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Research Paper

Eggshell crack detection based on the transient impact analysis and cross-correlation method

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ABSTRACT

To explore the transient impact process for cracked eggshell detection, an equivalent mechanical model was built based on a self-designed automatic excitation device. Through analysis of power spectrum from dynamic force signal, it was found that the impact speed affects only the impaction energy. In contrast, the material of the impact head and the weight of the excitation rod determine the energy and the cut-off frequency of the impaction. When the weight of impact tup is less than 6.62 g, the cut-off frequency of excitation impact can cover the egg's inherent frequency. Then, an optimized experiment system was designed to acquire the response acoustic signals. The cross-correlation analysis and Bayes classification methods were carried out to detect the cracked eggshell. In the conducted experiments, a crack detection level of 97% and a false rejection level of 1% were achieved. From the findings, it can be concluded that the proposed method will assist in optimizing the impact device and simplifying the classification algorithm for an online detection system.

1. Introduction

The eggs with broken shells are much easier to be infected by bacteria from outside. It may lead to food safety issues and economic losses to the egg industry. According to the previous studies, machine vision and acoustic analysis are two major nondestructive methods for the online eggshell crack detection system. However, the ma-chine vision's ability to inspect the hairline crack with the width ranging from 20 to 40 μm and length averaging to 30 mm is limited (Orlova et al., 2012). To address the problem, some researchers put eggs in negative-pressure devices to intensify the hairline cracks to a visible degree. Although it advanced the recognition accuracy of the microcracked eggs, the drawbacks of complex structure and low detection speed are unsuitable for real-time detection in practice.

So far, it has been proven that the most effective technique for eggshell crack online detection is the acoustic signal analysis method. In principle, four processes, such as sound or vibration signals production, feature extraction, feature selection, classification, must be carried out to recognize the crack eggs from intact ones. Recent studies attached great importance to the improvement of classification algorithms in the recognition stage. The combination of principal component analysis and linear discriminant analysis (Zhao et al., 2010), artificial neural network (Jindal and Sritham, 2003; Lin et al., 2010; Pan et al., 2011; Ding et al., 2015), support vector machine (Deng et al., 2009; Xiong, 2011), and supervised pattern recognition (Lin et al., 2009) were reported. Although a crack detection level of more than 90% and a false rejection level of less than 10% were achieved based on the complex and time-consuming algorithms, they are unsuitable for real-time detection. The novel analysis methods of wavelet-based signal analysis (Li et al., 2012) and acoustic feature optimization (Wang et al., 2016) were adopted to extract more useful features in the feature extraction and the feature selection steps.

Nevertheless, few studies have been conducted to improve the impaction device for optimizing the response signals in the signal production step. Presently, researchers have developed four feasible impact devices for acoustic production: a ball in a free-fall state (Zhao et al., 2009), an impact stick controlled by a motor (Coucke et al., 1997; Deng et al., 2009; Sun et al., 2013; Lin et al., 2018), an excitation ball attracted by the annular magnet (Wang et al., 2016), and a plate with seven steps (Jin et al., 2015). Acceptable performances have been achieved using the devices mentioned above, but the influences by the attribute of the impact devices (i.e. the materials of the impact head, impact speed and the weight of the impact devices) on the response signal are ambiguous. As the mechanical impact is the source of the acoustic response signals,

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Table 1
The measured parameters of egg samples.

	Weight/g		Egg shape indices		Crack length/mm	
	Range	Mean	Range	Mean	Range	Mean
First batch	(55.6, 88.2)	67.52	(1.20, 1.55)	1.28	–	–
Second batch	(53.1, 90.2)	68.95	(1.22, 1.51)	1.36	(16.3,49.8)	28.56

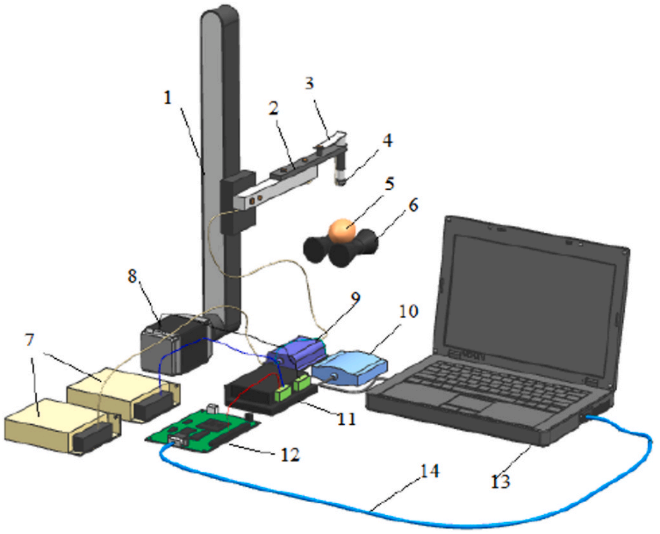


Fig. 1. Schematic diagram of the automatic excitation device.

the method to enhance the response signal's sensitivity to the crack on eggshell is treated as a critical research aspect.

The current study contributes to research in optimizing the impact device by dynamic mechanical analysis to improve the performance of eggshell crack detection. Specific objectives of this research were to (Orlova et al., 2012): build a mechanical model to analyze the process of the transient impact (Zhao et al., 2009); develop a setup used for the dynamic force signal generation and acquisition (Jindal and Sritham, 2003); verify the mechanical model and analyze the influence factors from the attribute of the impact devices to optimize the impact device (Ding et al., 2015); develop simple and efficient models for eggshell online detection.

2. Material and methods

2.1. Egg samples

All the egg samples were collected from a commercial poultry farm which were hatched in five days. Every sample was inspected individually by candling for the presence of cracks, and only intact eggs were selected. Two batches of eggs were used in this study.

The first batch of 30 intact eggs was used to analyze the transient impact process. The second batch of 100 intact eggs were used to test the performance of the proposed method in this study. The parameters of weight, egg shape indices, and crack length were measured and listed in Table 1.

After the acquisition of response signals from the intact eggs, crack on the eggshell surface were artificially inflicted by mechanical impact on random location of the eggshell. Observation by candling revealed 18-star cracks. The egg was distributed into eight equal regions on the eggshell along the minor axis (Sun et al., 2020). In the evaluation section of discrimination performance, eight microphones were employed to simulate the online detection condition. Every divided region of the egg was impacted from two directions (blunt end nearby, shape end nearby), and the response signals were acquired by corresponding numbered microphone. So, two series of eight response signals were acquired from the blunt end nearby, and shape end nearby for every egg sample.

2.2. Experimental system for mechanical analysis

The experiment system, which was used for mechanical analysis of the impact process, consisted of an excitation device, a saddle-shaped egg support, a synchronous belt module, a dynamic force sensing module, a data acquiring module, and a personal computer (PC). The schematic diagram of the system and the excitation device are shown in Fig. 1. The excitation device included a sleeve made of Teflon, which allowed the excitation rod to move vertically with slight resistance. A dynamic force sensor (YDL-1X) and a tup were fixed by the fasteners of screw and nut on the top of the ex-citation rod. On the other hand, a spring piece was placed at the end of the excitation rod to cushion the

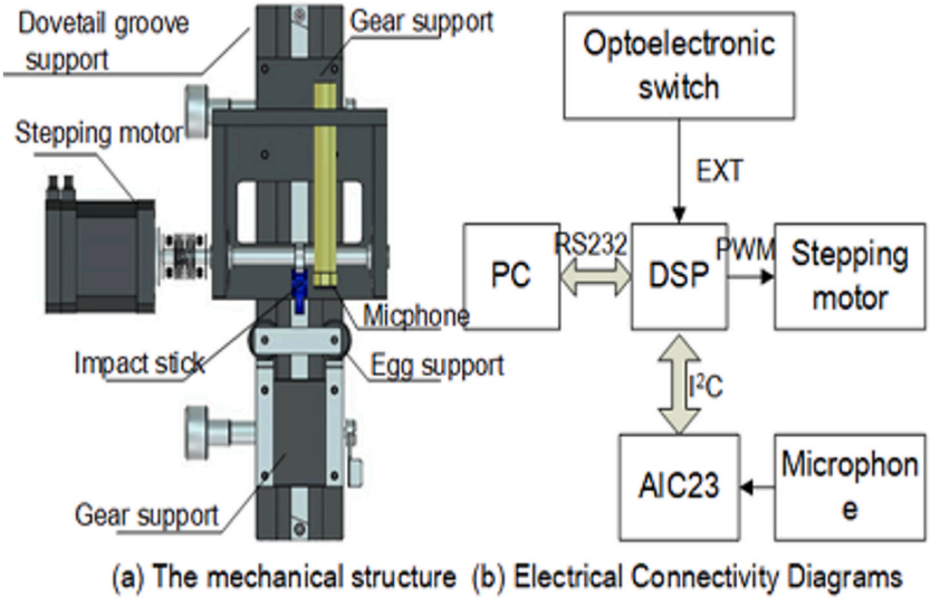


Fig. 2. Schematic diagram of the eggshell detection experiment.

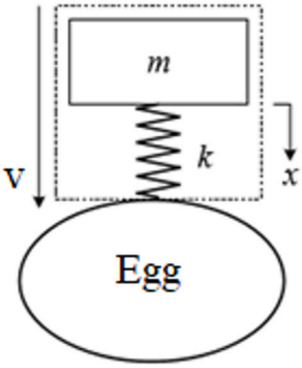


Fig. 3. The equivalent mechanical model.

impact effect. The excitation device was fixed on the synchronous belt module's sliding table, driven by a stepping motor.

Within this system, a PC with an application program based on LabVIEW was designed for motion control and data acquisition. A data acquiring module (USB–1208FS) with a sampling resolution of 12 bit was used to convert the analog signals to digital data and transmitted to this PC by USB2.0 for further processing. Meanwhile, a self-designed circuit with a digital signal processer (DSP, TMS32F2812, TI) was designed to control the stepping motor's speed and direction following the PC's commands through RS232. Moreover, a charge amplifier (DHF-7) was employed to condition the signal from the dynamic force sensor.

A sampling rate of 20 kHz was employed in the preliminary experiment, and 2000 sampling points were used to acquire completed signals which contained sufficient signal information.

2.3. Experimental system for eggshell crack detection

The experiment system for egg crack detection is shown in Fig. 2. Refer to (Sun et al., 2020) for the details of the experiment. During the experiment, 2048 was obtained at the sampling rate of 48 kHz. Then the acquired data was transported to the personal computer by RS232 and stored for future offline process.

2.4. Mechanical analysis for the transient impact

2.4.1. Mechanical model

As shown in Fig. 3, the transient excitation's equivalent mechanical model was abstracted into a single degree-of-freedom mass-spring mechanical system in this study. As the excitation rod is much heavier than the tup, they were considered a mass block and an undamped mass-spring, respectively.

When the tup knocked on the eggshell with a speed of $\dot{x}$, the differential equation of motion was given by:

$$m\ddot{x} + kx = 0 \tag{1}$$

where m is the weight of the excitation rod, k is the elastic coefficient of the tup.

The general solution of the differential equation with the initial conditions of $t = 0$, $x = 0$, $\dot{x} = \dot{x}_0$ was calculated as

$$x = \begin{cases} \dfrac{\dot{x}_0}{\sqrt{\dfrac{k}{m}}}\sin\left(\sqrt{\dfrac{k}{m}}t\right) & \left(0 \le t \le \pi\sqrt{\dfrac{m}{k}}\right) \\ 0 & (Others) \end{cases} \tag{2}$$

Then, the dynamic force was expressed as:

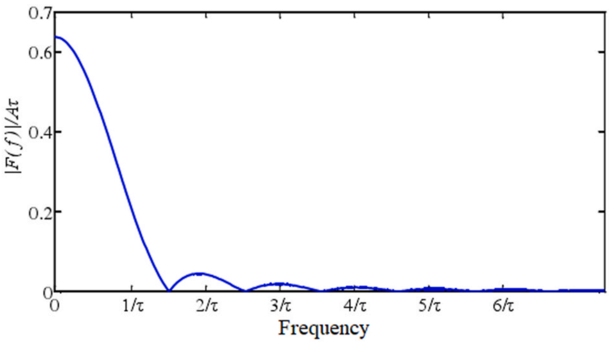


Fig. 4. The relationship between frequency and energy.

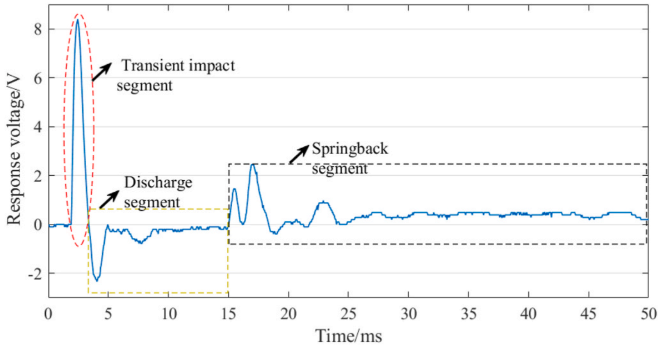


Fig. 5. The typical dynamic force signal.

$$\begin{aligned} f(t) = kx = \sqrt{km}\dot{x}\sin\left(\sqrt{\frac{k}{m}}t\right) & \quad \left(0 \le t \le \pi\sqrt{\frac{m}{k}}\right) \\ = \mathrm{A}\sin\left(\frac{\pi}{\tau}t\right) & \quad (0 \le t \le \tau) \end{aligned} \tag{3}$$

where A is the peak of impulse force and τ is the width of impulse force.

As shown in Equation (2), the dynamic force on the eggshell and the width of impulse force are influenced by the tup's elastic coefficient and the weight of the excitation rod. The dynamic force is also determined by an additional factor of the impact speed.

A frequency spectrum analysis of the dynamic force was conducted to analysis the frequency component resulted from the transient impact. The force spectrum was given by

$$F(f) = \int_{-\infty}^{\infty} f(t)e^{-jwt}dt = \int_0^{\tau} A\sin\frac{\pi t}{\tau}e^{-j2\pi ft}dt \tag{4}$$

The result of integral calculation is shown in the following expression:

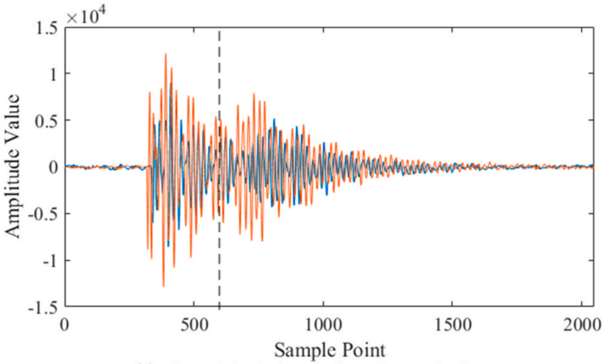
$$F(f) = \frac{2A}{\frac{\pi^2}{\tau^2} - 4\pi^2f^2}\frac{\pi}{\tau}e^{-j\pi f\tau}\cos(\pi\tau f) \tag{5}$$

Then, the modular operation was adopted to obtain the relationship between frequency and energy of the transient impact and the result was given by:

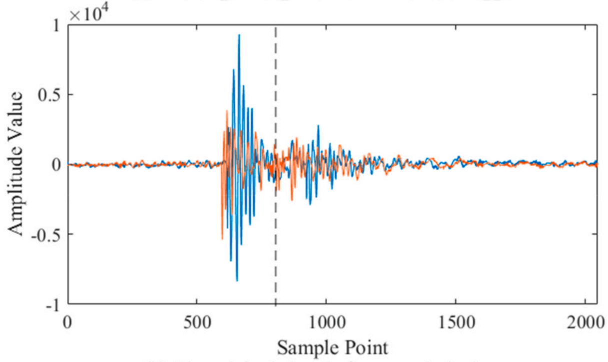
$$\frac{|F(f)|}{A\tau} = \frac{2}{\pi}\left|\frac{\cos(\pi\tau f)}{1 - 4\tau^2f^2}\right| \tag{6}$$

Following Equation (6), the relationship was displayed in Fig. 4. The energy of the transient impact is concentrated in the main lobe with the upper cut-off frequency of.

Based on the transient impact's spectral analysis, the upper cut-off frequency of the main lobe in the force spectrum is related to τ. Meanwhile, τ is determined by the tup's elastic coefficient and the weight of



(a) The original signals from intact duck eggs



(b) The original signals from crack duck eggs

Fig. 6. The typical time-domain response signals.

the excitation rod. Thus, the cut-off frequency can be adjusted by the parameters of the tup's elastic coefficient and the weight of the impact device.

2.4.2. Analysis of the dynamic force signal

The typical dynamic force signal that lasted 50 ms is displayed in Fig. 5. Three parts of the transient impaction segment, the discharging segment, and the spring-back segment were made of the impact process. The signal segment with a high fluctuation from 1.90 ms to 3.35 ms resulted from the transient impact on the eggshell. The response signal is larger than the other parts, and the peak of the response signal reached 8.40 V. After that, the negative signal segment attributed to the discharge of charge-amplifier was generated and kept for 15.05 ms. This process was stopped by the spring-back of the excitation rod. In the spring-back segment, the fluctuations of the positive dynamic force decreased gradually to stabilize. The peak value was 2.44 V, which was much smaller than that in the transient impaction segment. Hence, in the following study, the transient impaction segment was considered the efficient signal and utilized to further analyze the transient impulse signals.

2.4.3. Analysis of the influence factors

Based on the mechanical model analysis, there are three influence factors: the impact speed, the material of impact head, and the weight of the excitation rod to the transient impact process. Among them, the impact speed affects the impaction energy, while the materials of the impact head and the weight of the excitation rod determine the energy and the cut-off frequency of the impaction. To generate a resonance on the eggshell to enhance the energy and sensitivity to the eggshell quality in the response signals, the frequency component of the transient impact should contain the inherent frequency of the egg.

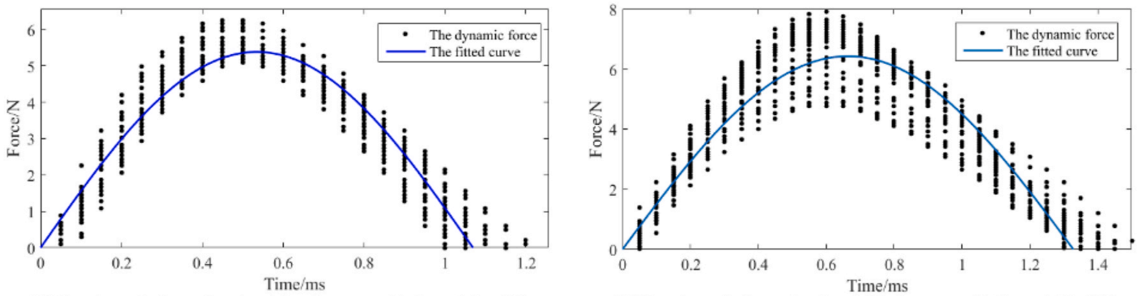
In this study, in order to protect eggshell against the effects of impaction, the material of nylon was selected as the excitation rod. Then, four different weights of excitation rods were designed to explore the influence rules on impulse force width.

During the experiment, 30 impacts were conducted on the eggshell to acquire the response dynamic force signals, and signals that resulted from the same impact rod were served as a dataset. The total number of the dataset was 4. Then the nonlinear least-squares curve fitting method (Johnson, 2008) with 95% confidence bounds was carried out to fit the half sine wave (as defined in Equitation (Deng et al., 2009)) using every dataset.

$$Y = a\sin(bX) \tag{7}$$

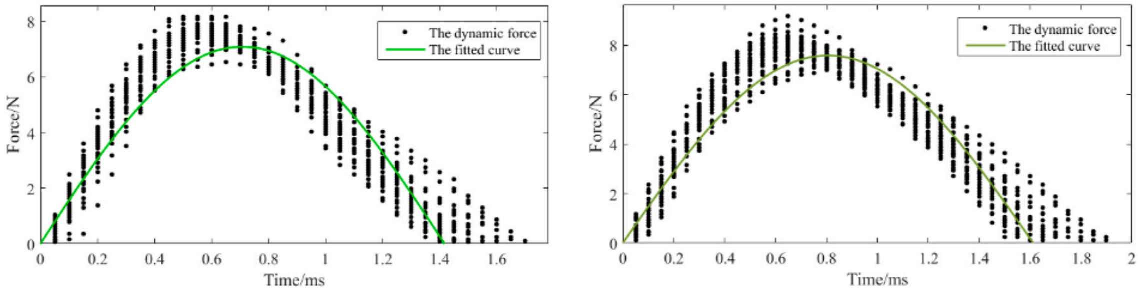
where Y is the dynamic force, X is the time, a and b are two specific coefficients.

Afterwards, the fitting goodness indicators of R-square (R^2) and the root mean squared error (RMSE) were calculated to prove the feasibility



(a) The dynamic force signal and fitted curves with the weight of 32g

(b) The dynamic force signal and fitted curves with the weight of 47g



(c) The dynamic force signal and fitted curves with the weight of 56g

(d) The dynamic force signal and fitted curves with the weight of 64g

Fig. 7. The acquired response dynamic force signals and fitted curves.

Table 2
The fitting models and the performance for different weights.

Weight/g	R^2	RMSE/N	Model
32	0.89	0.61	$Y = 5.379\ \sin(2.937X)$
47	0.86	0.83	$Y = 6.224\ \sin(2.366X)$
56	0.82	1.05	$Y = 7.284\ \sin(2.216X)$
64	0.84	0.99	$Y = 7.373\ \sin(1.948X)$

of the equivalent mechanical model of the transient excitation. Meanwhile, the relationship between τ and m was also explored based on the fitting results.

2.5. Process of the acoustic signal

2.5.1. Analysis of the acquired signals

The typical time-domain response signals from the crack egg and intact egg are shown in Fig. 6. As observed in Fig. 3, three parts were contained in the whole response signals: the impact response signal, the spring-back response signal, and the environmental noise (Zhang et al., 2017). There were about 250 sampling points in the impact response signals produced by the transient impact when nylon knocked the eggshell. As followed, the spring-back response signal with weaker energy, which resulted from the spring-back effect caused by pullback spring, contained about 500 sampling points. Furthermore, the rest of the acquired signals with the amplitude values close to zero were served as environmental noise, mainly circuit noise and background sound.

2.5.2. Data analysis methods

It has been proven that the cross-correlation between two different positioned measurements would be changed while damage occurs in most research works (Mojtahedi et al., 2011; Malekzehtab and Golafshani, 2013; Shahverdi et al., 2013; Ni et al., 2014; Asgarian et al., 2016; Hosseinlou and Mojtahedi, 2016; Diwakar et al., 2018). The basic theory to support cross-correlation function as a damage-sensitive feature is from the Natural Excitation Technique (NExT) (Li and Huang, 2020).

According to the previous studies, several mechanical impacts on the same egg were required to recognize the crack on the eggshell. Meanwhile, the response signals were sensitive to the thickness and stiffness of the eggshell and the impact force, acoustic signal acquisition sensors. In order to eliminate the individual difference of the response signals, the signals from the first microphone of each direction were selected as the reference signals. Then, the normalized cross-correlation coefficient (NCCC) between the reference and the other seven signals from the same direction were calculated for the eggshell crack detection.

3. Results and discussions

3.1. Analysis of the dynamic force

3.1.1. The fitting of the dynamic force

The acquired response dynamic force signals and fitted curves from the nylon impact heads were illustrated in Fig. 7. Moreover, the fitting models and the fitting goodness indicators of R-square (R^2) and the root mean squared error (RMSE) were listed in Table 2.

It is observed that, although the acquired dynamic force signals from each egg vary, the variation tendencies over the time from the same excitation rod are similar. Furthermore, the amplitude and duration of dynamic force signal increase with the weight of the excitation rod. The fitting models, which were fitted using the data resulted from four different excitation rods, obtained R^2 values of 0.89, 0.86, 0.82, and 0.84, and the RMSE values of 0.61, 0.83, 1.05, and 0.99, respectively. The high R^2 values and acceptable RMSEs indicated that the half-sine wave was a suitable curve model for presenting the response dynamic force signal. In other words, it is also proved that the mechanical model of the transient excitation built in this study is reasonable.

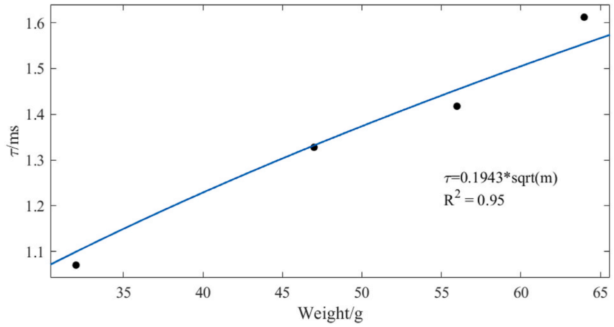


Fig. 8. The fitted relationship between cut-off frequency and weight.

3.1.2. The relationship between cut-off frequency and weight

According to Equitation (Zhao et al., 2009), the relationship between cut-off frequency and weight is given by

$$\tau = \frac{\pi}{b} = \frac{\pi}{\sqrt{k}}\sqrt{m} \tag{8}$$

Based on the fitted models' four coefficients, a curve-fitting equation following Equitation (RongXiong, 2011) was set up to obtain the relationship between τ and m , and the result shown in Fig. 8. A high correlation ($R^2 = 0.95$) was presented, and the coefficient of 0.1943 was adopted.

According to previous studies (Kemps et al., 2004; Perianu et al., 2010), as the egg's inherent frequency is around 3000 Hz, the value of τ should less than 0.5 ms. Therefore, the weight of the excitation rod is calculated as

$$\tau = 0.1943 \times \sqrt{\mathrm{m}} < 0.5 \Rightarrow m < \left(\frac{0.5}{0.1943}\right)^2 \approx 6.62g \tag{9}$$

In the experimental system for eggshell crack detection, the excitation rod's weight is 1.455 g. As a result, the energy of transient impact can cover 6402 Hz and can also meet the requirement of eggshell crack detection.

3.2. Evaluation of discrimination performance

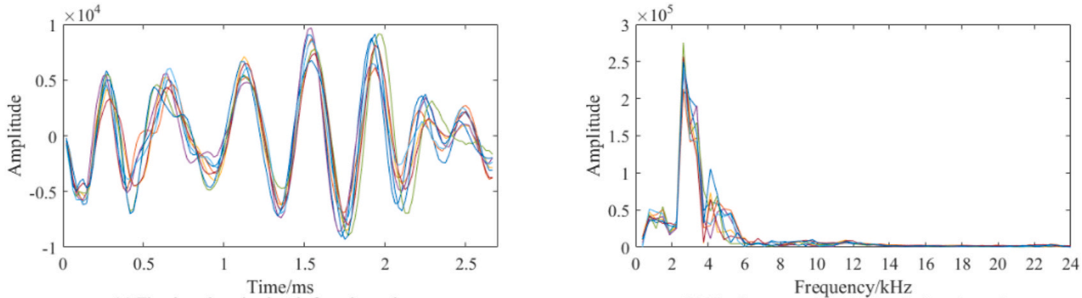
3.2.1. Analysis of the selected acoustic signal

In this study, the zero-crossing measurement method (Waghmare et al., 2012; Zhu et al., 2017) was used to determine the response signals' starting point. And the first 128 sampling points were selected as the interested signals for future processing. The typical time-domain signals and frequency domain signals were displayed in Fig. 9.

As shown in Fig. 9, the time domain response signals from the intact egg have a higher level of consistency than that from the crack egg. There is a slight difference in amplitude among the response signals from intact eggs. At the beginning of the transient impact within the first 0.5 ms, the crack egg's response signals have a similar tendency to the intact egg's signals. After that, the signals from intact eggs keep high repeatability, while the signals from the crack eggs are different from each other. As investigated from the frequency domain, the cut-off frequency of the response signal was about 6 kHz. Furthermore, the dominant frequency of the response signal from intact eggs was 2.6 kHz, while the dominant frequency of the signals from crack eggs were not steady.

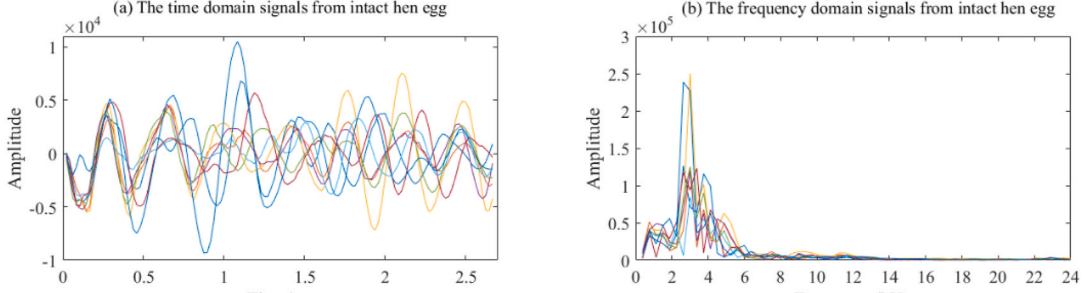
3.2.2. Feature analysis

As one or more impacts were conducted on the crack region, the NCCCs changed in a broader range, and at least one low NCCC could be acquired from most of the crack eggs. As a result, the values of NCCC from intact eggs are always higher than crack eggs. So, the statistical



(a) The time domain signals from intact hen egg

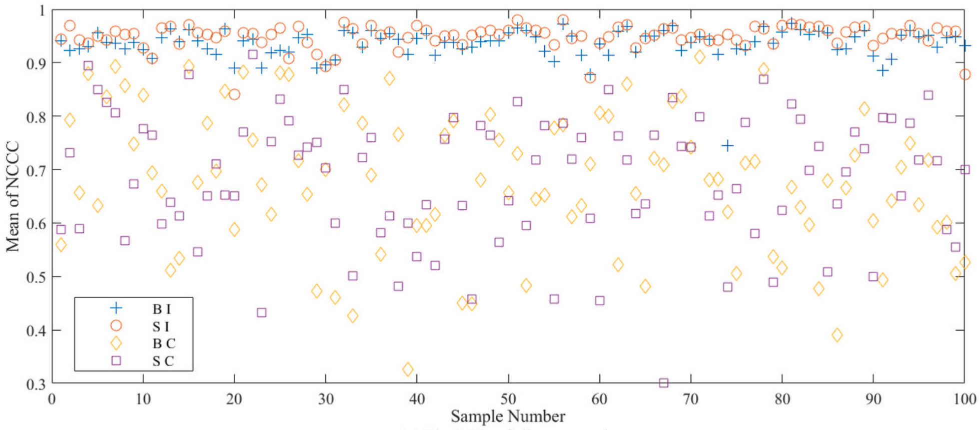
(b) The frequency domain signals from intact hen egg



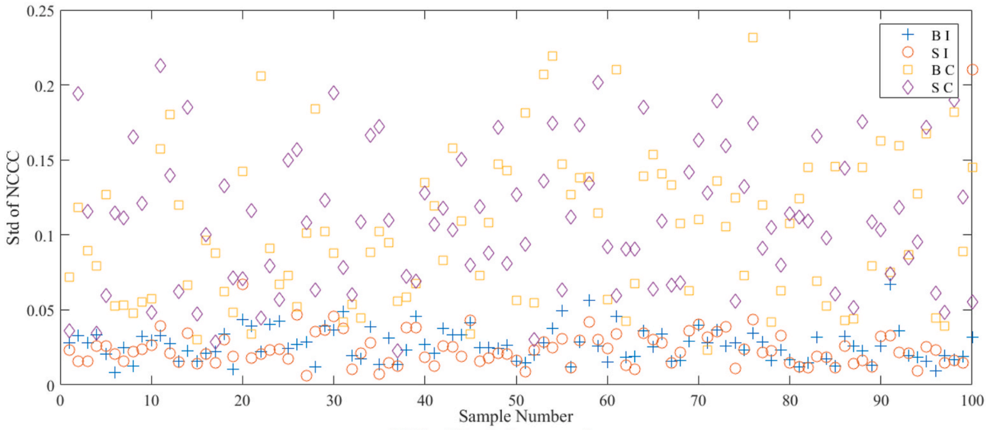
(c) The time domain signals from crack hen egg

(d) The frequency domain signals from crack hen egg

Fig. 9. The typical time-domain signals and frequency domain signals.



(a) The MNs of all egg samples



(b) The SNs of all egg samples

Fig. 10. The statistical parameters of MN and SN.

parameters of the mean value of NCCC (MN) and the standard deviation of NCCC (SN) from each impaction direction of all the egg samples were calculated to distinguish intact eggs and crack eggs, and the results shown in Fig. 10. In Fig. 10, the SI, BI, SC, and BC mean the data from shape end nearby of the intact eggs, blunt end nearby of the intact eggs, shape end nearby of the crack eggs and blunt end nearby of the crack eggs, respectively.

Obviously, most of the MNs from intact eggs are larger than 0.9,

Table 3

The Fisher's linear discriminant functions and classification results.

	Criterion	Direction	Misclassification Label	Accuracy (%)
Intact eggs	$Y1 = 113.839 \times MN + 30.111 \times SN - 54.722$	Shape	None	99%
	$Y2 = 83.241 \times MN + 89.559 \times SN - 33.797$	Blunt	100	
Crack eggs		Shape	**4**, 6, 7, 8, 10, 15, 19, **22**, 25, 26, **32**, 37, 60, 63, 69, 71,78	97%
		Blunt	**4**, 5, 15, **22**, **32**, 61, 68, 96	

while the MNs are scattered from 0.3 to 1 for the crack eggs. On the other hand, as the concentration degrees of NCCCs are high, a majority of SNs from intact eggs are smaller than 0.03. In consideration of the air chamber on the blunt end, the MNs from blunt end nearby of the intact eggs are always lower than that from shape end nearby and the SNs from blunt end nearby of the intact eggs are always higher than that from shape end nearby.

3.3. *Classification performance*

Bayes classification method with input variables of the MNs, and SNs were carried out to distinguish the intact and crack eggs in SPSS v.25. The Fisher's linear discriminant functions and classification results were listed in Table 3. In this study, if both directions from the same egg were recognized as intact, the egg will be classified as in-tact egg. On the other hand, if one or two directions were recognized as crack, the egg will be classified as cracked egg. Evidently, from Table 3, only one intact egg on the blunt shape labeled with the number 100 was misclassified as the crack egg. As some hairline crack closed to the ends, there are 17 crack eggs on the shape end, and 8 crack eggs on the blunt end were misclassified into intact. However, only three eggs, labeled 4, 22, and 32 were misclassified into intact eggs. As a result, the classification accuracies of intact eggs and crack eggs can reach 99% and 97%, respectively.

4. Discussion

This work presents a novel method for eggshell crack detection based on the transient impact analysis and cross-correlation method. Firstly, an equivalent mechanical model was built to analyze the transient impact process. It was found that the impact speed affected only the impaction energy, while the material of the impact head and the weight of the excitation rod determine the energy and the cut-off frequency of the impaction. Based on the self-designed automatic excitation device, four excitation rods with different weights were used to generate the transient impacts on the eggshell. The acquired dynamic force signals were used to fit the half-sine waves. The high R^2 values (0.89, 0.86, 0.82 and 0.84) and acceptable RMSEs (0.61, 0.83, 1.05 and 0.99) indicated that the assumption of the mechanical model was reasonable. Combined with the result of power spectrum analysis, when the weight of impact tup less than 6.62 g, the cut-off frequency of excitation impact can cover the inherent frequency of the egg. Finally, an experiment system was designed to generate and acquire the response acoustic signals by impaction on eggshell. The cross-correlation analysis method of signals from the same direction of each egg sample was proposed to get the normalized cross-correlation coefficient (NCCC). The statistical parameters of the mean value of NCCC (MN) and the standard deviation of NCCC (SN) were calculated and used as the input variables to Bayes classification method. In the conducted experiments, a crack detection level of 97% and a false rejection level of 1% were achieved.

As compared with other studies on eggshell crack detection application, this study's advantages mainly represented as follows: firstly, exploration of the transient impact process by the mechanical analysis; secondly, enhancing the sensitivity of the response signal to the crack on eggshell, and cross-comparison method with the consideration of remarkable influence factor. It can be concluded from the findings, that the proposed method would assist in optimizing the impact device and simplifying the classification algorithm for an online detection system.

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Data availability statement

Research data are not shared.

Ethical approval

Ethics approval was not required for this research.

1. Synchronous belt module; 2. Excitation tup; 3. Stainless steel shrapnel; 4. Dynamic force sensor; 5. Egg; 6. Egg support; 7. Power supply; 8. Stepper motor; 9. Charge-amplifier; 10. Data Acquisition Card; 11. Motor driver; 12. DSP; 13. Personal Computer; 14. Serial port line.

CRediT authorship contribution statement

Li Sun: Data curation, Methodology, Software. **Pengqi Zhang:** Investigation, Writing – original draft. **Siyu Feng:** Software, Validation, Visualization. **Min Qiang:** Supervision, Conceptualization. **Jianrong Cai:** Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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