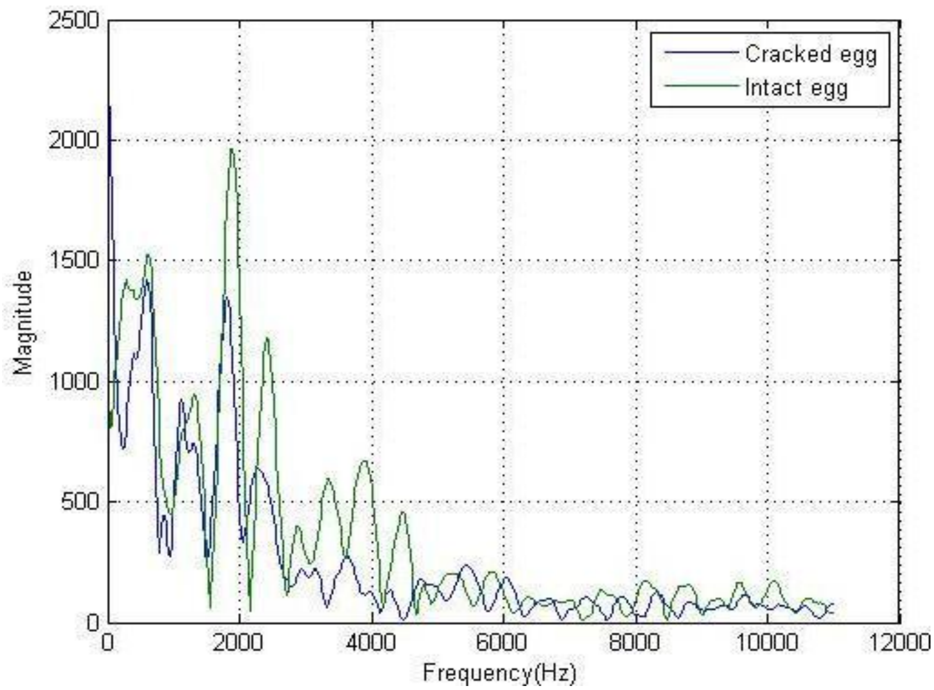

Figure 4. Typical frequency signal of the response of eggs.

$$F = \sum_{i=1}^{n} f_i , \quad P = \sum_{i=1}^{n} P_i .$$

The selected 100 intact eggs and 100 cracked eggs are randomly numbered from 1 to 100, respectively. Figures 5 - 8 give the distributions of feature values of the 200 egg samples. As an example, the No.7 cracked egg is very difficult to distinguish when using the normalization average of the frequency domain or the average x- coordinates of the domain centroid as the crack indicator (Figures 5 and 7).

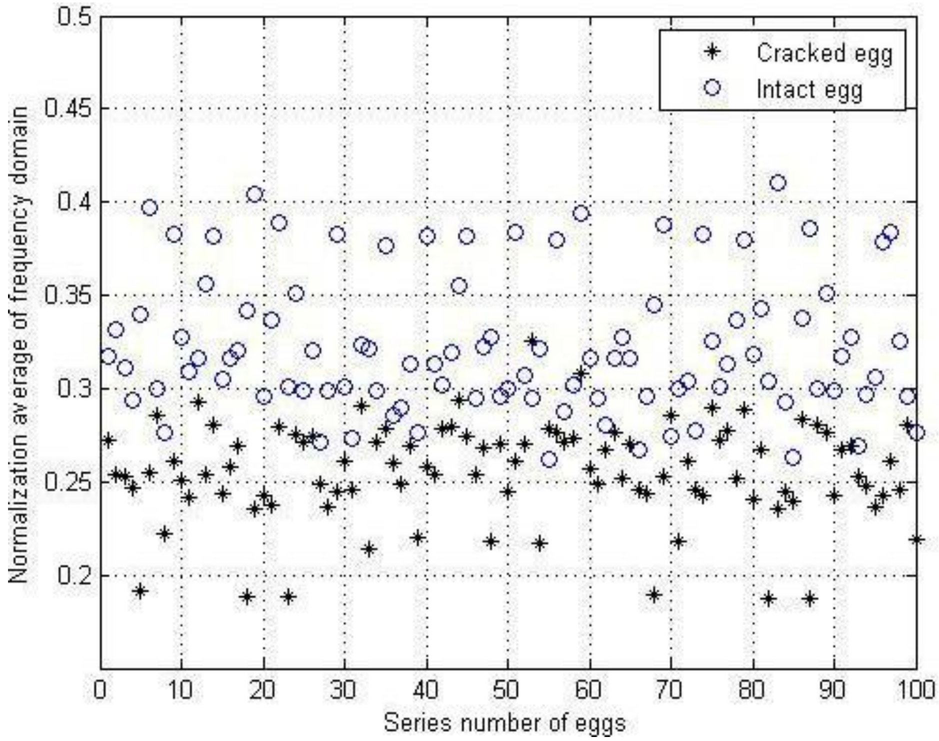

Figure 5. The distribution of the normalization average of the frequency domain for 100 intact eggs and 100 cracked eggs.

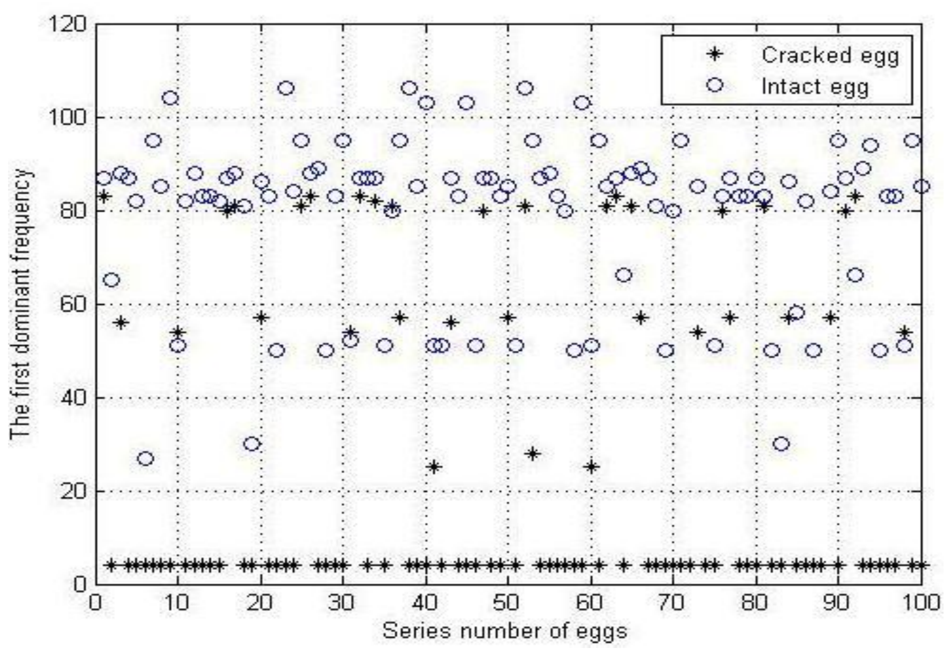

Figure 6. The distribution of the first dominant frequency for 100 intact eggs and 100 cracked eggs.

However, it can be clearly classified from the other two features (Figures 6 and 8). A possible method for improving the detection effect of the single-feature indicator is to construct new classification indicators based on the combination of the above frequency features. This is why the SVM technique is introduced in the

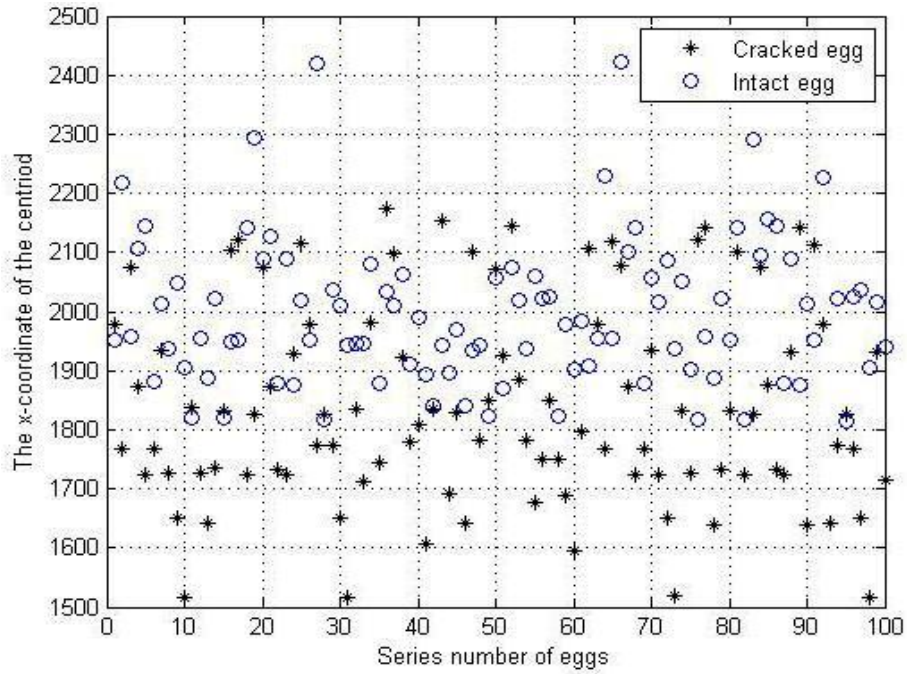

Figure 7. The distribution of the average x- coordinates of the frequency domain centroid for 100 intact eggs and 100 cracked eggs.

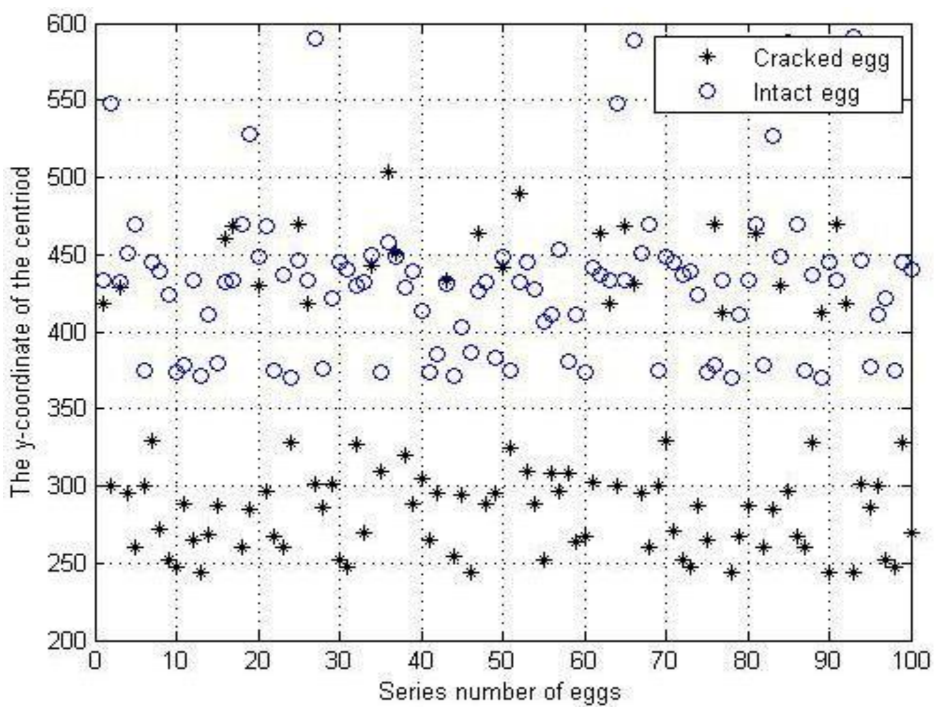

Figure 8. The distribution of y-coordinates of the frequency domain centroid for 100 intact eggs and 100 cracked eggs.

present paper.

There exist obvious level differences among the values of the different frequency features. Here some scale parameters are introduced to transform these feature values to the same value level. Corresponding to the above frequency features ((4) – (7)), the scaled fre-

Table 1. Training results of single feature classifiers, C = 250,   = 20.

Classifier	Training accuracy (%)	#SVs	Crack detection (%)	False reject (%)
SVM-P	90.5(181 / 200)	54	93	12
SVM-F	89.0 (178 / 200)	60	86	8
SVM-X	75.0 (150 / 200)	106	58	8
SVM-Y	87.5(175 / 200)	56	75	0

quency features are defined as follows:

$$P_c = \frac{\overline{P}}{C_P}, F_c = \frac{Fr}{C_f}, X_c = \frac{D_x}{C_x}, Y_c = \frac{D_y}{C_y} \quad (8)$$

where C_p, C_f, C_x and C_y are scale parameters which can be determined by considering the difference levels among the feature values of all sample eggs.

Let N denote the total number of sample eggs (or signals), $\overline{P}^{(i)}$, $Fr^{(i)}$, $D_x^{(i)}$ and $D_y^{(i)}$ denote the frequency features of the ith sample egg, respectively. In this paper, the scale parameters are given that

$$C_p = \max_{1\le i\le n}\left\{\overline{P}^{(i)}\right\}, C_f = \max_{1\le i\le n}\left\{Fr^{(i)}\right\},$$

$$C_x = \max_{1\le i\le n}\left\{D_x^{(i)}\right\}, C_f = \max_{1\le i\le n}\left\{D_y^{(i)}\right\}.$$

The above scaled features will be respectively denoted by letters P, F, X and Y if a simple expression is needed in the remaining part of this paper.

SVM performance

In this part, the various SVM training models based on the different feature selections are firstly discussed. The training data set is consisted of the scaled frequency features of the first group of sample eggs, in which the feature values of 100 cracked eggs are label1ed - 1 and the feature values of 100 intact eggs label1ed 1. In the experiment, an exhaustive search over the model parameters C and γ is performed in order to find the values where the total number of errors are minimum. The results for this search show the optimal values lay near the values C = 250 and γ = 20. The two particular values are used in all remaining experiments.

Table 1 gives the training results of single - feature classifiers. In Table 1, SVM-P denotes the SVM classifier based on the scaled feature P that is the normalization average of the frequency domain P_c. It is easy to see the connections between the classifier names and the selected features throughout this paper. From Table 1, the SVM-P is the best single-feature classifiers with 90.5% training accuracy, whereas the SVM-X reveals the worst training accuracy of 75%. The training accuracy associated with a feature also shows the crack-sensitive power of the feature. The results provided in Table 1 are consistent with the conclusions of relative researches (DE Ketelaere, 2000; Cho, 2004; DE Ketelaere, 2004; Wang, 2005).

This paper is interested in the multi- feature SVM classifiers based on the different combination of features. The results are shown in Table 2. Obviously, these multi-feature SVM classifiers reveal higher training accuracies than that of single- feature- based SVM classifiers. In fact, The SVM-PF, SVM-PY SVM-PFXY and all four three-feature classifiers are revealed with high training accuracies.

In what follows, a testing data set consisting of the feature value vectors of 55 cracked and 95 intact eggs is used to further test the performances of these SVM classifiers. For simplicity, only the best single-, binary-, three- and four- feature classifiers are taken into account. The results are shown in Table 3.

The results show that the SVM-classifier associated with more features generally gives a better testing accuracy. The SVM-PFXY is the best of all classifiers with the testing accuracy of 98%. The SVM-PF, SVM-PFY and SVM-PFXY reveal the same crack detection accuracy of 98.18%, but only the SVM-PFXY provides the smallest false reject accuracy of 2.12%.

SVM classification based on four excitations

In the above section, the SVM classifiers are set up in the case that the cracks are located in the right half surface of the eggshell centered at the impact point (Figure 1). From the point of view of consistency, a detection scheme based on four excitations is proposed. In this scheme, the eggshell would be impacted on the equator when rotating the roller approximately by 90° each time and the SVM classification is timely preformed by using the selected frequency features of the acoustic resonance as an input vector. The tested egg is classified as an intact one only when the egg is intact for all four detections.

The above scheme is tested with the randomly selected 240 sample eggs. In the experiment, the eggshell cracks are inspected and recorded by artificial method in advance. The actual detection accuracies are obtained by

Table 2. Training results of multi-feature classifiers, C = 250, = 20.

Classifier	Training accuracy (%)	#SVs	Crack detection (%)	False reject (%)
SVM-PF	98.0 (196 / 200)	21	98	2
SVM-PX	92.5 (185 / 200)	38	94	9
SVM-PY	98.0 (196 / 200)	21	99	3
SVM-FX	93.5 (187 / 200)	46	93	6
SVM-FY	94.0 (188 / 200)	37	95	7
SVM-XY	90.0 (180 / 200)	53	80	0
SVM-PFX	98.0 (196 / 200)	26	98	2
SVM-PFY	99.5 (199 / 200)	20	100	1
SVM-PXY	98.5 (197 / 200)	16	99	2
SVM-FXY	96.5 (193 / 200)	37	96	3
SVM-PFXY	99.5 (199 / 200)	19	100	1

Table 3. Testing results of the selected classifiers, C = 250, = 20.

Classifier	Testing accuracy (%)	Crack detection (%)	False reject (%)
SVM-P	80.00	70.91(39 / 55)	14.74(14 / 95)
SVM-PY	96.67	98.18(54 / 55)	4.21(4 / 95)
SVM-PFY	97.33	98.18(54 / 55)	3.16(3 / 95)
SVM-PFXY	98.00	98.18(54 / 55)	2.11(2 / 94)

Table 4. The results of SVM classification experiment based on four excitations, C = 250, = 20.

Classifier	Accuracy (%)	Crack detection (%)	False reject (%)
SVM-P	89.17(214 / 240)	91.36(74 / 81)	11.94(19 / 159)
SVM-PY	96.25(231 / 240)	98.77(80 / 81)	5.03(8 / 159)
SVM-PFY	97.50(234 / 240)	98.77(80 / 81)	3.14(5 / 159)
SVM-PFXY	98.33(236 / 240)	98.77(80 / 81)	1.87(3 / 159)

the comparison of the results of the artificial detection and SVM classification. The results are shown in Table 4. The experiment results are consistent with the testing results presented in Table 3. From Table 4, the four -exci-tation scheme shows a small improvement in crack detections and no significant change in false rejects.

CONCLUSIONS

This paper presents a detailed analysis of the classify-cation effects of SVM classifiers. It is shown that the SVM classifier based on the combination of features provides a better detection effect than that of the single- feature crack indicator. The main findings are summarized as follows:

1. The SVM-P, SVM-PF and SVM-PFY are respectively the best single-, binary- and three-feature classifiers (from Table 1 to Table 3). Generally, the SVM classifier associated with good crack-sensitive features shows a good detection effect.
2. The SVM classifier associated with more features generally shows a better detection effect (from Tables 2 and 3). For instance, the SVM-PFXY gives a higher testing accuracy than that of the SVM- PFY by taking account into the average x - coordinates of the frequency domain centroid (the worst crack-sensitive feature).
3. The crack detection percentage of SVM classification can be improved by increasing the number of measurements that is, reducing the distance between the excitation point and crack, whereas the false rejects reveals no significant change when increasing the number of measurements.

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