# Model for automatic detection of eggshell crack

Liu Jianying[1], Chen Jiayan[2], Ding Youchun[1], Ren Yilin[1],
Wang Shucai[1], Xiong Lirong[1], Chen Dongjiao[2], Wen Youxian[1※]
(1. *College of Engineering and Technology, Huazhong Agricultural University, Wuhan* 430070, *China*; 2. *East China Institute of Technology*, 330013, *China*)

**Abstract**: In order to establish models for cracked eggs and intact eggs, a detecting system that was composed of an automatic impact device and a response sensor controller was used. Characteristic parameters such as the average area of power spectrum ($x_1$), the difference between the maximum and minimum values of area of the power spectrum ($x_2$), the average of the x-coordinate of centriod ($x_3$), difference between the maximum and minimum values in the x-coordinate of centroid ($x_4$), the average of the y-coordinate of centriod ($x_5$), the difference between maximum and minimum values in the x-coordinate of centroid ($x_6$), the average peak resonant frequency ($x_1$) and difference between the maximum and minimum values in peak resonance frequency ($x_8$), were achieved for differentiating cracked eggs and intact eggs according to the analysis of their power spectra in this research. Bayes theorem was applied to develop discrimination models for cracked eggs and intact eggs. The test showed that the average accuracy of detection models was about 92%.

**Key words**: eggshell crack; detection; model; culling
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## 0 Introduction

In duck egg processing plants, culling of cracked eggs is an important working procedure, which was largely done by handwork currently. However, the quality of eggs by handwork detection cannot be guaranteed due to variable detection accuracy that results from difference in workers' experience, emotion and physical capability.

Two different techniques were employed in quality detection and sorting of eggs: machine vision and image analysis (Goodrum & Elster, 1992[1]; Patel, V C and et al, 1998[2]; Nakano K.; K Sasaoka and Y Ohtsuka, 2000[3]; M C Garcia-Alegre and et al, 2000[4]) and mechanical stiffness measurements (Duprat and et al, 1997[5]; J. Wang and et al, 2004[6]; B. De Ketelaere and et al, 2000[7]; Wen youxian and et al 2002[8]; H. K. Cho and et al, 2000[9]; Nakano K and et al, 2001[10]; Angela Ribeiro and et al, 2000[11]). The accuracy of the machine vision method relies on the resolution of the camera, the sorting algorithm and the type of defect. Machine vision inspection works excellently for dirty shells, broken shells and odd shapes, however, detection of small cracks is more difficult. The mechanical stiffness measurements were based on the measurement and analysis of the mechanical behaviour of the eggshell. B. De Ketelaere, et al developed a method that eggshell crack detection was based on the analysis of the acoustically measured frequency response of an egg excited with a light mechanical impact on different locations on the eggshell equator. This method allowed a crack detection level of 90% and a false reject level of less than 0.5%[7]. J. Wang, et al also developed an experimental system to generate the impact force, measure the response wave signal and analyze the frequency spectrum for physical property detection of eggshell. The dominant frequency increased with the increase of shell stiffness or egg density, and decreased with the increase of egg mass[6].

In this study, computer-based audio technology and data processing methods were applied to establish an experimental system for automatic detection of cracked eggs. In the system, audio response signals of intact eggs and cracked eggs were collected, followed by analysis of the differences between the two groups in power spectrum characteristics of audio signals. The results will therefore provide a useful method for auto-

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Biography: Liu Jianying: associate professor. College of Engineering and Technology, Huazhong Agricultural University, Wuhan 430070, China
Corresponding author: Wen Youxian, professor, College of Engineering and Technology, Huazhong Agricultural University, Wuhan 430070, China. Email: wenyouxian@mail.hzau.edu.cn

matic detection of cracked eggs

## 1 Material and methods

### 1.1 Composition of the experimental system

The experimental system was composed of an automatic impact egg device, a response sensor with power amplifying function[12], a PCI128 digital audio card and a controlling kernel PC[8]. Impact frequency of impact egg device was variable by adjusting the capacitance and the force of exciting eggshell could be regulated by the spring. The optimal audio signals were obtained when the response sensor was placed 2 cm away from the egg. The audio card used in the study was digital PCI128 with 8 Bit and 16 Bit single Chunnel and stereo Chunnel and it supports simultaneous recording and playing functions. The sampling frequency ranges from 5 kHz to 48 kHz and the type of control PC was PII800Hz/64MB.

### 1.2 Material and method

Fresh eggs including cracked eggs were supplied by Hubei Xiantao Food Corporation in China. The extent of eggshell crack in the eggs was varied from broken shells to small cracks. In this study, a program for audio signal collection and analysis was written. Response signals were obtained by using the function from MATLAB function library[13]. It was found that the sampling frequency of 22050 Hz was optimal for accurate sampling after comparing the results obtained under different sampling number. The subsequent data were processed by filter and presented further for power spectrum analysis. Power spectrum profiles of normal eggs and cracked eggs were compared, from which characteristic parameters can be retrieved for eggshell crack detection.

## 2 Parameters for cracking detection

Such characteristic parameters representing power spectrum profiles as resonance peak frequency, number of resonance peaks and centroid of power spectrum were retrieved. Multiple impact of a single egg was required for audio-based detection of cracked eggs. The reasons are that audio responses from one cracked egg upon each impact action can be greatly different due to the difference in physical characteristics of the cracked part and the intact part whereas audio responses from intact eggs during each impact always remain similar. Therefore, by impacting one egg several times, deviations in the audio signals collected of cracked eggs were far greater than those of intact eggs. Using this method cracked eggs can be effectively separated from normal ones. An egg was impacted once and four parameters were picked up.

Area of the power spectrum (Area):

$$Area = \sum_{i=0}^{k} P_i \tag{1}$$

Where $P_i$ —— amplitude of power spectrum at its frequency; $i$ ——number of egg signal frequency ($i$ = 0, 1, 2……, $k$)

Peak resonant frequency (Fres)

$$Fres = F(P_{imax}) \tag{2}$$

Where $P_{imax}$ —— the frequency corresponding to the largest amplitude in the power spectrum.

Centriod of the X-coordinate area in equation (1) ($C_x$)

$$C_x = \frac{\sum_{i=0}^{k} P_i \times f_i}{\sum_{i=0}^{k} P_i} \tag{3}$$

Where $f_i$ —— the frequency of $i$ in the power spectrum.

$Y$-coordinate of the centriod of the area in equation (1) ($C_y$)

$$C_y = \frac{\sum_{i=0}^{k} P_i \times \frac{P_i}{2}}{\sum_{i=0}^{k} P_i} \tag{4}$$

Four parameters mentioned above could be obtained by analyzing power spectrum of the audio signals generated by impact once first; average and extremum were obtained for each of the four parameters when impact the egg for several times, thus generating eight parameters.

Average area of power spectrum ($x_1$)

$$x_1 = \frac{1}{n} \sum (Area)_l \tag{5}$$

Where $l$ ——number of impacts, $l$ = 1, 2, …, $n$.

Difference between the maximum and minimum values of area of the power spectrum ($x_2$)

$$x_2 = \max[(Area)_i] - \min[(Area)_i] \tag{6}$$

Where $i$ - (0, 1, …, $n$ - 1)

Average of the x-coordinate of centriod ($x_3$)

$$x_3 = \frac{1}{n} \sum (C_x)_i \tag{7}$$

Difference between the maximum and minimum values in the x-coordinate of centroid ($x_4$)

$$x_4 = \max[(C_x)_i] - \min[(C_x)_i] \tag{8}$$

Average of the y- coordinate of centriod ($x_5$)

$$x_5 = \frac{1}{n} \sum (C_y)_i \tag{9}$$

Difference between the maximum and minimum values in the x-coordinate of centroid ($x_6$)

$$x_6 = \max[(C_y)_i] - \min[(C_y)_i] \tag{10}$$

Average peak resonant frequency ($x_7$)

$$x_7 = \frac{1}{n}\sum (Fres)_i \quad (11)$$

Difference between the maximum and minimum values in peak resonance frequency ($x_8$)

$$x_8 = \max[(Fres)_i] - \min[(Fres)_i] \quad (12)$$

$x_1$, $x_2$, $x_3$, $x_4$, $x_5$, $x_6$, $x_7$, $x_8$ were selected as significant parameters for differentiating normal eggs and cracked eggs

## 3 Bayes analysis of eggshell crack detection

### 3.1 Bayes theorem[14]

Supposing each sample indexed by $p$ parameters $x_1$ $x_2 \cdots x_p$ belongs to one of $K$ classes, $B_1$, $B_2$, $\cdots$, $B_K$, using Bayes discriminance to differentiate to which class a given random sample denoted $X = (x_1, x_2 \cdots x_p)$ belongs, the discrimination error will be minimized. Bayes theorem could be explained as follows: suppose the probability densities of the sample $X$ of $B_1$, $B_2$, $\cdots$, $B_K$ are $f_1(x)$, $f_2(x)$, $\cdots$, $f_K(x)$, and the prior probability of $X$ belonging to one of $K$ categories is $P(X/h)$, according to the method of total probability calculation, the total probability of $X$ occurrence is:

$$P(X) = \sum_h P(h) \times P(X/h)$$

According to Bayes formula, the posterior probability of $X$ belonging to one of $K$ categories is:

$$P(k/K) = \frac{P(k) \times P(X/k)}{\sum_h P(h) \times P(x/h)} = \frac{P(k) \times f_k(x)}{\sum_h P(h) \times f_h(x)}$$

The denominator in the above formula is fixed, so the larger the numerator, the greater the probability of $X$ belonging to $B_K$. Suppose:

$$\eta_k(X) = P(k) \times f_k(x)$$

After calculating $\eta_k(x)$ one by one, then according to the value of

$$\eta_k^*(X) = \max_k(\eta_k(X))$$

it will be decided whether $X$ belongs to $B_K$.

### 3.2 Developing estimation formula of differentiation function

Supposing the distribution of the collectivity of each class is $N(\mu_k, \sum)$, and $k = 1, 2, \Lambda, K$ so

$$f_x(x) = \frac{\left|\sum^{-1}\right|^{1/2}}{(2\pi)^{\frac{p}{2}}}\exp\{-\frac{1}{2}(x-\mu_k)'\sum^{-1}(x-\mu_k)\}$$

in the formula above: $x = (x_1, x_2, \Lambda, x_p)'$,

$$\mu_k = \{\mu_1^{(k)}, \mu_2^{(k)}, \Lambda, \mu_p^{(k)}\}',$$

$$\sum = (\sigma_{ij})_{p\times p}$$

There is an observed matrix $\{x_{ij}^{(k)}\}_{p\times p}$, in which $x_{ij}^{(k)}$ is the ith observed value of the jth variable belonging to $B_k$ class $K$ is the category number and $n_k$ represents the number of samples in $B_K$ and $\sum n_K = n$. According to the observed data matrix above Coefficient $c_0^{(k)}$, $C_1^{(k)}$, $\cdots$, $c_p^{(k)}$ should be calculated to establish the estimation formula. The estimation formula worked out is $\eta_k(x)$: $y_k(x) = c_0^{(k)} + \sum_j c_j^{(k)} x_j$.

For a given sample $x = (x_1, x_2, \Lambda, x_p)$, by substituting it into the differentiation function, the value of $y_k(x)$ could be worked out. If $y_k^*(x) = \max_k y_k(x)$, $x$ belongs to $B_K^*$, indicating that the Bayes differentiation is complete.

### 3.3 Test of differentiating effect for multiple parameters

Supposing the distribution of the collectivity of each class is $N(\mu_k, \sum)$, the differentiating effect for multiple parameters lies on the differentia of the average of each collectivity. Under the conditions when the covariance matrix of each class is equal, the following hypothesis was made

$$H_0: \mu_1 = \mu_2 = \cdots = \mu_K$$

For this, we introduced Wilks statistics $\Lambda = \frac{|W|}{|T|}$, in which $W = (w_{f_1f_2})_{p\times p}$ is the deviation matrix within each class and $(q_{f_1f_2})_{p\times p}$ is the deviation matrix among classes and $T$ is the total mean deviation matrix. $T = W + Q$.

$$w_{f_1f_2} = \sum_k \sum_i (x_{j_1 i}^{(k)} - \bar{x}_{j_1}^{(k)})(x_{j_2 i}^{(k)} - \bar{x}_{j_2}^{(k)}),$$

$$q_{f_1f_2} = \sum_k n_k(\bar{x}_{j_1}^{(k)} - \bar{x}_{j_1})(\bar{x}_{j_2}^{(k)} - \bar{x}_{j_2}),$$

$$\bar{x}_{j_1} = \frac{1}{n}\sum_k n_k \bar{x}_{j_1}^{(k)}, \quad \bar{x}_{j_2} = \frac{1}{n}\sum_k n_k \bar{x}_{j_2}^{(k)}$$

It can be proven that if $n$ is big enough, distribution for statistics $\chi^2 = -\left[(n-1) - \frac{1}{2}(p+K)\right]\ln\Lambda$ is $\chi^2(P(K-1))$. For a given significance level $\alpha$, if $\chi^2 > \chi^2_\alpha(P(K-1))$, the value of $\Lambda$ is considered small. In addition, relative to the mean deviation of each internal $K$ class the mean deviation is big, i.e., the differentia of each class is big and $\mu_k$ is not equal. Therefore, the hypothesis $H_0$ would be refused, from which we judge that the effect of the estimation formula of differentiation functions is good.

### 3.4 Statistics results

Experiments were carried out according to the methods stated in the previous part and a set of data from 220 normal eggs and 148 cracked eggs were collected. However, the data were too large to be listed here. The differentiation models of normal eggs and cracked eggs using SAS[15] were developed.

Differentiation function of cracked eggs is as follows:

$$G_0 = -3.65949x_1 + 0.11949x_2 + 0.73058x_3 + 0.03436x_4 + 243.78146x_5 + 8.77368x_6 - 0.02960x_7 + 0.00356x_8 - 1956$$

Differentiation function of normal eggs is as follows:

$$G_1 = -3.62178x_1 + 0.14472x_2 + 0.73680x_3 + 0.03445x_4 + 239.72219x_5 + 7.01143x_6 - 0.02807x_7 + 0.00292x_8 - 1957$$

Results from the SAS output: in Table 1, $F = 100.63$, but $F_{0.001} = 3.3585$, $F(8, 359) > F_{0.001}(8, 350)$, it can be concluded that the differentiation function is very significant.

**Table 1 Statistics of Wilks' Lambda**

| Statistics | DF of parameters | DF of observed value | F Value | Pr> F |
|---|---|---|---|---|
| Wilks'Lambda | 8 | 359 | 100.63 | < 0.0001 |

In addition, $\chi^2$ inspection was carried out, $n = 368$, $p = 8$, $K = 2$, $\Lambda = 0.30839878$, degree of freedom $p*(K-1) = 8$, $\chi^2 = -\left[(n-1) - \frac{1}{2}(p+K)\right]\ln\Lambda = 425.84$, and the threshold value $\chi^2_{0.001}(8) = 20.515$, $\chi^2 > \chi^2_{0.001}(5)$. Again it shows that the differentiation function is very significant.

### 3.5 Evaluation of the model

To further evaluate the preciseness of the models, detection was carried out in a much larger sample in which 1100 normal eggs and 1260 cracked eggs were included. Detection data were generated and collected upon execution of the differentiation system. Among the 1100 normal eggs, 80 were wrongly identified as cracked eggs; so the average detection accuracy of the good egg model was 92.27%. On the other hand, among the 1260 cracked eggs, 100 eggs were wrongly identified as good eggs; so the average detection accuracy of the cracked egg model was 92.06%.

## 4 Conclusion and discussion

Bayes discriminance is based on normal (Gaussian distribution) distribution collectivity, thus presenting more sufficient and complete information about the collectivity and therefore the accuracy of Bayes is higher.

In this study, eggs even with hairline cracks hardly discernable by naked eyes can be identified correctly using the presented models. The discrimination errors for cracked eggs arise mainly from the fact that not all the impact can happen just at or quite near the cracking spot by the impact device. The results show that the accuracy can be improved by increasing the times of impact or detecting different spots by rotating the egg. But other issues may also come up together with the time increase in impact, such as elongation of the data processing period and subsequent reduction in efficiency of the system.

**[References]**


[1] Goodrum J W, Elaster R T. Machine vision for crack detection in rotating eggs[J]. Transactions of the ASAE, 1992, 35(4): 1323- 1328.

[2] Patel V C, McClendon R W, Goodrum J W. Color computer vision and artificial neural networks for the detection of defects in poultry enns[J]. Artificial Intelligence Review, 1998, 12, 163- 176.

[3] Nakano K, Sasaoka K, Ohtsuka Y. A study on non-destructive detection of abnormal eggs by using image processing[J]. Asian Federation for Information Technology in riculture, 2000: 345- 352.

[4] Garcia-Alegre M C, Ribeiro A, Guinea D, et al. Eggshell defects detection based on color processing [A]. SPIE 2000 Electronic Imaging Conf[C]. CA, Jan. 2000.

[5] Duprat F, Grotte M, Pietri E, et al. The acoustic impulse response method for measuring the overall firmness of fruit[J]. Journal of Agricultural Engineering Research, 1997, 66(1): 251- 259.

[6] Wang J, Jiang R J, Yu Y. Relationship between dynamic resonance frequency and egg physical properties[J]. Food Research International, 2004, (37): 45- 50.

[7] Ketelaere B De, Coucke P, Baerdemaeker J. De. Eggshell crack detection based on acoustic resonance frequency analysis[J]. Journal of Agricultural Engineering Research, 2000, (76): 157- 163.

[8] Wen Youxian, Wang Qiaohua, Zong Wangyuan, et al. Study on crack detection of duck eggs [J]. Huazhong Agricultural University Transaction, 2002. 6.

[9] Cho H K, Choi W K, Paek J H. Detection of surface cracks in shell eggs by acoustic impulse method [J]. Transactions of ASAE, 2000, 43(6): 1921- 1926.

[10] Nakano K, Usui Y, Motonaga Y, et al. Development of non-destructive detector for abnormal eggs [R]. Workshop on Control Applications in Post-Harvest and Processing Technology, 2001: 71- 76.

[11] Angela Ribeiro, Maria C. Garcia-Alegre, Domingo Guinea. Automatic rules generation by G. A. for eggshell detect classification[A]. European Congress on Computational Methods in Applied Sciences and Engineering[C]. 2000. Barcelona.

[12] Qing Zenghuang. Electrotechnics and Electronics (The 4th edition) [M]. Beijing: Higher Education Publishing Company, 1997.

[13] Chen Yayong. Specification of MATLAB Signal Processing[M]. Beijing: People Post Publishing Company, 2001.

[14] Yu Jialin. Agricultural Trial Multivariate Statistical Analysis [M]. Beijing: China Agricultural University Publishing Company.

[15] Gao Huixuan. SAS System, specification of SAS/STAT

[M]. Beijing: Beijing Statistic Publishing Company.

# 蛋壳破损自动检测模型研究

刘俭英[1], 陈家焱[2], 丁幼春[1], 任奕林[1], 王树才[1], 熊利荣[1], 陈冬娇[2], 文友先[1※]
(1. 华中农业大学工程技术学院, 武汉 430070; 2. 东华理工学院, 南昌 330013)

**摘 要**: 为了建立蛋壳破损检测模型, 试验采用敲蛋装置与声检测控制器组成的计算机蛋破损检测系统获取被检蛋声音信号数据。通过对蛋声音信号的功率谱分析而得到反映蛋壳破损特征的参数: 功率谱面积的平均值 $x_1$, 最大功率谱面积与最小功率谱面积的差值 $x_2$, X 轴方向上质心的平均值 $x_3$, X 轴方向上质心最大值与其最小值的差 $x_4$, Y 轴方向上质心的平均值 $x_5$, Y 轴方向上质心最大值与其最小值的差 $x_6$, 共振峰频率的最大值 $x_7$ 和共振峰频率的最大值与其最小值间的差值 $x_8$; 再通过Bayes原理建立与蛋壳破损特征参数相关的蛋壳破损模型。检验结果表明模型准确率达到92%。

**关键词**: 蛋壳破损; 检测; 模型; 剔除