Comparative study of acoustic signals of rolling eggs on inclined plate and impulse response in eggshell crack detection

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Abstract: The potential of acoustic signals of rolling eggs on an inclined plate and impulse response for nondestructive detection of eggshell crack was investigated. Discriminations of hairline cracked and star cracked eggs from intact ones were carried out using artificial neural network. Ten features were used based on one-way ANOVA F-test statistics. According to the result, holdout detection accuracy of the inclined plate and impulse response methods were 92.3% and 94.6%, respectively. The results indicated that these two methods were potentially useful for discrimination of eggs according to detection of different eggshell cracks.

Keywords: eggshell crack, inclined plate, impulse response, neural network, classification

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1 Introduction

Microbial pathogens can easily invade cracked eggshell and cause problems for table egg quality and safety (Attar and Fathi, 2014). On the other hand, cracked eggs significantly influence the hatchability rates and cause economic loss (Barnett et al., 2004). The first and most important egg quality criterion for the egg industry and its consumers is intact shell (Nedomová et al., 2009). Six to eight percent of the total production of eggs are often cracked and damaged (Eissa, 2009). Therefore, systematic identification of egg defects such as eggshell cracks is one of the main concerns of egg industry.

Gross cracks, hairline cracks, and star cracks account for major eggshell damages (Devegowda and Ravikiran, 2008). Gross cracks are large cracks and holes that usually cause shell membrane to break (Arivazhagan et al., 2013). As the age of the hen rises, more gross cracks occur. They happen in one to five percent of the total production (Cutts et al., 2007). The birds themselves and any sharp protrusions coming into contact with the egg can cause gross cracks (Gupta, 2008).

Generally, hairline cracks run lengthwise along the shell (Arivazhagan et al., 2013). Since it is difficult to detect hairline cracks, it is necessary to maximize candling efficiency. Varying with flock age, incidence of this problem is usually one to three percent of total production (Cutts et al., 2007). Hairline cracks often form as a result of an egg hitting an inflexible surface (Gupta, 2008).

As fine cracks radiating outwards from a central point of impact, star cracks often slightly indented (Arivazhagan et al., 2013). Their incidence usually varies from one to two percent of total production with flock age (Cutts et al., 2007). They are often visible under normal light, but they are more easily seen during candling. Star cracks often form as a result of collision between eggs (Gupta, 2008).

Eggs that have completely broken shells are often removed from incubation due to the high probability of egg dehydration and in order to prevent bacterial contamination. Given difficulty of diagnosis or economic conditions, however, eggs with hairline cracks and star cracks are usually included in the incubation process (Khabisi et al., 2012).

Due to the remarkable ratio of cracked eggs to the total product, techniques to enhance the breeding of

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hairline cracked eggs have recently been focused on in different studies (Narahari et al., 2000). Studies indicated that hatchability results could be improved by covering broiler breeder eggs with hairline cracks with nail polish (Simsek and Gurses, 2009).

Therefore, both intact eggs discrimination from cracked ones and detection of cracks types are equally important. It is shown that hairline and star cracks have different impacts on incubation parameters and chick quality (Khabisi et al., 2012).

Image processing (Leiqing et al., 2007; Li et al., 2012) and acoustic response (Wang and Jiang, 2005; Zhao et al., 2010) were proposed in the past as nondestructive techniques to determine eggshell cracks. The acoustic technique is known as the most widely employed nondestructive detection method for evaluation of the texture of agricultural products (Zhang et al., 2014). This method is based on measuring the sound emitted by agricultural product as it vibrates while being gently tapped with a small pendulum or hammer.

Most previous studies focused on utilizing different algorithms and techniques to classify eggshell cracks. Consistency within a single product, the measurement speed, the instrumentation cost and the required sorting efficiency are among criteria for selecting techniques (Nys et al., 2011).

A new technique has been proposed for separating cracked and intact eggs from each other. Using this technique, crack in the eggshell can be detected by rolling eggs on a plate that has seven steps. This technique is simpler and cheaper than other techniques, through which 90% of the cracks with a 10% false rejection can be detected (Jin et al., 2015).

This research was carried out to evaluate the feasibility of the acoustic signals of rolling eggs on inclined plate to classify eggs according to the different eggshell cracks detection. Comparison of results from the inclined plate (IP) and the impulse response (IR) was another objective of this study.

2 Materials and methods

2.1 Egg samples

A total number of 438 fresh intact eggs, which were inspected individually by candling, were collected naturally from a commercial poultry farm. Eggs were maximal 3 days old when they arrived at the laboratory. The mass of eggs ranged from 40.3 to 81.8 g with an average of 53.1 g and standard deviation of 4.3 g. Irregular eggs were not incorporated in the data analysis.

The samples were divided into intact, hairline cracked and star cracked subsets. The cracks of the eggs were made deliberately. To create a hairline crack, an inclined plate with a length of 15 cm and an angle of 10° were used (after preliminary tests). At the end of the plate, an inflexible wall was built. The samples were released on the inclined plate that collided with the end wall and hairline crack in perpendicular to the egg equator was created. This crack type was only visible with a candling lamp.

In order to create star crack, preliminary tests were performed using a pendulum with a hollow metal ball on the end. 50 g metal ball released from rest at the initial angle of 45° and collided with the samples. Star crack was visible without the aid of a candling lamp.

Figure 1 shows eggshell crack types using two methods. These two images were obtained using candling. Finally, 146 intact eggs, 146 hairline cracked eggs and 146 star cracked eggs were used in the experiment.

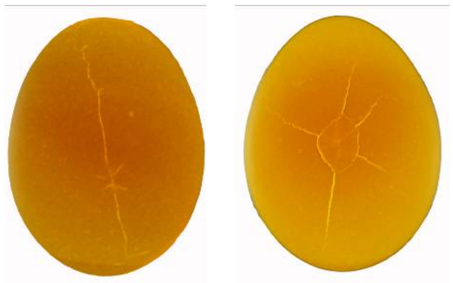
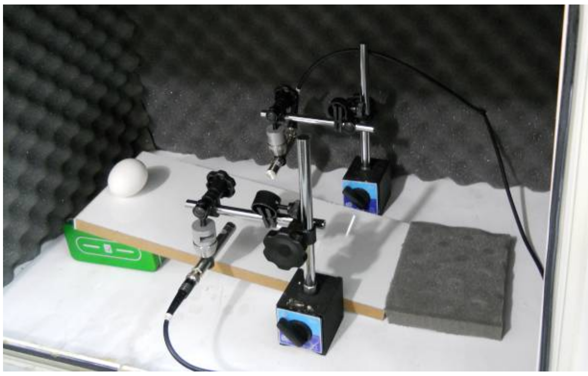


Figure 1 Typical eggshell crack types, (left) hairline crack and (right) star crack

2.2 Acoustic measurements

According to Figure 2 (left), a smooth veneered MDF plate of length 35 cm was placed into acoustic box at inclined angle of 10°. A microphone was installed a few millimeters from the surface of the plate on the middle of path to collect sound signals made by eggs rolling down.

According to Figure 2 (right), the microphone located a few millimeters from the surface of the sample and was positioned at 180 degrees from the point of impact. The impact device consisted of a pendulum with a plastic ball on the end. The test was performed using an instrumental free falling plastic mass (3.3 g) with a 17 mm diameter spherical head. The impact tests were made with drop height of 95 mm.



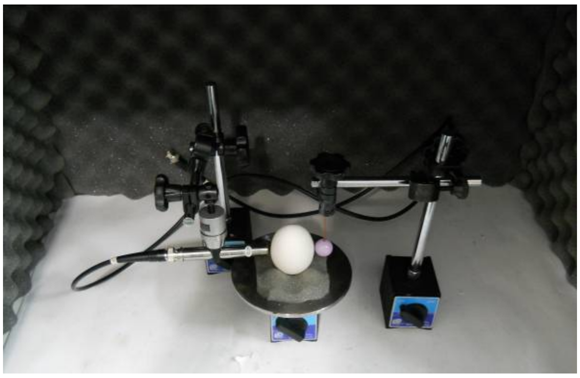


Figure 2 Experiment setup, IP (left) and IR (right)

In this study, used equipment for measuring the acoustic signals of eggs was: microphone model MA231, amplifier model MP201 and data acquisition system model MC3022 that all of them are made by BSWA. The considered microphone is a type 1. The received signal saved on a desktop computer, using Scope V1.32 software. Before beginning the measurement, microphone was calibrated by calibrator model CA111, which creates 94 dB the constant sound level in a pure frequency 1 kHz. Calibrator should be selected the type 1 because the selected microphone was type 1.

2.3 Feature extraction

Fifteen characteristics points of the frequency spectrum, presented in Table 1, were used for the classification. These statistical parameters are easy to compute and widely used in diagnostics issues. Using these parameters as input to the classifier is supported in previous studies (Ebrahimi and Mollazade, 2010; Jalali and Mahmoudi, 2013; Omid, 2011).

Table 1 Features and their formula

No.	Feature	Formula	No.	Feature	Formula
F1	Maximum	$Max = MAX_{i=1}^{N}(x_i)$	F9	Skewness	$S = \frac{E(x_i-\mu)^3}{\sigma^3}$
F2	Minimum	$Min = MIN_{i=1}^{N}(x_i)$	F10	Moment	$M = E(x_i-\mu)^3$
F3	Mean	$\mu = \frac{1}{N}\sum_{i=1}^{N} x_i$	F11	Sum	$Sum = \sum_{i=1}^{N} x_i$
F4	Variance	$V = \sigma^2$	F12	Root Mean Square	$RMS = \sqrt{\frac{\sum_{i=1}^{N}(x_i)^2}{N}}$
F5	Standard Deviation	$\sigma = \sqrt{\frac{\sum_{i=1}^{N}(x_i-\overline{x})^2}{N-1}}$	F13	Coefficient Variation	$CV = \frac{\sigma}{\mu}$
F6	Energy	$E = \sum_{i=1}^{N}\lvert x_i\rvert^2$	F14	Crest Factor	$CF = \frac{Max}{RMS}$
F7	Power	$P = \frac{\sum_{i=1}^{N}\lvert x_i\rvert^2}{N}$	F15	Dynamic Range	$DR = \frac{Max}{Min}$
F8	Kurtosis	$K = \frac{E(x_i-\mu)4}{\sigma^4}$			

2.4 Feature selection

Removal of irrelevant or redundant features and improvement in recognition accuracy for all classifiers are major role of feature selection (Unay et al., 2011). ANOVA test can be run as the feature selection for problems where the input is constant and the output is categorical such as multiclass classification problem (Guyon et al., 2008). Therefore, unimportant attributes from the dataset using IBM SPSS modeler 14.2 software are skipped by using feature selection method based on one-way ANOVA F-test statistics. In this method, features are ranked by sorting according to the ascending order of P value. If ties occur, sort by F in a descending order, and if it still ties, sort by number of cases in a descending order (IBM SPSS Modeler, 2011).

Prior to designing a classifier as a precaution, data normalization is a useful step that is often adopted when the feature values vary in different dynamic ranges. When normalization is absent, features with large values have a stronger effect on the cost function in designing the classifier. Values of all features have been limited within predetermined ranges using data normalization (Theodoridis et al., 2010). In this study, the sample data are normalized to make samples in the range from 0 to 1.

2.5 Classification

The Artificial Neural Network (ANN) is a mathematical model which is derived from biological neural systems. The ANN is a massively parallel distributed processor that is able to model complex relationship between inputs and outputs or recognizes patterns in dataset. Tasks involving grading, sorting, and identifying agricultural products usually involve the conditions of ANN (Jayas et al., 2000).

The ANN used in this research was a multilayer perceptron (MLP) with three layers. The ANN model was obtained using the default optimal back propagation algorithm implemented in IBM SPSS Modeler. This algorithm builds a network with one hidden layer and automatically computes the best number of neurons in the hidden layer (IBM SPSS Modeler, 2011). The input layer consisted of ten neurons representing selected features. The output layer had three neurons, which corresponded to intact, hairline and star cracked eggs. The hyperbolic tangent activation function and the softmax function are used for the hidden and output layers, respectively (IBM SPSS Modeler, 2011).

The testing sample is an independent set of data records which is used to track prediction error during training so as to prevent overtraining. The holdout sample is another independent set of data records that is used in order to measure the results. The holdout sample has never been used by ANN during the training and testing processes.

3 Results and discussion

3.1 Feature selection

Ranking of features indicated that out of 15 features, 10 features were the most important features related to the eggshell crack detection. Results of feature selection for IP and IR methods are shown in Table 2. Results showed that features such as mean, variance, skewness, moment, coefficient variation and crest factor are important for both IP and IR classification. In addition, kurtosis is unimportant for both of two methods.

Table 2 Ranked features in descending order

IP		IR	
No.	Feature	No.	Feature
14	Crest Factor	13	Coefficient Variation
1	Maximum	11	Sum
9	Skewness	3	Mean
10	Moment	5	Standard Deviation
2	Minimum	12	Root Mean Square
7	Power	4	Variance
13	Coefficient Variation	10	Moment
3	Mean	6	Energy
4	Variance	9	Skewness
15	Dynamic Range	14	Crest Factor

3.2 Classification performance

In order to achieve the optimal performance for the network, several arrangements for the number of neurons in hidden layer were tested. The effectiveness of ANN model is dependent on its accuracy of prediction. Table 3 summarizes the classification accuracy results obtained by ten different networks for IP method. According to the results, the classification accuracy of model and holdout was on average 98.52% and 91.92%, respectively. Among ten selected structures, fifth ANN model including 4 neurons in the hidden layer was found to be the best model for IP eggshell crack classification (Table 3). The reason of this selection is that the accuracy of ANN model 5 for holdout data set was close to the average accuracy.

The accuracies of ten different networks for IR method are summarized in Table 4. As shown in Table 4, the classification accuracy of model and holdout was on average 98.69% and 94.36%, respectively. According to the results, ANN model 7 including 6 neurons in the hidden layer was chosen because the accuracy of this model was close to the average accuracy. Although the holdout accuracies of ANN model 2 and 7 were close to each other, the ANN model 7 has lower neurons in the hidden layer. Decrease in network size and analysis time can be achieved using lower number of neurons in the hidden layer (Amiryousefi et al., 2012).

Table 3 ANN model and holdout accuracies (IP)

Model No.	Input layer neuron	Hidden layer neuron	Output layer neuron	Model accuracy, %	Holdout accuracy, %
1	10	3	3	98.19	90.38
2	10	7	3	98.45	90.38
3	10	6	3	98.45	94.23
4	10	6	3	98.96	90.38
5	10	4	3	98.45	92.31
6	10	5	3	98.19	88.46
7	10	4	3	98.96	94.23
8	10	4	3	99.48	94.23
9	10	5	3	98.70	90.38
10	10	7	3	97.41	94.23
Average				98.52	91.92

Table 4 ANN model and holdout accuracies (IR)

Model No.	Input layer neuron	Hidden layer neuron	Output layer neuron	Model accuracy, %	Holdout accuracy, %
1	10	7	3	97.91	96.36
2	10	10	3	97.65	94.55
3	10	7	3	99.22	96.36
4	10	6	3	99.74	92.73
5	10	10	3	98.43	92.73
6	10	4	3	98.43	92.73
7	10	6	3	98.43	94.55
8	10	9	3	98.43	92.73
9	10	7	3	100	98.18
10	10	5	3	98.69	92.73
Average				98.69	94.36

Therefore, the 10-4-3 and 10-6-3 network topologies were selected as the superior structure for IP and IR eggshell crack classification, respectively. The topologies of selected structure are shown in Figure 3.

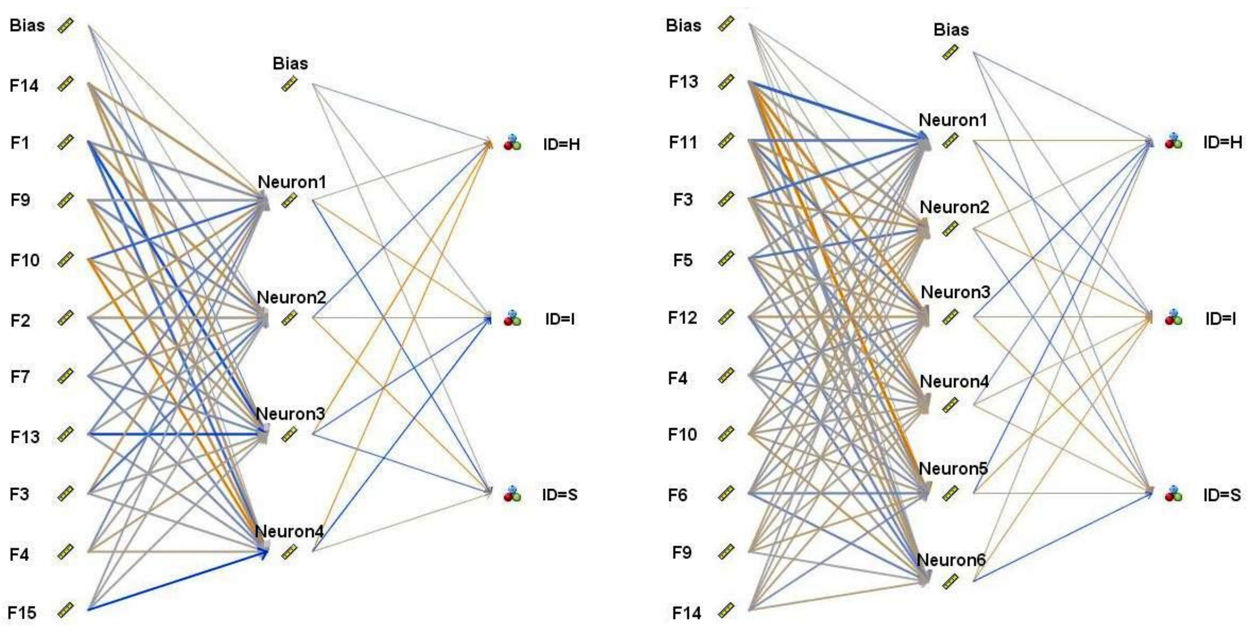


Figure 3 ANN topology, IP (left) and IR (right)

Table 5 shows the confusion matrices of holdout data set for IP and IR method. Confusion matrix shows the IP method could separate star and hairline cracked eggs based on the defining features successfully. In other words, all hairline and star cracked eggs tested were correctly discriminated. But the model has the lower ability to separate intact and star cracked eggs.

As can be observed from Table 5, the detection accuracy of intact and hairline cracked eggs for IR method were more than IP method. There is slight difference between detection accuracy of star cracked eggs of these two methods. Generally, the detection accuracy of IP and IR methods were 92.3% and 94.6% in the holdout set, respectively.

Table 5 Holdout confusion matrices, IP (left) and IR (right)

Actual	Predicted			Actual	Predicted		
	H	I	S		H	I	S
H	90.9 %	9.1 %	0.0 %	H	94.7 %	5.3 %	0.0 %
I	0.0 %	91.7 %	8.3 %	I	0.0 %	94.7 %	5.3 %
S	0.0 %	5.6 %	94.4 %	S	5.9 %	0.0 %	94.1 %

In general, ANN classifier has succeeded in assigning eggs into right classes, but the classification accuracy needs to be improved. Performance of ANN classifier may be further improved using more training data. It should be noted that the success of the classifiers has been compared with the classification results of human experts. A 100% correct recognition accuracy; therefore, it is not expected from a human expert.

As mentioned previously, different algorithms and methods were used in eggshell crack detection. Table 6 summaries result of this study and some of previous studies which used similar methods. These studies all had a crack and intact detection accuracy over 90%.

Among several works introduced in Table 6, study conducted by Jindal and Sritham (2003) yielded the best crack detection accuracy. Table 6 also shows that relatively low accuracy value was obtained for intact detection as conducted by Jindal and Sritham (2003), using 188 features. The computational time and memory requirements for building a predictive model are maximized using a large number of features.

As can be observed from Table 6, IP method of this study yielded the highest detection accuracy of intact eggs. Also, crack detection accuracy of IP method with values of 97.2%, was slightly less accurate than results achieved by Jindal and Sritham (2003).

Table 6 Comparison of different methods used for eggshell crack detection

Method	Egg samples	Number of features	Crack detection accuracy, %	Intact detection accuracy, %	Holdout accuracy, %	Reference
Impulse response and neural network	562	188	98.7	90.0	94.1	Jindal and Sritham, 2003
Impulse response and neural network	260	5	93.2	90.9	92.1	Lin et al., 2009
Impulse response and neural network	500	6	92.0	96.0	94.0	Pan et al., 2011
Inclined step-plate and Mahalanobis distance	240	2	91.7	90.0	90.8	Jin et al., 2015
Inclined plate and neural network	438	10	92.5	91.7	92.3	This study
Impulse response and neural network	438	10	97.2	94.7	94.6	This study

According to Table 6, crack detection accuracies of previous works are higher than intact detection accuracies, except for Pan et al. (2011). The results of this study agree with previous works (Jindal and Sritham, 2003; Lin et al., 2009; Jin et al., 2015). Table 6 also reveals that holdout accuracies obtained with IR methods are higher than those obtained with IP methods. These methods all had holdout accuracy over 90%, therefore, they perform well in egg discrimination.

In this study, holdout accuracy of IR method was about 2.5% higher than IP method. But, accuracy should not be the only criterion for selecting the best method. Simplicity and cheapness of methods are other criteria. It can be concluded that IP method has many advantages like simplicity and cheapness, while IR method is more accurate. Therefore, selecting one of these two methods depends on the request of user. If accuracy is more needed, then IR method is a better choice, otherwise, the user should select IP method.

In future studies, the robustness and generality of these two methods could be compared when they used in a sorting machine.

4 Conclusions

In the present study, the ANN technique was used for classification of eggs in three classes according to detection of different eggshell cracks (intact, hairline cracked and star cracked). A comparative study was carried out on two different methods (IP and IR). Ten features of the frequency spectrum were used for the classification.

The overall results sufficiently indicated that the proposed methods in the current study were effective techniques for detecting eggshell crack in a non-destructive pattern. The analysis indicated that holdout detection accuracy of IP and IR methods were 92.3% and 94.6%, respectively.

In comparison, detection accuracy of IR method was only slightly better than IP method, while the latter one is simpler and cheaper method than the former. Therefore, further research is recommended to provide an improved accuracy of discrimination that can be obtained from data fusion of these two methods.

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