**Application of Statistical Features in Vibro-acoustic Signals to Detect Early Browning Disorder in Pears Compared with Food Chemistry Method**

**Abstract:** Browning in pears is one of the most serious diseases in pear fruit, which is caused by *Alternaria alternata*. The browning process is accompanied by changes in the chemical properties of the fruit, which affect its taste and nutritional composition. Additionally, as a typical postharvest disease, internal browning in pears can cause fruit tissue decay during storage that can reduce the shelf stability of fruit, and bring serious losses to sellers. Because it is difficult to identify the browning pears by appearance, a non-destructive detection technology is highly desirable to correctly discriminate a pear at the early stage of browning for increasing the market value. Firstly, 11 and 7 statistical features were calculated from the time-domain and frequency-domain, respectively. Then, sensitive features in time-domain set, frequency-domain set and combined feature set were selected by the frequency-domain set. These selected features were used to train classifier based on K-nearest neighbor algorithm under different K-values. With the selected combined features adopted, the constructed KNN classifier performed the best classification performance. It allowed a high overall accuracy of 91.8 % to classify the healthy and browning pears. Also, the F1 value of 92.6 % indicated that the classifier can be successfully generalized. Therefore, the classification model established in this study is effective for identifying the early browning disorder in pear fruit.

**Keywords:** Pear; Browning disorder; Feature extraction; K-nearest neighbor; Vibro-acoustic method.

### I. INTRODUCTION

Korla pears (*Pyrus bretschneideri Rehd.*) are extremely susceptible to infection by *Alternaria alternata* (*A. alternata*) [1]. During the growth and storage, A. alternate penetrates the fruit through the calyx, infecting the core area as well as the adjacent pulp, resulting in internal browning disorder. Monitoring and detecting the Pathogenetic process of browning disease still poses significant challenges that mainly due to the symptoms are in no way recognizable from their outer appearance, especially in the early stage. At present, according to commercial practice, the majority of pears are consumed fresh or utilized in the production of processed foods such as juice, fruit wine, puree, and jams [2]. The fruit sellers hope that the damaged fruit caused by *A. alternata* should be discriminated against as early as possible to reduce infection incidence of healthy pears and increase market acceptability. For fruit product industry, some diseased fruits need to be detected to reduce the potential risk of fruit products to customers. Hence, to ensure the safe consumption of pear fruit products, detection of early browning disorder in pears is worth attention.

During the browning process, changes in certain chemical components such as soluble solids content (SSC), titratable acidity (TA), and total sugar in pears may lead to darkened color, bitter taste, and deteriorated flavour, which ultimately affect the quality, nutritional value, and sensory characteristics of the fruit [3]. Multiple studies have concentrated on the specific chemical composition of pear fruit, which have effectively measured parameters such as total sugars, TA and SSC through the application of high-performance liquid chromatography [4]. Additionally, Studies have revealed that healthy and browning fruits possess distinct volatile organic compounds (VOCs), which constitute their unique aroma profiles. These unique fragrances, which can be evaluated through gas chromatography-mass spectrometry, often play a crucial role in the selection of fruits by consumers, even determining their purchasing decision. However, the above detection methods may face challenges due to complex sample preparation and high equipment costs, along with the potential for long analysis times. Further, pre-treatment operations like extraction, elution, or evaporation could result in sample damage. Therefore, an easily implementable, reliable and nondestructive method for detecting such browning pears is highly desirable.

There are several viable candidates for detecting internal disorders of pear fruit, such as time-resolved reflectance spectroscopy, near infra-red reflectance, X-ray CT scans and magnetic resonance imaging [5-8]. Despite their success on a laboratory scale, there has been very little implemented on in-line commercial units.

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because of the expensive and relatively complex equipment and the time-consuming measurement. For the past several decades, vibro-acoustic technology has drawn widespread attention because of its simplicity, rapidity and cost-effectiveness. This method has been successfully applied for nondestructive detection of internal defects in fruit [9-11]. For vibro-acoustic techniques, the main challenge is extracting features that are beneficial for classification and recognition. Lei et al. considered the statistical feature parameters extracted from response signals can reflect the intrinsic properties of materials more comprehensively [12]. Abbaszadeh et al. were the first to introduce this idea for detecting the ripeness of watermelons [13]. They applied eight frequency-domain parameters to effectively distinguish ripe watermelon from unripe watermelon. Except useful in the frequency-domain analysis, it has been demonstrated that statistical features of the time domain are also highly powerful for the ripeness classification of watermelon [14]. Recently, a new idea using the combined features of the time-domain and frequency-domain signals have been proposed and successfully employed to detect different machinery faults [15-17]. Consequently, the time-domain features, frequency-domain features and combination of these two domain features are all available in the classification task problems. However, there is not clear that which domain signal is more suitable for identifying the internal disorders of pears.

Before the extracted statistical parameters are fed into a subsequent classifier, data dimension reduction is highly necessary to be performed because not all these features are equally sensitive to the class target. It is used to eliminate the insensitive features, which can avoid the curse of the data dimensionality and improve the generalization capability of the classifier [18]. Various techniques exist to condense the dimensionality of feature spaces such as principal component analysis [19], independent component analysis [20], genetic algorithm [21], distance evaluation technique [22,23], etc. Given the simplicity and reliability of Distance Evaluation Technology (DET), it is adopted for the selection of the representative features under different browning conditions of pears.

After the sensitive features selection, the identification accuracy for the class target can be further improved by a proper classifier. A frequently used machine learning algorithm named as K-nearest neighbor (KNN) has been proven to be the effective and practical tools in pattern classification problems. Extensive researches have been published that KNN achieves better performance on different data sets within their experiments. Abbaszadeh et al. used the KNN classifier to the ripe and unripe watermelons with a satisfactory accuracy of 95% [13]. Rasyid et al. applied the KNN algorithm to obtain an overall classification accuracy exceeding 93% in discriminating the maturity level of tangerines [24]. In the field of faults diagnosis of machine, Patil et al. and Vishwendra et al. used this algorithm to identify the fault types in reciprocating compressors and ball bearings, respectively [25,26]. The average classification accuracies in both studies were higher than 97%.

In this study, the specific objectives were to: (i) evaluate the feasibility of vibro-acoustic technology with the piezoelectric transducers for the browning disorder in pears; (ii) build KNN classifiers with statistical feature parameters extracted from vibro-acoustic response signals for identifying an early browning disorder in pears; (iii) compare the performance of KNN classifiers with three types of domain features for discriminating the early browning pears.

II. MATERIALS AND METHODS

A. Samples
Pear fruit were harvested at the green mature stage from an orchard at Korla in Xinjiang, China (41°45’ N, 86°5’ E). After harvesting, pears without any visible external damage were immediately transported into a cooling facility (-2 to 0 °C, 85-95 % RH) for storage.

B. Preparation of Pear Samples with Internal Browning
Referred to the method published by Nitta [27], the generations of the pear samples with browning symptom were artificially injected by a spore suspension of the causal agent from the calyx end of a fruit into its core using a syringe. 200 µL spore suspension of Alternaria sp., with a concentration of 2.0×10⁹ mL⁻¹, were inoculated into each of the one hundred randomly selected pears. After treatment, all pears were stored in a chamber (25 °C, 80 % RH) for development of internal disorder until used for further testing. As a control, 100 randomly selected pears were also stored at another same chamber but not do any treatment. During storage, after the fruit removal the chambers should be immediately resealed to reach settled conditions.
C. Assessment of the Internal Browning

In order to inspect the presence of browning symptom visually, pear fruit was cut along the equatorial side. A compact digital camera was used to photograph the cross-section of opened pear. The photographs were obtained from approximately the same position as the transverse slices directly above. With the image-processing software PhotoShop applied, area percentage of browning in pear photograph was calculated for quantitatively determining the extent of disorder development [28].

D. Acoustic Measurement and Signal Acquisition

Our prior research has thoroughly documented the acoustic setup deployed for firmness evaluation of differently shaped pears [29]. With this device adopted, the treatment group and control group of each 10 pears were randomly chosen from the chamber to be conducted the acoustic testing at 12 h intervals. The obtained typical time-domain and frequency-domain response signals from a healthy pear and a browning pear were depicted in Figure 1(a) and (b), respectively.

![Figure 1. Typical (a) time domain and (b) frequency domain response signals of an healthy and browning pear.](image)

E. Feature Extraction

Each pattern is identifiable by a unique set of features that distinguish the specific sample from the rest. The task preceding classification is to determine which features will characterize the pattern that need to be classified in the best possible way [30]. Upon the manifestation of internal anomalies within inspected items, the amplitude and properties of time-domain signals could diverge from those of the normal ones. Moreover, alterations in the frequency spectrum’s characteristics could introduce novel frequency elements and a distinct pattern of convergence.

For a sample, 11 representative statistical feature parameters of time-domain signal were calculated as follows:

1) The mean ($T_1$)

$$T_1 = \frac{1}{n} \sum_{i=1}^{n} x_i$$

where $x_i$ denotes the $i$th sample point within a sampled signal. M signifies the variation in signal amplitude.

2) The root mean square ($T_2$), peak ($T_3$), short-time energy ($T_4$) and square root amplitude value ($T_5$)

$$T_2 = \sqrt{\frac{1}{n} \sum_{i=1}^{n} x_i^2}$$

$$T_3 = \max |x_i|$$

$$T_4 = \sum_{i=1}^{n} x_i^2$$

$$T_5 = \left( \frac{1}{n} \sum_{i=1}^{n} \sqrt{|x_i|} \right)^2$$

They are sensitive to the signal energy and thus imply the dynamic component and intensity of vibration energy of signal.
3) The kurtosis ($T_6$), kurtosis factor ($T_7$), clearance indicator ($T_8$), impulse factor ($T_9$), crest factor ($T_{10}$) and shape factor ($T_{11}$)

\[
T_6 = \frac{1}{n} \sum_{i=1}^{n} x_i^4
\]  

(6)

\[
T_7 = \frac{T_6}{T_2^4}
\]  

(7)

\[
T_8 = \frac{T_3}{T_5}
\]  

(8)

\[
T_9 = \frac{T_3}{n \sum_{i=1}^{n} |x_i|}
\]  

(9)

\[
T_{10} = \frac{T_3}{T_2}
\]  

(10)

\[
T_{11} = \frac{T_2}{n \sum_{i=1}^{n} |x_i|}
\]  

(11)

They indicate the dispersal pattern of the impulse waveform.

Furthermore, the following 7 statistical feature parameters of the frequency-domain response signal are typically defined for use in classification mission:

1) The mean ($F_1$)

\[
F_1 = \frac{1}{m} \sum_{i=1}^{m} y_i
\]  

(12)

where $y_i$ represents the spectral representation of a signal $x_i$, while $f_i$ denotes the frequency associated with the $i$th spectral component. The $F_1$ indicates vibration energy intensity of spectrum.

2) The variance ($F_2$), standard deviation ($F_3$) and kurtosis ($F_4$)

\[
F_2 = \frac{\sum_{i=1}^{m} (y_i - F_1)^2}{m - 1}
\]  

(13)

\[
F_3 = \frac{\sum_{i=1}^{m} (y_i - F_1)^3}{m (F_2)^{3/2}}
\]  

(14)

\[
F_4 = \frac{\sum_{i=1}^{m} (y_i - F_1)^4}{mF_2^2}
\]  

(15)

They represent extent of dispersion or concentration of spectrum.

3) The gravity ($F_5$), mean square ($F_6$) and root mean square ($F_7$)

\[
F_5 = \frac{\sum_{i=1}^{m} y_i f_i}{\sum_{i=1}^{m} y_i}
\]  

(16)

\[
F_6 = \frac{\sqrt{\sum_{i=1}^{m} y_i f_i^2}}{\sum_{i=1}^{m} y_i}
\]  

(17)

\[
F_7 = \frac{\sqrt{\sum_{i=1}^{m} y_i f_i^4}}{\sum_{i=1}^{m} y_i f_i^2}
\]  

(18)

They reflect the location change of dominant frequency band. After extracting features in both time and frequency domains, three types of feature vectors containing rich information about the measured signal are generated. These include sets of features from the time domain, frequency domain, and a combined set from both domains, thus providing more comprehensive data for identifying browning pears. To ensure comparability among
features of varying scales, the data underwent min-max normalization to render them dimensionless before their input into the subsequent classifier.

**F. Feature Selection**

Although all features may identify the browning disorder in pears, they have different sensitivity contributions to the class target. And for a classifier, when all features within a given set are directly utilized by a classifier, it can lead to a significant increase in computational load and a corresponding decrease in identification precision. Before feeding feature set into a classifier, hence, the crucial aspect lies in selecting the sensitive features that distinctly identify the browning pears. Generally, the sensitive features have similar feature values for samples belonging to the same class and significantly different values for different classes. Here, the distance evaluation technology (DET) utilized for selecting sensitive features from feature set. The specific producer of this method has been reported in detail by Yang et al. [31].

Accordingly, the distance evaluation factor $\lambda_j$ value of all the features in each set can be calculated. Then, a ranked feature set in terms of their $\lambda_j$ values was acquired, and the first n features with higher sensitivities can be selected and applied to the further processing.

**G. K-nearest Neighbor Classifier**

The K-nearest neighbor (KNN) classifier was applied in identification of the browning pears. The KNN algorithm is a non-parametric, distance-based and lazy method, which is considered a straightforward yet effective classification technique in the machine learning classification method [32]. The fundamental principle of KNN method is that the samples of the same class tend to cluster together, whereas the outliers are located at a significant distance from their K closest neighbor. This means that KNN algorithm requires a definition of distance between two training samples and a defined threshold (the K-value) for the decision rule [33]. Euclidean distance is widely preferred, and the K-value was determined using a 10-fold cross-validation approach.

When training KNN classifier, the first n sensitive features in each feature set were fed into the classifier (with a predefined K-value) one by one according to the evaluated results of the DET, as depicted in Figure 2. In this study, K-value was considered between 1 and 10, with a step size of 1. When one of the two following termination criteria was achieved, the training process would be stopped. One is that the training accuracy obtained from 10-fold cross-validation is improved to 100%. In this case, the selected feature subset and corresponding K-value can be determined to construct the KNN classifier. The other is that if the training accuracy of cross-validation method does not reach to 100%, all features in the feature set will be inputted in turn. By doing this, the KNN classifier is constructed by selecting the proper feature subset and corresponding K-value with the greatest training accuracy. The discrimination capability of KNN classifier was assessed by using the confusion matrix, which includes recall, accuracy, precision and F$_1$-measure [34].

![Figure 2. The construction method of the KNN classifier.](image)

In the figure 2, 11, 7 and 18 represent the number of statistical features in the time-domain set, frequency-domain set and the combined feature set, respectively.
III. RESULT AND DISCUSSION

A. Determination of the Extent and Number of Browning Pears

Kadowaki et al. pointed out that pears with the browning symptom within the region of seed locule were deemed sellable without eliciting complaints from customers [9]. For preventing healthy pears from being infected, sellers should remove diseased pears at an earlier stage. In this case, we select the pears with browning area higher than 18 % (below the minimum value of the seed locule area) and lower than 30 % as the browning samples (Figure 3). After the experiment, 74 browning pear samples and 89 healthy pear samples are applied for constructing the classifier. In the construction process, 70 % of samples are chosen at random for training data set and the remained 30 % as the testing data set.

B. Selected Features for Inputting to the Classifiers

To reduce the input complexity for the classifiers and avoid the negative impact of the non-sensitive features, the DET was employed for evaluating sensitivity of each feature in the feature set. In order to meet the training rules of the classifier described in section 2.7, all features should be sorted in terms of the $\lambda_j$ values from large to small. Through doing this, minimum number of features that clearly characterize the browning pears can be selected to construct the classifier with the highest identification accuracy and computational efficiency.

All evaluation factors $\lambda_j$ are displayed in Figure 4, where a greater $\lambda_j$ indicates increased sensitivity to browning in pears. For time-domain set, the descending order of features are $T_8, T_{11}, T_6, T_5, T_9, T_8, T_6, T_5, T_3, T_9, T_4, T_7$ and $T_{10}$. For frequency-domain features, their sensitivities are in the sequence of $F_2, F_6, F_7, F_3, F_1, F_4$, and $F_5$. When combining two types of domain features, the sequence is $T_{11}, F_2, T_6, T_5, F_7, F_6, T_1, F_3, F_4, F_1, T_5, T_8, T_5, T_3, T_2, T_4, T_{10}$ and $T_7$.

C. Construction of the KNN Classifiers

After above operations, the initial $n$ sensitive features can be fed into KNN classifier sequentially to train following steps of Figure 3. Table 1 display the outcomes of training results for KNN classifiers using different feature sets and K-values. Obviously, training accuracies of each classifier using three types of feature sets can up to 100 %. Accordingly, the time-domain feature set consisted of the $T_8, T_{11}$ and $T_6$ is determined for constructing

Figure 3. Photographs of the internal disorder in pear fruit. (a), intact equatorial plane of pear fruit; (b-f), those of infected fruit with internal browning.

Figure 4. Distance evaluation factors $\lambda_j$ of all features in each set.
the KNN classifier which belongs to $K = 4$. Using the frequency-domain feature parameters to construct the KNN classifier ($K = 7$), the $F_2$, $F_6$, $F_7$, $F_3$, $F_1$ and $F_4$ can be selected as the appropriate feature set. When applying the combined feature set, the $T_{11}$, $T_6$ and $T_5$ of time-domain signal and $F_2$ of frequency-domain signal are proper to be applied as the classifier input. In this case, the value of $K$ is selected as 5.

<table>
<thead>
<tr>
<th>$K$ value</th>
<th>Time-domain Feature set</th>
<th>Training accuracy</th>
<th>Frequency-domain feature set</th>
<th>Training accuracy</th>
<th>Combined Feature set</th>
<th>Training accuracy</th>
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<tr>
<td>1</td>
<td>$T_8 + T_{11} + T_6 + T_5 + T_3$</td>
<td>99.17%</td>
<td>$F_2 + F_6 + F_7 + F_3 + F_1 + F_4$</td>
<td>99.09%</td>
<td>$T_{11} + F_2 + T_6 + T_5 + F_6$</td>
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<td>2</td>
<td>$T_8 + T_{11} + T_6$</td>
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<td>$F_2 + F_6 + F_7 + F_3 + F_1 + F_4$</td>
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<td>$T_{11} + F_2 + T_6$</td>
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<td>3</td>
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<td>99.17%</td>
<td>$F_2 + F_6 + F_7 + F_3 + F_1 + F_4$</td>
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<td>100%</td>
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<td>99.17%</td>
<td>$T_{11} + F_2 + T_6 + T_5 + F_6$</td>
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<td>$T_{11} + F_2 + T_6 + T_5$</td>
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<td>6</td>
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<td>$T_{11} + F_2 + T_6 + T_5$</td>
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D. Performance Analysis of the Constructed KNN Classifiers

After training, the testing samples were utilized to evaluate classification and generalization performance of constructed classifiers. The classification results of KNN classifiers with the training accuracy of 100 % are depicted in Figure 5. The constructed classifier using the time-domain feature set has a classification accuracy of 87.8 %, which is slightly higher than that of the classifier using the frequency-domain set (81.6 %). This is due to that time-domain signal provides the clear insight about its processing with global characteristics, so as to be effective in accurate identification of the abnormal class compared with frequency-domain features [35]. However, the evaluation ability of single-domain features is limited. Thus, the information of single domain may be not capable to comprehensively and accurately characterize the browning pears. When using combination of these two domain features, overall classification accuracy can reach to 91.8 %. Applying this KNN classifier, 2 healthy pears were wrongly discriminated as browning with an error rate of 7.4 % and 2 browning pears were wrongly discriminated as healthy with an error rate of 9.1 %. Consequently, the combined features can be used as a more proper alternative for improving classification accuracy.
Figure 5. The classification results of KNN classifiers based on the features obtained from: (a) time domain; (b) frequency domain; (c) the combination of time domain and frequency domain.

Generally, the indices “precision” and “recall” were employed to assess exactness and completeness of the classifier, respectively. But they were easily optimized either one separately, so the harmonic mean \( F_1 \) between these two indices was utilized to further evaluate the generalization ability of the classifier. Figure 6 shows the results of precision, recall and \( F_1 \) for KNN classifiers with different feature sets. Among these classifiers, application of the combined feature set stands out while that of the frequency-domain feature set performs worst. It further proves that the combined features are effective in accurate discrimination of internal browning disorder in pear fruit.

Figure 6. \( F_1 \), precision and recall of the KNN classifiers based on the features obtained from: (a) time domain; (b) frequency domain; (c) the combination of time domain and frequency domain.

IV. CONCLUSIONS

Over the last decade, internal browning disorder caused by *Alternaria* species complex has created epidemic over the world. Given that this disorder results in significant economic losses, it has become essential to explore strategies for controlling and mitigating its propagation. The vibro-acoustic technology associated with piezoelectric transducers is employed to detection of the pears with browning area lower than 30 \%. Statistical features are extracted from both the time and frequency domains to construct the time-domain set, frequency-domain set and the combined set, respectively. Then, all parameters in each feature set are sorted according to the sensitivity to the browning pears by the DET. Based on the training rules, the KNN classifiers with the minimum number of sensitive features under different \( K \)-values can be constructed. Finally, the KNN classifiers with training accuracy of 100 \% are employed to discriminate the browning pears.

With the combined statistical feature parameters, the classifier exhibits the highest discrimination accuracy. With \( K = 5 \), combined feature set consisted of the \( T_{11}, T_6 \) and \( T_5 \) of time-domain signal and \( F_2 \) frequency-domain signal is used as the classifier input. Applying the classifier, an overall accuracy of 91.8 \% can be obtained. Also,
high $F_1$ value (92.6 %) verifies that the constructed KNN classifier has better generalization ability. Therefore, the vibro-acoustic method associated with the statistical features and KNN classifier is effective and promising for detecting the pears at the early stage. These findings offer a theoretical foundation for the industrial implementation of real-time in-line detection and automatic grading of internal disorders in pear fruit.

**REFERENCES**


