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Acoustic feature extraction and optimization of crack detection for eggshell

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ABSTRACT

Research on egg crack detection has been conducted based on acoustic method, especially those on the extraction of different features and those that compare sound and cracked eggs. Thus, an excitation device that is driven by solenoid was developed in the current study to generate acoustic signals by impacting an egg. Time and frequency domain features that were used and customized by previous researchers and customized were extracted. F-ratio was used to evaluate the effect of every feature on the discrimination of sound and cracked eggs, and correlations between features were investigated. Features with remarkably low F-ratio values and those with relatively low values in pairs of highly correlated features were disregarded. Classification accuracy reach 99.2% using neural network with features reduction in this method and features reduction will assist in simplifying recognition algorithms and in reducing computations in on-line systems.

1. Introduction

Eggshell crack detection is a crucial module in egg grading systems. Eggs whose shell surface are cracked pose greater health risks for consumers than intact eggs do (Todd, 1996). Research on the automatic detection of eggshell cracks are mainly based on machine vision (Lawrence et al., 2008; Jones et al., 2010; Yoon et al., 2012) and acoustic method (Ketelaere et al., 2000). Conventional procedure of egg crack detection in egg grading system is human inspection, which is very popular in China and other developing countries or small egg processing factory. Usually, eggs were rolling above light source to make cracks clear to inspectors. The accuracy of this method is highly affected by the experience and number of inspectors, and the increasing capacity of egg grading system makes this method more difficult and, hence, less reliable. Machine vision is the method developed from human inspection. But this method is only researched in laboratory because of its low detection speed and high computation load. It is quite difficult for machine vision to see micro cracks at atmospheric pressure that researchers put eggs in a negative-pressure devices to make the cracks larger in order to be detected. MOBA (Netherlands) and other companies apply acoustic method in egg crack detection, and can achieve 98% or more detection accuracy. Adjustment of accuracy is also possible for different demands. However, there is few research have done for acoustic features selection and optimization and comparison of accuracy among different conditions.

Acoustic detection is an extensive eggshell crack detection method that discriminates cracked eggs through the sound or vibration signals of excited eggs. Following signal collection, three processes must be performed obtain recognition results: (1) Feature extraction, which extracts acoustic features from the original signal and converts these features into an appropriate format for further processing; (2) feature selection, which selects the most relevant feature set among all of the candidate features; (3) recognition, which recognizes the patterns on the processed feature set derived from stage (2) to distinguish cracked eggs from sound ones.

Many algorithms have been applied in the recognition stage, such as principal component analysis (PCA) and linear discriminant analysis (LDA) (Zhao et al., 2010), support vector machine (SVM) (Deng et al., 2010), support vector data description (SVDD) (Lin et al., 2009). Additional features have been proposed to improve discrimination performance, but they are complex and expense increased amounts of computer resources. Therefore, they are unsuitable for real-time detection. Given this knowledge, features with poor discrimination performance or those that are highly correlated should be eliminated to save time and to simplify algorithms. This objective can be achieved by evaluating and comparing

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features; however, few studies have been conducted.

The current study contributes to research in field of selecting eggshell crack features and of comparing the acoustic responses of eggs after excitation. Different types of features are extracted from the time and frequency domains. F-ratio is used as a figure of merit in feature comparison to evaluate the distribution of each feature that can measure the "distinguish ability" (Sambur, 1975). The correlations between features are also investigated.

2. Materials and methods

2.1. Egg sampling

Two hundred and fifty brown eggs of different sizes and weights were collected from a local hatchery, namely Guangda Chicken Farm in Hangzhou, Zhejiang. These eggs were brought to the laboratory for feature selection and neural networks training. All of the eggs hatched in two days, and those with natural cracks or breakage were abandoned. A total of 100 sound eggs were selected. Cracks were artificially inflicted on the equators of the remaining eggshells. Moreover, 100 cracked eggs with crack lengths were within 2 $\pm$ 0.5 cm were obtained. Cracks were observed using a portable digital microscope (3R-WM401USB, Japan) and measured with a micrometer. The weights, longitudinal lengths and equatorial lengths of all 200 eggs were determined and recorded. The range of weights and of the egg shape indices (the egg shape indices were determined by dividing longitudinal length by equatorial length) were (38.5, 61.2 g) and (1.18, 1.52), respectively.

Another 500 eggs were collected from Guangda Chicken Farm and brought to the laboratory for neural networks testing, in which half eggs were white and another half were brown, these two kind of eggs are from the most common hens in China. The averaged (50 samples) thickness of the two kind of eggs were measured by the portable digital microscope after all these experiments, the result is 0.35 $\pm$ 0.025 mm (brown eggs) and 0.33 $\pm$ 0.027 mm. We make crack on 150 eggs from either kind of eggs, in which 50 eggs have cracks on equator, 50 eggs have cracks on blunt end and another 50 eggs have cracks on sharp end. All the cracks' lengths were within 2 $\pm$ 0.5 cm.

2.2. Experimental system

The experimental system consisted of an excitation that was device driven by an electromagnet, a saddle-shaped roller to support the egg, an electret microphone that was mounted on the excitation device, and a drive circuit that controlled the electromagnet, as well as a signal acquisition, transmission and analysis system. The schematic diagram of the system and the experimental system are shown in Fig. 1.

The excitation device included a stationary housing made of polyformaldehyde (POM). An axially movable tube was placed within this housing. This tube was driven by a solenoid that surrounded the stationary housing. An excitation ball which is attracted by the annular magnet can vibrate axially, if en egg is located under the downwards falling tube, the ball will be arrested by the egg. The ball will bounce upwards then fall downwards because of attraction of the annular magnet, and it will vibrate several times in this way. A 4 mm (diameter) $\times$ 1.5 mm (thickness) electret microphone (Panasonic WM-G10D, Japan) was installed within the tube and used to acquire acoustic signals from the vibrating ball. The distance in tube descent was adjusted to 10 mm for all eggs. In the preliminary experiment, the minimum peak impact force that can break an egg was measured. A peak impact force of $\leqslant$ 30 N dose not crack eggs; hence, a force of 20 N was applied in the subsequent experiment.

An egg from training set was placed on the roller, if the egg was a cracked egg, rotate it to ensure that the excitation device can impact the crack on the egg. Each egg was impacted thrice in the same area continuously (as per the results of the primary experiment, three instances of impact on a cracked egg did not extend the crack, and three instances of impact on a sound egg dose not generate a new crack). Three series of signals were acquired from each egg.

Every egg from the testing set was impacted from three directions (impacted on equator, blunt end and sharp end), We adjusted excitation device to meet the three direction which are shown in Fig. 2. Each egg was impacted once at each direction.

2.3. Conditioning and analysis of acquired signals

The signals acquired by microphone were transmitted into an NI Compact-RIO system. Within this system a NI9234 module was used to convert the analog signals to digital data. A threshold was set to trigger sampling. The Compact-RIO system establishes a connection with a remote PC through a network, and the sampling data are transmitted to this PC for further processing. The LabVIEW program was installed on the PC. Data processing and feature extraction algorithms were applied in this program.

A sampling rate of 51.2 kHz was employed in the preliminary test, and the numbers of sampling points were determined. In the primary experiment, 512, 1024 and 2048 sampling points were used. The set of 1024 sampling points obtained at a sampling rate of 51.2 kHz was employed for the remaining experiments because it contained sufficient signal information. A Butterworth band-pass filter with a low cutoff frequency of 500 Hz and a high cutoff frequency of 8000 Hz was utilized because of its flat passband. The time domain signals were converted for the frequency domain was performed through fast Fourier transform in combination with the Hanning window function in the LabVIEW program. Time and frequency domain features were extracted, and F-ratio was used to discriminate between sound and cracked eggs. Moreover, the correlation between features were calculated.

2.4. Criteria for feature evaluation

F-ratio is defined as the ratio of the between-class variance to the within-class variance (Chakroborty and Saha, 2010). It is widely used as a criterion to evaluate the extracted features of sound and speech because of its low computation requirement and easy implementation (Prasad et al., 2007). The statistic of the ratio is proportional to the ratio of the variance of the means of cracked and sound eggs' feature distribution to the average variance of each distribution. Thus, the farther apart individual distributions are with respect to average spread, the higher the F-ratio. The variances within each class are generally unequal, the pooled within-class variance was used to define the F-ratio. That for the *ith* feature is therefore expressed as

$$F_i = \frac{B_i}{W_i} \tag{1}$$

where B_i is the between-class variance and W_i is the pooled within-class variance. These variables are given by

$$B_i = \frac{1}{K}\sum_{k=1}^{K}(\mu_{ik} - \mu_i)^2 \tag{2}$$