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Discrimination of Golab apple storage time using acoustic impulse response and LDA and QDA discriminant analysis techniques

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ABSTRACT- Firmness is one of the most important quality indicators for apple fruits, which is highly correlated with the storage time. The acoustic impulse response technique is one of the most commonly used nondestructive detection methods for evaluating apple firmness. This paper presents a non-destructive method for classification of Iranian apple (*Malus domestica Borkh*. cv. Golab) according to the duration of storage. Several data preprocessing methods were tested: normalization, detrending, Savitzky-Golay smoothing, first and second derivatives, multiplicative scatter correction, standard normal variate and moving average. It was observed that the maximum average F_{β} value of classification on the test dataset (0.84) belongs to non-preprocessing. In this study, principal component analysis (PCA) technique was performed to determine the key variables that explain most differences in the spectra. Seven principal components were used to calibrate linear discriminant analysis (LDA) and quadratic discriminant analysis (QDA) classifiers. The classification accuracy for LDA and QDA models were about 80.56% and 83.33%, respectively. The results indicated that the acoustic impulse response method is potentially applicable for the detection of apple firmness.

INTRODUCTION

All agricultural fresh crops are living organisms, even after harvest, and they must remain alive and healthy until they are either processed or consumed. The energy needed to continue living comes from food reserves in the product itself by respiration process. Product temperature has the greatest influence on respiratory activity. Rapid and uniform cooling, as soon as possible after harvest to remove field heat, is critical in lowering the respiration rate. This reduces the rate of deterioration, and helps provide longer shelf life. A rule of thumb is that a one-hour delay in cooling reduces a product's shelf life by one day (Florkowski et al., 2009).

In Iran, apples were grown on 134000 ha in 2012, yielding a total of 1700000 tons. About 76 million tons of apples were grown worldwide in 2012 and Iran is the seventh-leading producer, with more than 2.2% of world production (FAO, 2012).

"Golab" is one of the most commonly grown apple cultivars in Iran. This cultivar is grown in different regions of country but suffers from relatively short storage life, and consequently is available only during the apple season in June to September (Hajizade et al., 2008). The fresh apples are often firm, crisp and juicy, but the flash of a fresh apple gradually deteriorates and becomes soft, dry and mealy during storage.

Agricultural crops and food products quality inspection is based on two external and internal quality assessments (Alfatni et al., 2008). External characteristics such as shape, size and external defects can be easily detected but internal characteristics such as tissue texture cannot be detected by merely examining the fruit's external characteristics (Alfatni et al., 2008). Textural characteristics of fruits are defined by crispness, juiciness, hardness and firmness (Harker et al., 2003). Consumers regard these characteristics as aspects of fruit's freshness (Peneau et al., 2007). Among them, the firmness is very important (De Belie et al., 2000; Kim et al., 2009).

Texture of apples can be judged by a sensory panel. But sensory analysis is expensive and limited to a small number of samples because it employs humans as sensory instruments. Moreover, it cannot be used for measuring quality properties in real time, an aspect particularly important for agricultural products (Corollaro et al., 2014).

More objectively, texture of apples can be assessed by different destructive or non-destructive measuring devices. However, most destructive methods are inefficient and time-consuming and are not suitable for being implemented on in-line classification machines.

The demand for high-quality fruit calls for reliable and rapid sensing technologies for the nondestructive measurement and sorting of apples (Mendoza et al., 2014). Over the past decades, considerable work has been carried out on the development of nondestructive methods for the measurement of fruits firmness (Garcia-Ramos et al., 2003; Khalifa et al., 2011; Lu, 2007; Mendoza et al., 2014; Peng and Lu, 2008; Ruiz-Altisent et al., 2010). The acoustic technique is the most commonly used nondestructive detection method for evaluating the texture of agro-products (Zhang et al., 2014).

Analysis of the acoustic fruit response to mechanical impulse in the frequency domain detects internal properties of the whole fruit, including firmness (Shmulevich et al., 2003). The acoustic response method is based on the measurement of the sound emitted by a fruit as it vibrates in response to a gentle tap with a small pendulum. The signal is captured by a microphone, and the principal frequency of vibration is then calculated by means of a fast Fourier transform (Studman, 2001). Moreover, acoustic response method has the advantage of being compatible with several types of transducers and analysis techniques (Macrelli et al., 2013).

The objectives of this research were:

- To evaluate the feasibility of the acoustic impulse response for the discrimination of apples based on the duration of storage,
- To compare the classification results obtained by the linear and quadratic discriminant analysis methods.

MATERIALS AND METHODS

Fruit samples

One hundred and twenty of Iranian local apple cultivar "Golab" without any visible external damage were used in this study. Apples at commercial maturity were harvested in summer 2013 from an orchard of Arak University, Arak, Iran. Physical properties of the samples such as mass and volume were measured. Fruit weight was measured by an electronic balance with an accuracy of 0.05 g. Fruit volume was determined by immersing apples in a known volume of water and measuring the displacement. Table 1 shows the basic morphological properties of the tested samples.

Table 1. Physical properties of the apple samples

	Average	Maximum	Minimum	Standard Deviation
Mass (g)	71.68	123.50	39.85	18.02
Volume (cm^3)	94.44	150	40	23.77

The apples were divided randomly into three groups of forty and submitted to the following regimes:

A One week in a cold room at 6.2°C and 20.4% RH
B Two weeks in a cold room at 6.2°C and 20.4% RH
C Three weeks in a cold room at 6.2°C and 20.4% RH

Prior to the analyses, fruits were kept at room temperature.

Acoustic measurements

The equipment used for measuring the textural quality of the apples was a microphone model MA231, an amplifier model MP201, and a data acquisition system model MC3022 (BSWA Technology Co., Ltd, Beijing, China). The microphone is a type 1 which is based on standard IEC 61672 (IEC 61672, 2002). The received signals were saved on a desktop computer, using Scope V1.32 software. Before beginning the measurement, the microphone was calibrated by a calibrator (model CA111, BSWA Technology Co., Ltd, Beijing, China), which creates the constant sound level of 94 dB in a pure frequency of 1 kHz. The calibrator should be selected as the type 1, i.e., the same as the selected microphone, which is based on standard IEC 60942 (IEC 60942, 2003).

According to Fig. 1, the microphone was located a few millimeters far from the surface of the sample and was positioned at 180 degrees from impact point, i.e., the opposite side of the impact point (Shmulevich et al., 2003; Wang et al., 2006).

Fig. 1. View of the acoustic response equipment

The impact device consisted of a pendulum with a plastic ball at the end. The impact device should be very light so that repeated impacts of the pendulum did not cause any damage to the fruit tissue (Tiplica et al., 2010). Therefore, 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 conducted at a drop height of 95 mm. During the tests, the apples were placed on a hard round surface. For each test, duplicate measurements were carried out on the selected area located around the equatorial zone of the apple surface and the average value was used for further analysis.

Data Preprocessing

Data preprocessing of the sound spectra was applied to diminish the effect of noises. Some researchers have defined a normalized spectrum through dividing the amplitude at each frequency by the maximum amplitude of the spectrum (Diezma-Iglesias et al., 2006). In this study, common spectra preprocessing methods were applied on the data sets. These methods consisted of normalization, detrending, Savitzky-Golay, the first and second derivations, multiplicative scatter correction (MSC), standard normal variate (SNV), and moving average. Furthermore, in order to compare the results, non-preprocessing data sets were tested as well. Further details of these data preprocessing have been reviewed by other researchers (Nicolaï et al., 2007; Sun, 2009). The Unscrambler X10.3 software was used to perform spectral data preprocessing.

Figs. 2 and 3 show typical acquisition signals of different storage periods in time and frequency domains, respectively.

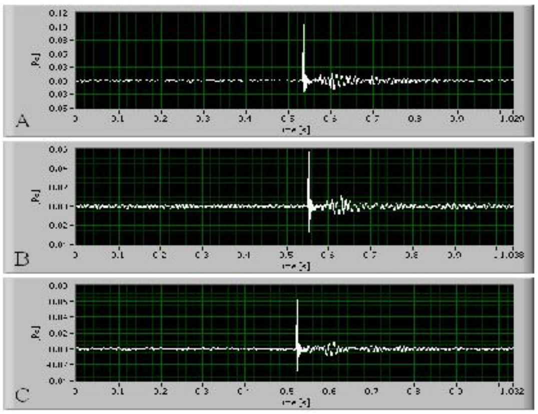

Fig. 2. Typical time domain signals of the apples

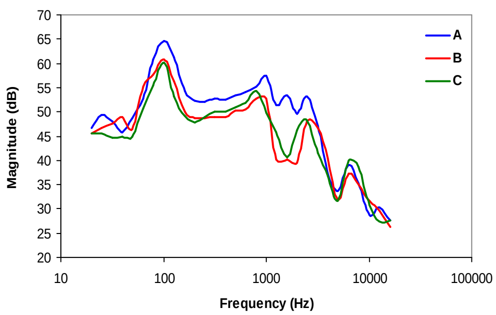

Fig. 3. Typical frequency domain signals of the apples

Principal Component Analysis

Principal component analysis (PCA) is known as a statistical procedure which is used to reduce the dimensions of a given data set while retaining the variability existed in the set (Mucherino et al., 2009). In this study, the PCA technique was performed to determine the key variables (one-third octave bands) that explain the most differences in the spectra. Based on the number of training data set (84 samples), seven principal components (PC_1- PC_7) were obtained to calibrate linear and quadratic discriminant analysis classifiers.

Discriminant Analysis

The linear discriminant analysis (LDA) and quadratic discriminant analysis (QDA) classifiers were used for discrimination purpose. These classifiers are attractive because they have closed-form solutions that can easily be computed, are inherently multiclass, and have proven to work well in practice. Moreover, there are no parameters to tune for these algorithms (Hastie et al., 2009). Hold out method was used to test the classifiers performance. [To evaluate the LDA and QDA, 30% of the samples (36 samples) were randomly assigned to test and training was performed with the rest of the data (84 samples)]. After applying the training procedure, classification results were presented in the form of confusion matrixes. The same process was repeated for all the pre-processing methods. In order to assess the classification results as well as the ability to generalize the models, harmonic mean of precision and sensitivity was calculated by Eq. 1 (Han et al., 2012). In this measure, both sensitivity and precision are effective on the model.

$$F_\beta = \frac{(1+\beta^2)\times Precision \times Sensitivity}{(\beta^2 \times Precision) + Sensitivity} \qquad (1)$$

where, F_β is the harmonic mean of the precision and sensitivity whose value is in the range between zero to one, and β is the weight factor.

To increase the ability to generalize the model, weight factor (β) was considered to be two (Han et al., 2012). With this value, the model sensitivity in Equation (1) would be twice as much as the precision. Unscrambler X10.3 software was used for LDA and QDA analyses.

RESULTS

Preprocessing Results

The effect of different preprocessing methods on LDA classification accuracy is presented in Table 2. It is observed that the maximum average value of F_β (0.84) for classification on the test data set belongs to the non-preprocessing method. It is also seen that F_β index in testing model decreases considerably with pre-processing method in combination of the first and second derivations with Savitzky-Golay in all classes. This suggests that there is useful information within the spectra that is removed by derivatization or enhancing the existed noises. This might describe the weakness of LDA model to classify spectra by means of the first and second derivation pre-processing methods. The same results have been reported by other spectroscopy studies (Ishikawa and Gulick, 2013).

PCA Results

As can be seen in Fig. 4, there is a difference between the mean magnitudes at one-third octave band. Of course, the difference in the frequency range from 125 to 6300 Hz is greater than that of other frequencies. With regard to the use of all data related to the one-third octave band spectrum for classification, the PCA method was used. Principdle Component Analysis (PCA) derive a small number of independent linear combinations (principal components) of a set of variables that retain as much of the variability as possible in the original variables.

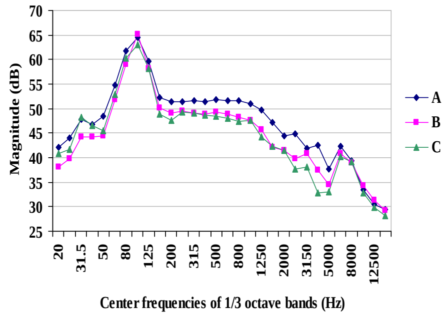

Fig. 4. Mean magnitude of data set at one-third octave band

Classification Results

The classification accuracy for LDA was 80.56%. For the dataset used in this experiment, the LDA classifier did quite well. After running the LDA classifier over the data, the same data were used to generate and test a QDA classifier. The result from the QDA classifier was not quite similar to the results for the LDA classifier. Results show that with QDA, the accuracy of 89.20% and 83.33% are obtained on train and test data sets, respectively (**seen** in Fig. 5). Because this data is not so easily separable, there is a difference between the simpler LDA and more complex QDA classifier. The reason is that LDA can only learn linear boundaries and QDA can learn quadratic boundaries; therefore, LDA is a much less flexible classifier than QDA (James et al., 2014).

The main feature that makes this dataset significantly harder to classify is that the three classes are more or less merged together, rather than being distinct. However, classes "B" and "C" overlap somewhat more than classes "A" and "B" do. Fig. 6. provides confusion matrices that summarize the classification results using LDA and QDA techniques. In their research, Zude et al. (2006) have applied partial least-squares (PLS) calibration models on spectra of acoustic impulse resonance frequency and VIS/NIR spectrometer on apple fruit Malus domestica 'Idared' and Golden Delicious to predict fruit flesh firmness and soluble solids content on tree and in shelf life. They expressed that the prediction of fruit flesh firmness of stored Golden Delicious / Idared apple fruits was not possible. Regarding the results, to discriminate Golab apple storage time using acoustic impulse response, LDA and QDA classification techniques are preferable to regression models like PLS (Zude et al., 2006).

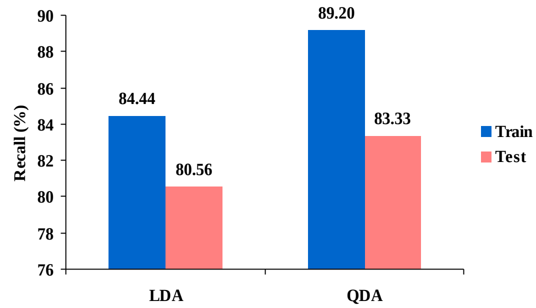

Fig. 5. Classification result for LDA and QDA models on training and testing data sets

Actual	**Predicted** A	B	C
A	8	1	3
B	0	10	2
C	0	1	11

LDA

Actual	**Predicted** A	B	C
A	9	0	3
B	0	10	2
C	0	1	11

QDA

Fig. 6. LDA and QDA confusion matrices (test data set)

These two methods are compared by using F_β. The F_β of 0.81 and 0.84 are achieved by LDA and QDA, respectively. This shows that LDA and QDA methods can successfully be generalized and achieved a state-of-the-art performance.

CONCLUSIONS

Overall, this project served to illustrate LDA and QDA classifiers can accurately predict the class of spectra and therefore, storage time class. There was not as much difference between the QDA and LDA classifiers, as it would have been expected; the QDA classifier appeared more accurate. Further studies on data fusion from applying acoustic impulse response are needed.

The results indicated that the mentioned method is potentially applicable for the detection of apple firmness. Hence, the proposed method could be used for the industrial grading system.

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تحقیقات کشاورزی ایران (۱۳۹۵) ۳۵(۲) ۶۵-۷۰

طبقه‌بندی سیب گلاب براساس زمان نگهداری با استفاده از پاسخ فرکانسی و روش‌های تجزیه و تحلیل تشخیصی LDA و QDA

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واژه های کلیدی:

سفتی

روش غیر مخرب

پیش‌پردازش

تحلیل مولفه‌های اصلی

چکیده- سفتی بافت یکی از مهمترین شاخص‌های کیفیت برای میوه سیب به شمار می‌آید که همبستگی بالایی با زمان نگهداری دارد. یکی از رایج‌ترین روش‌های تشخیص غیرمخرب برای ارزیابی سفتی سیب، پاسخ فرکانسی است. این مقاله روشی غیرمخرب برای طبقه‌بندی سیب رقم گلاب براساس زمان نگهداری ارائه می‌نماید. روش‌های متعدد پیش‌پردازش داده از جمله هنجارسازی، شیب‌گیری، هموارسازی ساویتزکی-گولای، مشتق‌گیری اول و دوم، تصحیح پراکنش افزاینده، توزیع نرمال استاندارد و میانگین‌گیری متحرک مورد بررسی قرار گرفت. مشاهده شد که بیشینه مقدار معیار F_β مربوط به وضعیت بدون پیش‌پردازش بوده و مقدار آن برابر ۰/۸۴ به‌دست آمد. در این تحقیق روش PCA برای تعیین متغیرهای اصلی که بیانگر بیشترین تفاوت در طیف فرکانسی است مورد استفاده قرار گرفت. تعداد هفت مولفه اصلی برای کالیبره‌کردن مدل‌های LDA و QDA مورد استفاده قرار گرفت. دقت طبقه‌بندی برای مدل‌های تحلیل تفکیک خطی و درجه دوم به ترتیب ۸۰/۵۶ و ۸۳/۳۳ درصد به‌دست آمد. نتایج نشان دادند که روش پاسخ فرکانسی از توانمندی بالایی برای تشخیص بافت میوه سیب برخوردار است.