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Application of acoustic impulse response in discrimination of apple storage time using neural network

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Abstract

Improved nondestructive techniques for classification fruit during storage could be an efficient way to quality assessment of stock in the fruit trading. Fresh apple gradually deteriorates and becomes soft and dry during storage. During two months storage at 6.2°C and 20.4% relative humidity, the average firmness loss was obtained 29.14% and 32.02% for Golden Delicious and Red Delicious, respectively. Therefore, the potential of acoustic impulse response for non-destructive classification of apple fruits of different storage duration was examined. Golden Delicious and Red Delicious apples were classified using artificial neural network. Ten features of the sound impulse response of apples excited with a light mechanical impact on the equator of samples were extracted. The features used in classification of apples were the five first amplitudes and frequencies corresponding to these amplitudes. Based on exhaustive search method, different feature vectors including two, three, four and five features were also tested to find out the best feature vector combination for an optimal classification success. The feature vector including five features produced better classification results in general compared to other feature vectors for both Golden Delicious and Red Delicious apples. According to the result, five-featured vectors provide the highest F1-score of 84.9% and 84.7% for Golden Delicious and Red Delicious, respectively. The results indicated that acoustic impulse response method was potentially useful for classifying of apples according to duration of storage, but the classification accuracies need to be improved.

Introduction

Agricultural and food 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 can not detected by merely examining the fruit's external characteristics (Alfatni *et al*., 2008). Textural characteristics of fruits 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, firmness is a very important one (De Belie *et al*., 2000; Kim *et al*., 2009).

The apple fruit is in high demand through out the year and hence a considerable quantity is generally stored in cold storages in Iran. The fresh apples are often firm, crisp and juicy, but the texture of a fresh apple gradually deteriorates and becomes soft, dry and mealy during storage.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 determined with a range of different destructive or non-destructive measuring devices. However, destructive methods are inefficient and time-consuming and they 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). Considerable work has been carried out over the past decades on the development of nondestructive methods for measurement of fruits firmness (Garcia-Ramos *et al*., 2003; Lu, 2007; Peng and Lu, 2008; Ruiz- Altisent *et al*., 2010; Khalifa *et al*., 2011; Mendoza *et al*., 2014). The acoustic technique is the most commonly used nondestructive detection method for evaluation of 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

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response method is based on measurement of the sound emitted by a fruit as it vibrates in response to a gentle tap with a small pendulum. In order to develop a robust classification model, different pattern recognition algorithms have been studied by researchers. A thorough review of published literature reveals that many artificial neural network classifiers have been used for classifying agricultural products (Jayas *et al*., 2000). Artificial neural networks offer much faster and more flexible approach in classification fields (Kavdir and Guyer, 2008). Therefore artificial neural networks have been widely applied to identifying, grading and sorting of agricultural products.

Most of previous studies have been concentrated on few particular points of the acoustic signal such as dominant frequency. In order to indicate the capability of acoustic impulse response, the whole spectral range was explored in this study. Therefore, the present research was carried out to evaluate the feasibility of the acoustic impulse response and artificial neural network for classification of apples according to detection of apple texture during storage time.

Materials and Methods

Fruit samples

The experiment was done on 'Golden Delicious' and 'Red Delicious' apples. A total of seventy eight samples from each cultivar without any visible external damage were used in this study. Apples at commercial maturity were hand harvested in October 2013. Morphological properties of samples such as mass and volume was 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 (Tabatabaeefar and Rajabipour, 2005).

The each cultivar of apples was divided randomly into two groups of thirty nine. The first group of each variety transported to the laboratory and the second groups were stored for two month in a cold room at 6.2°C and 20.4% RH. Prior to the analyses, fruits were kept at room temperature.

Destructive measurement

Flesh firmness was defined as the maximum force required pushing the Magnus-Taylor probe into the fruit flesh. A knife was used to remove the skin from the two opposite sides of each fruit. A handheld penetrometer (Fruit pressure tester, model: FT 327, Netherlands) equipped with a standard 8 mm diameter Magnus-Taylor tip was used (Subedi and Walsh, 2009). The firmness was measured at each of the two equatorial positions. Firmness of each fruit was reported as the mean value of the two readings. The results were expressed in kg.

Acoustic measurements

In this study, used equipment for measuring the tex¬tural quality of apples 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 which is based on standard IEC 60651. 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, which is based on standard IEC 60942.

The microphone located a few millime¬ters from the surface of the sample and was positioned at 180 degrees from the point of impact (Van Linden *et al*., 2004). 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. During the test, the apples were placed on a hard oval surface. For each test apple, two 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. The sound signal was transformed to frequency signal using fast Fourier transformation (FFT). The proposed method consists of three main steps, as follows: 1- scalar feature selection, 2- feature vector selection and 3- the classification process using artificial neural network technique.

Feature selection

Ten characteristics points of the frequency spectrum, presented in table 1, were used for the classification. In the next step, feature selection is used in order to decrease the complexity of computing and redundancy of features. Feature selection can be divided into two steps, feature scalar selection and feature vector selection. Feature scalar selection selects features individually and feature vector selection selects the best feature vector combinations based on the mutual correlation between features (Dua and Du, 2011). In this study, features normalized to zero mean and unit variance. Then ranking them utilizing scalar feature selection, which employed the Fisher's discriminant ratio criterion and a cross-

Table 1. Features and their expression

No.	Feature	Expression
1	P1	The amplitude of the first peak of the spectral curve
2	F1	The frequency corresponding to P1
3	P2	The amplitude of the second peak of the spectral curve
4	F2	The frequency corresponding to P2
5	P3	The amplitude of the third peak of the spectral curve
6	F3	The frequency corresponding to P3
7	P4	The amplitude of the forth peak of the spectral curve
8	F4	The frequency corresponding to P4
9	P5	The amplitude of the fifth peak of the spectral curve
10	F5	The frequency corresponding to P5

Table 2. Ranked features in descending order

Golden Delicious		Red Delicious	
No.	Feature	No.	Feature
1	P1	1	P1
10	F5	10	F5
2	F1	6	F3
8	F4	8	F4
3	P2	4	F2
6	F3	9	P5
4	F2	2	F1
7	P4	3	P2
9	P5	7	P4
5	P3	5	P3

correlation measure between pairs of features, was done (Theodoridis and Koutroumbas, 2009). The exhaustive search method to feature vector selection is used in this study to select the best combination of features, according to scatter matrices approach (Theodoridis and Koutroumbas, 2009).

Artificial neural network

The Artificial Neural Network (ANN) is a mathematical model inspired by biological neural systems. The ANN is a massively parallel distributed processor with the ability to model complex relationship between inputs and outputs or recognition patterns in data. The feed forward network with multilayered perceptrons is very powerful and commonly used in engineering. In this study, a feed forward network with three layer perceptrons was used. Input layers of the networks consist of two, three, four and five neurons according to different combination of features. The networks contain one hidden layer with twenty neurons according to trial and error and output layers with two neurons: before storage and after storage. Hyperbolic tangent sigmoid was used as transfer function of both hidden and output layers. The ANN training procedure was conducted by Matlab program with scaled conjugate gradient backpropagation. The data were randomly divided into a training sample (70%), a validation sample (15%) and a test sample (15%). The holdout method was used for training and testing the models.

Results and Discussion

Fruit properties

The mass of Golden Delicious ranged from 101.25 to 192.80 g, with an average of 142.72 g and volume ranged from 120 to 240 cm3, with an average of 171.68 cm3. In addition, the mass of Red Delicious ranged from 94.45 to 198.15 g, with an average of 153.67 g and volume ranged from 110 to 240 cm3, with an average of 174.23 cm3.

Destructive results

Firmness of apple fruits is recorded at harvest and after storage period. These two cultivars showed loss of firmness assessed after two months of cold storage. These results are in agreement with the results presented by other researchers (Kühn and Thybo, 2001; Costa *et al.*, 2012) which showed that different apple cultivars did not retain sufficient firmness during storage. The firmness loss of the Golden Delicious was less than Red Delicious. During two month storage, the average firmness loss was 29.14% and 32.02% for Golden Delicious and Red Delicious, respectively.

Scalar feature selection

Results of scalar feature selection are shown in Table 2. According to Table 2, features ranked in descending order for Golden Delicious and Red Delicious. Seven highest-ranked features out of ten features were selected. By doing scalar feature selection, it is concluded that frequency features have significant effect on classification more than amplitude features. For this reason, first dominant frequency for classification of fruits has been used in previous researches (Wang *et al*., 2006; Valente *et al*., 2009). Although, using second and third dominant frequency for classification of fruits has been reported (Gómez *et al.*, 2005; Pathaveerat *et al*., 2008). In addition, some researchers have studied lots of algorithms using maximum amplitude (Diezma-Iglesias *et al*., 2004; Tiplica *et al.*, 2010).

Feature vector selection

The highest ranked are identified and feature vector selection is employed to select the combination that maximizes the class-separability. The exhaustive search method is used in this study to select the best combination of two, three, four and five features out of the seven previously selected. Results of feature vector selection are shown in Table 3.

Table 3. The best feature vector

	Golden Delicious		Red Delicious	
	Feature No.	Class Separability	Feature No.	Class Separability
2-Feature combination	1, 10	1.13	1, 4	1.07
3-Feature combination	1, 3, 10	1.10	2, 1, 4	1.05
4-Feature combination	2, 1, 3, 10	1.08	2, 1, 4, 8	1.05
5-Feature combination	2, 1, 3, 6, 10	1.06	2, 1, 4, 6, 8	1.04

Table 4. ANN confusion matrices and F-measure results

	Golden Delicious				Red Delicious			
Feature Vector	2	3	4	5	2	3	4	5
Accuracy (%)	72.6	75.3	77.4	82.2	71.4	75.0	77.1	85.7
Precision (%)	74.6	74.7	77.8	79.7	76.8	83.0	77.1	86.8
Sensitivity (%)	68.5	76.7	76.7	86.3	61.4	62.9	77.1	84.3
Specifity (%)	76.7	74.0	78.1	78.1	81.4	87.1	77.1	87.1
NPV (%)	70.9	76.1	77.0	85.1	67.9	70.1	77.1	84.7
F-measure (%)	69.6	76.3	76.9	84.9	64.0	66.1	77.1	84.7

Classification performance

Table 4 provides confusion matrices that summarize the ANN classification results. The five-featured vectors produced the most successful classification results in general for both cultivars. The ANN classifier that used four input features yielded the second best classification result. The feature vector including four features produced slightly better classification results than three features.

Although the class separability obtained (Table 3) using different feature vector were close to each other, the five-featured vector showed better classification results compared to the other vectors for both cultivars. Therefore, improved classification results can be expected with more input features (Kavdir and Guyer, 2008). Observation of confusion matrix reveals that classification accuracy in Red Delicious is slightly higher than Golden Delicious. The more firmness loss in Red Delicious cultivar after two months of cold storage which indicates that obvious differences between classes, might be the reason for higher classification accuracy.

Generally, ANN classifier was successful in assigning the test patterns into the right classes. Using more training data may further improve the performance of ANN classifier. In addition to the system's classification accuracy, it was used F1-score to evaluate the system. It is important to evaluate precision and sensitivity in conjunction, because it is easy to optimize either one separately. In order to quantify this with a single measure, the F1-score, harmonic mean of precision and sensitivity, was used. This measure is produces scores ranging from 0 to 1 and defined as following equation:

$$F_1 = 2 \times \frac{Precision \times Sensitivity}{Precision + Sensitivity} \qquad (1)$$

The features vectors are compared by using F1-score (Table 4). As can be seen in Table 4, results of Golden delicious show that five-featured provides the best results with an F1-score of 84.9%. Conversely, the two-featured, provides the worst results with an F1-score of 69.6%. According to Table 6, the highest F1-score of 84.7% is achieved by five-featured for Red Delicious. On the other hand, the lowest F1-score of 64% is shown by two-featured for Red Delicious.

The results indicated that acoustic impulse response method was potentially useful for classifying of apples according to duration of storage, but the classification accuracies need to be improved. It should be noted that the successes of the classifiers are being compared with the classification results obtained from the human expert. Subjectivity is involved in the classification performed by the human expert even though the expert followed the standards. Therefore, it is not expected that an expert could perform a 100% correct classification. Possible measurement errors from devices should also be considered (Kavdir and Guyer, 2008). Using other features of acoustic signal and using other feature vector selection techniques such as sequential forward and backward selection and forward floating search selection may improve classification accuracy.

Conclusions

Acoustic features of apples such as frequency and amplitude were measured and used in artificial neural networks to determine a feasible way of matching feature vector for an optimal classification result. The findings of this study can be summarized as follows:

The ANN classifier using all the five features in the input set produced the highest classification result. The success of this classification by ANN shows that they perform better in mapping the non-linear relations between input patterns and output classes when they have a higher number of inputs. Further researches on applying supervised pattern recognition such as support vector machine and K-nearest neighbors algorithms for classification of apple fruits are suggested.

According to classification performances, using different feature vector increases the F1-score from 69.6% to 84.9% for Golden Delicious. As well, using different feature vector increases the F1-score from 64% to 84.7% for Red Delicious. To improve classification performances, using the other feature vector selection such as sequential backward selection and forward floating search selection are suggested. Although fresh and stored apples are very similar in terms of shape and appearance but multilayer feedforward network can recognize the pattern and classify them in correct classes.

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