Identification of damaged corn seeds using air-coupled ultrasound

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Abstract: Corn, an important staple in many countries around the world, is subject to a very inefficient germination rate due to worm-damaged seeds. However, air-coupled ultrasound is a rapid, safe and widely accepted method for the early detection of such damage. In this study, the current effectiveness and future prospects of this technique for identifying damaged seeds were explored. The presented procedure started with drawing a sample of 810 seed particles, consisting of 400 that were intact, 400 manually damaged and 10 damaged by worms. Then the principal component analysis (PCA) method was used to reduce the dimensions of air-coupling ultrasonic information and extract the top ten principal components. Finally, a KNN decision tree by using SIMCA software and a Fisher recognition model by using MATLAB software were constructed. The pattern recognition was established by using KNN, which has the most accurate recognition rate. The correct recognition rate of modeling for the front and back data of the intact particles was 98% and 100%, respectively; and for the manually damaged particles, 99% and 97%, respectively. The results show that the model developed by using air-coupled ultrasonic data can classify corn seed particles both with and without holes to provide a basis for the development of a seed selection system, which has a significant role in improving the clarity and the germination rate.

Keywords: damaged corn seed identification, air-coupled ultrasonic, principal component analysis, KNN

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1 Introduction

Corn is one of the most widely cultivated food crops in the biosphere. Worldwide, the land area devoted to planting corn is the third largest, after rice and wheat. The planting range is from latitudes of 58°N to 40°S. It is preferable to cultivate the first generation (self-cross line) of hybrid corn seeds because their parents have diverse and distinguishable genetic traits. The second generation of seeds is not as favorable because of truncated features, which result in a smaller yield. Thus, the first generation is optimal, especially when inbred. Since healthy seeds will yield healthy produce, they must first be evaluated as healthy before they are sown. Clarity is one of the four principal health indicators (along with purity, moisture content and germination rate) used to determine sowing quality and authenticity as well as impact on the commercial value of the seeds. Seed clarity refers to a proportion, i.e., the ratio of normal to total weight, including impurities. According to the crop seed inspection procedures prescribed in "GB3543-1983", the clarity analysis sample test is divided into four parts: (1) good seed, (2) waste seed, (3) impure organic, and (4)

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impure inorganic. During the growing and storage process, some seeds are spoiled by worms, resulting in a decrease in the clarity of the entire batch. Worms most frequently cause irreversible damage to the embryo of seeds, rendering them incapable of germination, thus resulting in their classification as wasted seeds. If these seeds are subsequently mixed with healthy seeds, the quality of the entire batch will be adversely affected and results result in a lower germination rate.

The main clarity processing methods use an air-sieve cleaner and spiral separator. The air-sieve screen cleaner is composed of an air-blast system and a series of screen meshes that use the buoyancy and width or thickness of seeds for cleaning. However, this method is affected by the size and shape of the impurities, the wind velocity and mesh size during the clarity screening process, factors that do not meet the national standard[1,2], let alone filter out damaged seeds. Therefore, a swift and secure screening method which can fulfill the demand of corn seed clarity processing is needed. Several scholars who inspect agricultural products have noted that impacted acoustic emission is the basis for a device that separates pistachio nuts with closed shells from those with split-shells[3]. Also, Onaran et al.[4] developed a prototype system to detect empty hazelnuts by dropping kernels onto a steel plate and processing the acoustic signal generated upon impact with the plate. They found that 98% of filled, developed kernels and 97% of empty kernels were accurately classified. In addition, Smail Khalifahamzehghasem and colleagues[5] developed an intelligent walnut recognition system by combining acoustic emissions analysis, a decision tree and a fuzzy inference system (FIS) that exhibited an overall classification accuracy of 94.7%, thereby indicating that the model can be implemented for separating empty shells from filled walnuts. Another example is that of Mei and Guo[6], who adopted a method based on the combination of a decision tree and fuzzy inference system to identify and classify intact, moth-eaten and mildewed corn particles by using a collision acoustic signal. The accuracy of their experiment was 97.6%, 92.9% and 96.4%, respectively, for each kind of particle. Thus, those findings substantiated the effectiveness of acoustic detection of corn seed damaged by worms. Although this technique provides a new effective approach for seed grading, it should not be used for seed testing and sorting because of accuracy issues.

Air-coupled ultrasound is a rapid and nondestructive testing technology that has acquired high frequency, good direction, strong penetrating power and high precision features. This technology using air as a coupled non-contact medium without the coupling agent also possesses good surface compliance and can identify very thin material. Having consulted recent literature[7,8], gone through germination tests, and ascertained that the seeds used in the tests were indeed irradiated by ultrasound and that the frequency and intensity were identical with the reported identification experiments, we are confident that ultrasonic irradiation was not harmful to the corn seed. Therefore, this method is very appropriate for identifying damaged corn seed particles. Air-coupled ultrasonic testing technology has been extensively used in numerous areas. A number of academics have applied it to the detection of both defective aviation components[9,10] and steel materials[11] and the analysis of material properties. These studies have authenticated the assertion that the precision of defect detection can reach 1 mm[12,13].

In this study, the experiments used the pattern recognition method for detecting and distinguishing damaged maize seeds from intact particles. Pattern recognition has been proved to have been used successfully in material defects testing. Li[14] choose the SVM (support vector base) as a pattern recognition classifier to identify a flat bottom hole and a flat pan, two types of simulated defects, with recognition rates of 90% and 95%, respectively. Both Drai and colleagues[15] and Vieira et al.[16] studied welding defects such as lack of penetration, incomplete fusion cracks and pore identification as well as classification based on ultrasound, with accuracy rates above 85%.

These experimental outcomes assist in the development of a recognition model based on air-coupled ultrasound for detecting and distinguishing corn seeds damaged by worms from intact particles. The goal is to compare and analyze a variety of pattern recognition methods to develop a high recognition rate and decent stability recognition model for seeds damaged by worms.

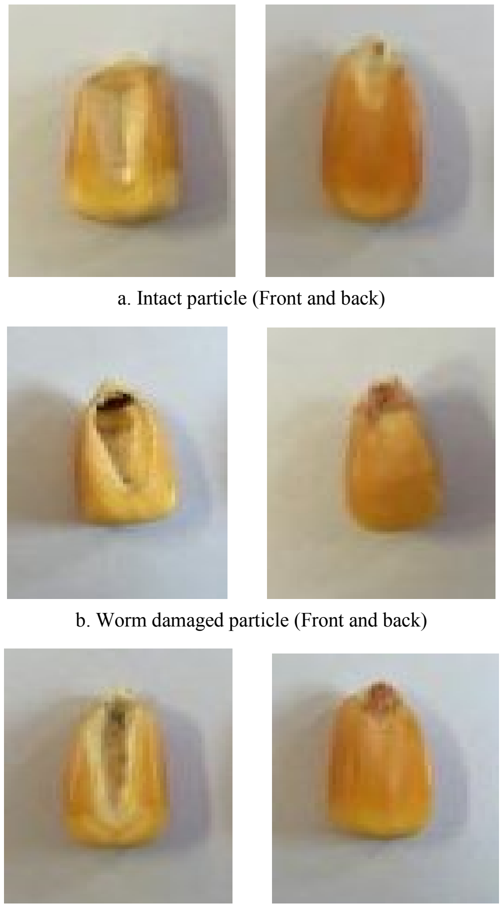
2 Materials and methods

2.1 Samples

Numerous corn seed varieties exist, each of which varies in size, shape and humidity ratio. However, the elastic modulus will have minor transformations, and the level of ultrasonic wave diffraction around the seeds will be assorted. Stored seeds usually need to be processed due to their moisture content being less than 13%. Compared with the difference in ultrasonic signals that is caused by seeds with and without holes, the elastic modulus difference is caused by factors including moisture content differing in range, i.e., less than 13%, as well as variety, and degree of diffraction due to size, all of which have insignificant effect on ultrasonic signals. Moreover, the species are usually detected individually, rather than as multiple varieties mixed together. If different varieties of seeds are used to build the model, it will have an adverse effect on the recognition performance model, in which case a specific model can be created.

All of the 810 stored corn seed particles from the three varieties used in this study were harvested in the Tong Zhou district of Beijing in September. In this study, many seeds with holes should have been used. However, because the amount of available seeds with holes drilled by worms was less, this experiment focused on manually damaged, instead of moth-eaten, particles. The total consisted of 400 intact, 10 worm-damaged and 400 manually damaged particles. The shape of the seeds used was flat in nature, the dimensions having a length of 12-14 mm, a width of 7.5-9.5 mm and a thickness of 3.8-5 mm.

The hole size of corn seeds damaged by worms was different, as well as that in those manually damaged, thus demonstrating that the damaged seeds could be identified regardless of the hole size. The hole sizes of the seed, regardless of how the damage occurred, had a length of 8-9.5 mm, a width of 2.5-3.5 mm and a thickness of 1.5-2.5 mm. Physical diagrams of seed particles are shown in Figure 1.



a. Intact particle (Front and back)

b. Worm damaged particle (Front and back)

c. Manually damaged particle (Front and back)

Figure 1 Corn seed particles

2.2 Data acquisition

The front sides of intact corn seeds are slightly concave; but when there are holes, the front is much more sagged. Therefore, the reflections of the ultrasonic signal from both sides of the seeds are not identical, resulting in inconsistency in the collected signal strength of the transmission wave, which may affect the recognition of seeds. Considering that in practical application the range of seeds is uncontrollable, we observed every seed on both sides, i.e., front and back, to verify that the orientation of the seed would not influence the recognition.

The air-coupled ultrasonic signal acquisition system used in this study is illustrated in Figure 2. The Ultran NCG500-D13 model transducer has a center frequency of 400 kHz and a 40 mm center distance, taking the way of once-receive and once-sent. The first step in the signal acquisition process is to place one seed particle in the focal point of the transducer. To fulfill the placement requirements, a plastic tape layer is inserted between the transducers. Second, use any signal generator (e.g., Tektronix AFG3102) to produce a 12-cycle, continuous sine-wave original excitation signal with a frequency of 400 kHz. Third, use a power amplifier (China: ekNet Electronics Company Amplifier Research 75A250A) to boost the excitation signal (V_{pp}) to 200 V to drive the transducer and transmitter from the seed. Fourth, filter the ultrasonic signal received by the transmitter / receiver with the controlling computer (Panametrics-NDT Model 5900PR produced by Pan American NDT), and increase the gain to 60dB.The A/D conversion of the ultrasonic signal is completed by the NI-5114 card. Thus, the professional analysis software CScan1 on the upper computer can be convenient for acquiring the ultrasonic signal data. The commercial mathematics software Matlab2014a (MathWorks, Inc., USA) was used to simulate the model processes, including de-noising, feature extraction, classification and identification.

Our method included using this acquisition system to collect ultrasonic data from both sides of 810 seed particles (front and rear back), individually, yielding 1620 sets of data having 2048 individual data points to be collected. However, because there was some noise in the collected data, it could not be utilized to develop a model. Therefore, we considered the data points from 1000 to 1400 (listed in Table 1) to shape a model and test its performance. Graphs of the original ultrasonic signals are depicted in Figure 3.

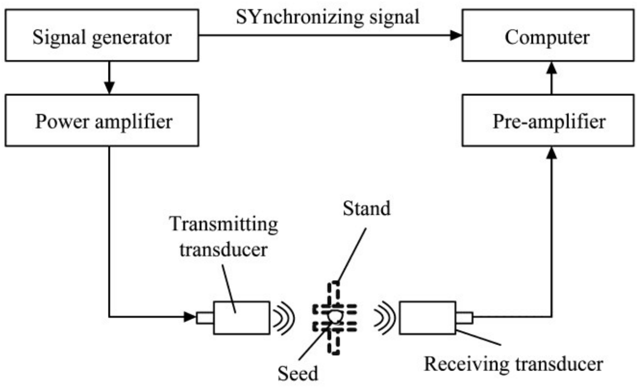
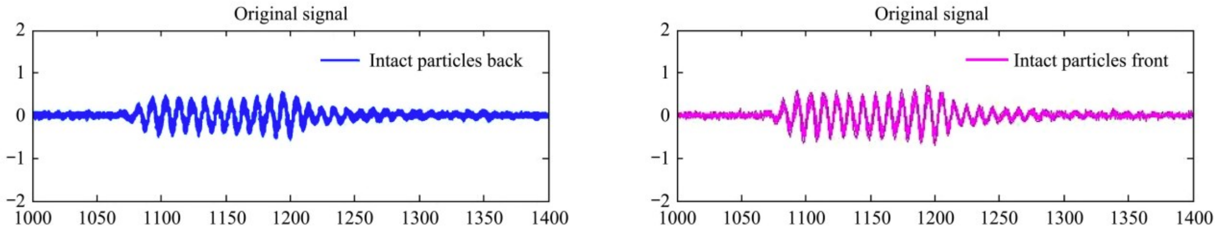


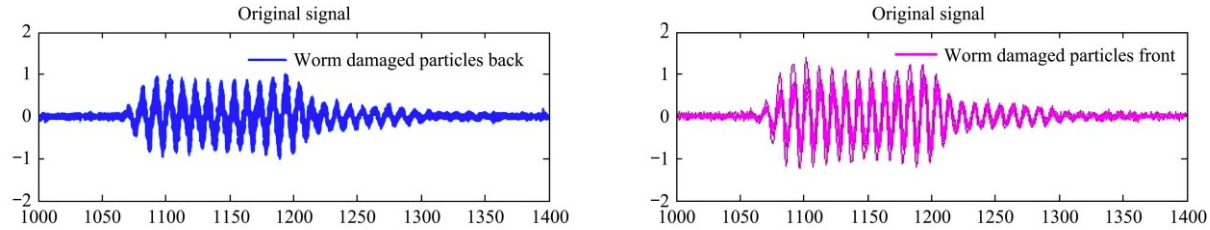
Figure 2 Air-coupled ultrasonic signal acquisition system

Table 1 Acquisition of air-coupled ultrasonic signal numbers of corn-seed particles

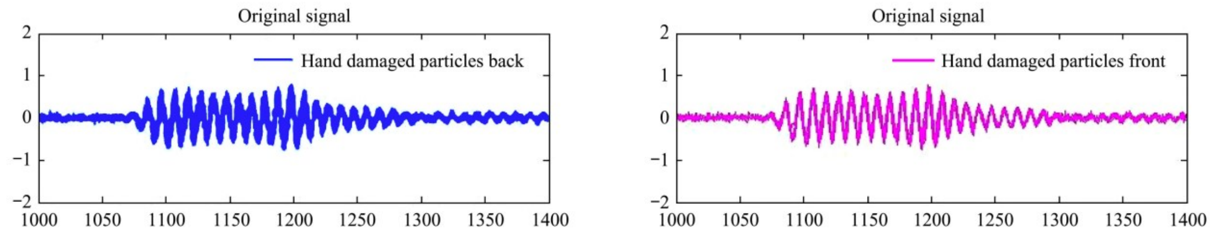
Orientation	Intact particles	Manually damaged particles	Worm-damaged particles
front	400	400	10
back	400	400	10



a. Intact particles



b. Worm damaged particles



c. Manually damaged particles

Figure 3 Original ultrasonic signals of seeds

2.3 Modeling

2.3.1 Noise filtering

The noise from the original air-coupled ultrasonic wave signal will have an impact on the recognition results. Since a single wave can be used to analyze a signal in the time and frequency domains simultaneously, the wave can effectively distinguish the mutation portion of the noise in the signal, thereby de-noising it. In this study, an orthogonal structure and compactly supported Daubechies wavelet were used to reduce the signal noise. We used a Db4 wavelet to decompose the signal into five layers to obtain a set of wavelet coefficients; then, we thresholded the coefficient to obtain the estimated coefficients to make the difference between estimated and wavelet coefficients as small as possible and finally use the estimated coefficients to reconstruct the signal. After de-noising, the signal to noise ratio (SNR, SNR=20lg (*PS*/*PN*), with *PS* and *PN* representing the effective power of the signal and noise) was increased from 7.15 to 23.06. The de-noised data were then used as input for the feature selection.

2.3.2 Feature selection

The principal component analysis (PCA)[17,18] method was adopted to reduce the dimensions of the air-coupled ultrasonic information. In this study, the ultrasonic signal data acquired consisted of 2048 d, an excessive and overlapping quantity. This redundant information had insignificant value in the experiment. As graphically plotted in Figure 4, after the feature was sorted, more than 97% of the primary data were retained in the top ten principal components; hence, those top ten were extracted in this experiment. This extraction can make the data of high-low-dimension space conducive for analysis and for reducing the loss of information.

2.3.3 Classification methods

In this experiment, four statistical pattern recognition methods, namely, the Nonlinear K-neighbor（KNN）, SIMCA, linear Fisher Distinguish and Decision Tree cluster[19], were applied to build recognition models for corn seeds having holes and worm damage The collected data possessing extracted features were used to build four recognition models by the aforementioned methods, respectively, in KNN, *k*=4. The model prediction performance was evaluated by a correct recognition rate, defined as the number of samples in the correct identification /the number of the sample which should be identified×100%.

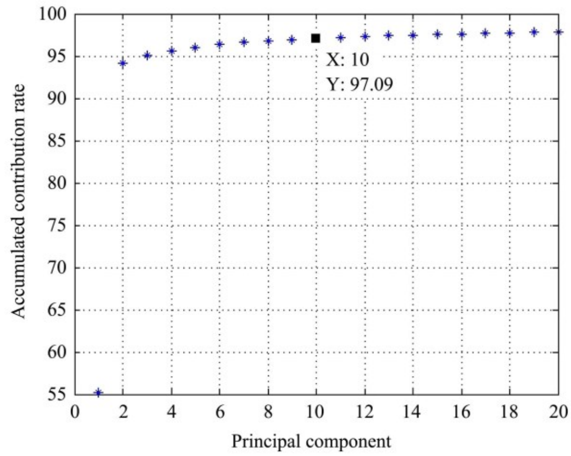


Figure 4 Accumulated contribution rates of prior 20-dimensional principal components

3 Results and discussion

3.1 Comparison of manually and hand-damaged particles

In considering the difference between manually and worm-damaged seed particles, it was hypothesized that this model was incapable of identifying particles drilled by moths because the model is based on identification of manually drilled particles.

Front and back ultrasonic signal data were collected from one hundred particles with hand-drilled holes and ten moth-eaten particles, after which the signals data were de-noised and the first ten-dimensional features finally extracted by using PCA. Obviously, one may observe that the front and back data of both hand-drilled and moth-eaten particles are mixed together in the PCA features space (Figure 5).

Thus, it has been demonstrated that the difference between moth-eaten and hand-drilled particles of the same variety are indistinguishable, exhibiting almost no effects on the results. Therefore, the manually drilled particles could be replaced with moth-drilled which became the basis for follow-up in this study.

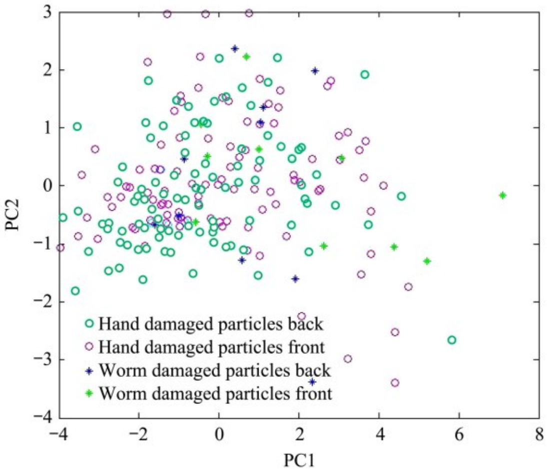


Figure 5 Spatial distribution of manually and moth-damaged particles in PCA

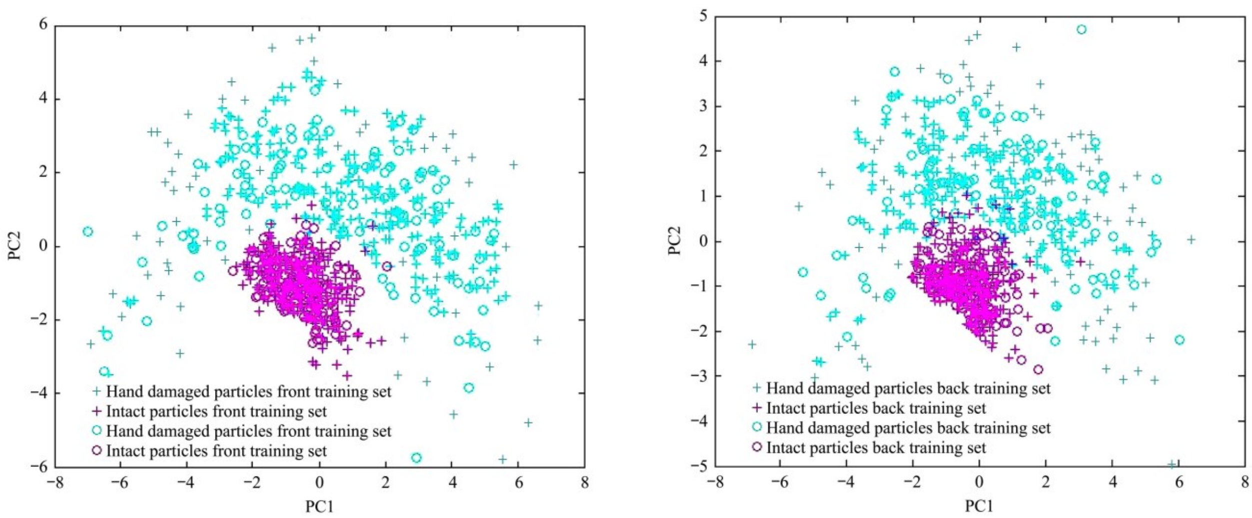
3.2 Comparative analysis of recognition models

3.2.1 Each side of data model

The structure of the recognition model consisted of choosing intact and manually damaged seeds to obtain front-side air-coupled ultrasonic signal data from 300 pieces, respectively, yielding a total of 600 pieces of data for a training set. The data was used to set up four kinds of recognition models. We obtained positive air-coupled ultrasonic signal data from 100 pieces of intact and manually damaged seeds, respectively, producing a total of 200 pieces of data as an experimental set to test the correct identification rate of the model. Then, the experimental set underwent the same de-noising and feature extraction processing regarding front-side ultrasonic data of intact and damaged particles, and vice versa.

The PCA spatial distribution of data from each side of the particles with hand-drilled holes and the intact particles is graphed in Figure 6. In addition, the minority particles exhibited a clear boundary between ultrasonic data, whether from the front or the back of the vast majority of both intact and damaged seeds. Therefore, the ultrasonic method can distinguish between intact and hole-damaged seeds. The difference between different particles of the same variety is greater than the difference between the front and back signals from the seeds. These results thus suggest that intact particles can be separated from damaged ones.

The intact and damaged particles were classified by the four identification methods listed in Table 2.



a. Front side b. Back side

Figure 6 PCA spatial distribution of data from each side of particles with manually damaged and intact particles

Table 2 Identification results from different models for data of each side Unit: %

	Identification method	KNN		SIMCA		Fisher		Decision tree	
		Intact	Damaged	Intact	Damaged	Intact	Damaged	Intact	Damaged
Correct recognition rate	Front	98	99	99	90	99	90	94	87
	Back	100	97	100	96	100	96	93	92
	Average	99	98	99.5	93	99.5	93	93.5	89.5

From the table, it can be concluded that the KNN, SIMCA and Fisher identification models have better prediction results, especially for the data pertaining to the back side of intact particles. The correct recognition rate is 100% for all sets. Compared with the other three methods, the KNN obtained the best recognition rates. The correct recognition rates for each side of both the intact and the damaged particles are greater than 97%, rendering the model more reliable. The correct rate of the model based on the decision tree is less than that of the others, being 87% for the front side of the damaged particles. However, it remains to be proved that air-coupled ultrasonic technology is feasible to use for the identification of corn seed particles, whether intact or holes damaged.

3.2.2 Modeling by two-sided seed data

In the actual production application of corn-seed clarity processing, the model is used to identify the damaged seeds from a large amount of seeds where the orientation is uncontrollable; hence, building a model that can identify seeds, regardless of the orientation is needed. The evolution of the identification model process is as follows: (1) Select a sample of 300 seed particles consisting of 150 intact and 150 hand drilled; (2) Follow the air-coupled ultrasonic signal data on both sides of the elements of the selected sample, to obtain a total of 600 pieces of data to be used for establishing four kinds of recognition models; (3) Choose another sample consisting of 100 particles drawn equally from intact and hand-drilled; (4) Replicate the aforementioned trial; (5) Total the data on 200 particles to experiment test the performance of the model; (6) Collect the statistical data from the correct recognition rate model of intact and holed particles, respectively.

The PCA spatial distribution of the front and back side data for both damaged and intact particles is shown in Figure 7. As listed in Table 3, KNN can be considered as the preeminent pattern recognition method, the model of which has higher factual recognition rate for the ultrasonic data from the intact and damaged particles.

3.2.3 Comparative analysis of models

According to Tables 2 and 3, the data for the seeds taken from either side are either separate or hybrid. The correct recognition rate of the KNN model for intact and damaged particles is the most precise among the four methods. This result is supported by the argument[20] that the KNN recognition method uses the factual information of all the known points while making judgments; therefore, the recognition effect will be better than with other methods.

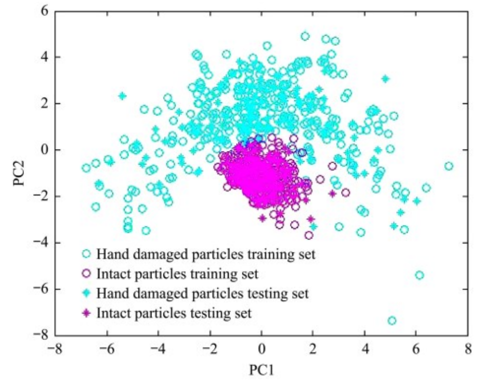


Figure 7 Spatial distribution of manually damaged and intact particles in PCA

Table 3 Recognition results for different models Unit: %

Identification method	KNN		SIMCA		Fisher		Decision tree	
	Intact	Damaged	Intact	Damaged	Intact	Damaged	Intact	Damaged
Correct recognition rate	100	97	99	94	99	94	100	94

As listed in Tables 2 and 3, most of the recognition methods are acceptable for the intact particles. The main reason may be that those particles are similar in shape, size and in embryonic uniformity. Due to the size and the depth of the holes, the difference is relatively large between the damaged particles. Thus, the attenuation of the ultrasonic signals will be different after penetrating into the seed, the difference in the signals causing the distribution of the seed samples at the PCA space to be relatively dispersed. The distance of a small part of the damaged particles from the center is greater than the distance from the intact particles to the center of the model. Therefore, the damaged particles were incorrectly identified as intact seeds, thereby leading to a reduction in the correct recognition rate.

Among researchers engaged in similar studies, Mei and Guo used an impact sound signal to identify intact and insect-damaged particles of corn seeds at accuracy rates of 97.6% and 92.9%, respectively. In our study, the accuracy of the recognition rates for intact and insect-damaged particles was higher than the minimum recognition rates of 3.6% and 5.9%. However, if compared with the model established by the KNN recognition method in this research, the correct recognition rate for both intact and damaged particles is still lower.

4 Conclusions

The results have demonstrated that the model established by using air-coupled ultrasonic data is the best for identifying intact and damaged particles of corn seeds. The pattern recognition established by KNN has acquired the highest average accurate recognition rate and the highest correct recognition rate among the tested models for intact and damaged particles, which may reach 97% and 100%, respectively. Although the precise recognition rate is relatively low for some models, the lowest range is 87% to 93%. The results of this study have great practical significance in the production and processing of corn seeds. Our method can individually pick out the moth-eaten seeds that are mixed among a large number of intact seeds, thereby improving the clarity of the seed and furthering the germination rate. Finally, this method satisfies the detection requirements without damaging the physical and chemical properties of the seeds, thus making it an efficient and environmentally-friendly method.

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