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Acoustic detection of apple mealiness based on support vector machine

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ABSTRACT- Mealiness degrades the quality of apples and plays an important role in fruit market. Therefore, the use of reliable and rapid sensing techniques for nondestructive measurement and sorting of fruits is necessary. In this study, the potential of acoustic signals of rolling apples on an inclined plate as a new technique for nondestructive detection of Red Delicious apple mealiness was investigated. According to destructive confined compression tests, the mealiness of apples was evaluated by the hardness and juiciness measurements. In addition, support vector machine (SVM) models were developed to classify apples. The radial basis function (RBF) as the kernel was used in SVM models. According to exhaustive search method, the model with nine features combination was found to be the best model. Results indicated overall accuracy of 85.5 % to classify apples in mealy and healthy groups. The results indicated that this method is potentially useful for apple mealiness detection.

INTRODUCTION

Consumers consider crispness, juiciness, firmness and hardness as important attributes of fresh fruits (Peneau et al., 2007). Unfortunately during storage, the textures of fresh fruits such as apples gently turns out to get soft and dry (Seppä et al., 2013). Therefore, a reliable technique to detect the quality of fruits plays an important role in this industry.

Sensory panel is one of the conventional methods to detect texture of apples. But sensory analysis has some disadvantages. It is expensive, cannot be used for on-line detection and is not practical for all samples (Corollaro et al., 2014).

More objectively, there are various tools to detect apple mealiness. These measuring tools may be destructive or nondestructive. Destructive methods are inefficient and time-consuming. On the other hand, they cannot be used for on-line classification equipment. Therefore, the use of reliable and rapid sensing techniques for nondestructive measurement and sorting of fruits is necessary (Mendoza et al., 2014). Considerable work has been performed on development of nondestructive methods for measurement of apple mealiness in the past years (Moshou et al., 2003; Arana et al., 2004; Bechar et al., 2005; Valero et al., 2005; Huang et al., 2012).

Generally, the acoustic method is known as a reliable nondestructive detection technique. A number of acoustic techniques for evaluation of textural characteristics of different fruits has been investigated (Arana et al., 2004; Diezma-Iglesias et al., 2006; Zhang et al., 2014).

The acoustic response technique is based on capturing the sound signals of fruits when vibrating in response to a light impact (Studman, 2001). The detection system based on acoustic response comprises fruit rolling devices and an exciting set. Researchers are interested in developing simple, cheap and rapid non-destructive techniques to investigate the attributes of fruits (Tiplica et al., 2010).

The present research was carried out to evaluate the feasibility of the acoustic signals of rolling apples on an inclined plate in order to discriminate mealy and healthy apples.

MATERIALS AND METHODS

Sample Preparation

A total of 180 ‘Red Delicious’ fresh apples without any damage were used in this study. The apples were divided randomly into two equal groups. Therefore, 90 samples were selected randomly as the fresh group and transported to the laboratory and the remaining samples were exposed to ambient temperatures for up to two months to develop mealiness because storage will make samples mealy (Arana et al., 2004; Valero et al., 2005).

Acoustic Test

According to Fig. 1, a curved plastic plate was located on the table. The plate had 55 cm length and was inclined at 10°. The inclined plate feathered a step on the middle of path with a step height of 4 mm. A microphone was installed a few millimeters away from the surface of the plate adjacent to the step for recording sound signals while apples were rolling down. The acoustic signals were recorded using BSWA equipment and included a data acquisition system (Model MC3022) and one microphone (Model MA231).

Fig. 1. Experimental setup

Confined Compression Test

The confined compression test is considered as a reference technique for detecting fruit mealiness (Bechar et al., 2005; Huang et al., 2008; Arefi et al., 2016). Confined compression tests were carried out using SANTAM universal testing machine for apple mealiness detection. Cylindrical samples of 17 mm height and diameter were extracted from each fruit. A barrel with a hole of sample size was used and fruit sample was confined in it. A deformation of 2.5 mm at 20 mm/min velocity was applied using a probe of 15.3 mm dia (Arefi et al., 2015). The area of juice spot that spread on a filter paper beneath the barrel was recorded as juiciness (cm^2). The slope between 1/3 and 2/3 of the maximum force in the force–deformation diagram was calculated as hardness (kN/m) (Huang and Lu, 2010). Apples with a juiciness area above 5 cm^2 and hardness of greater than 40 kN/m were considered as healthy (Huang and Lu, 2010).

Feature Extraction

Fifteen statistical parameters of the time domain signals (Fig. 2), presented in Table 1, were used to classify apples. These statistical parameters are easy to compute and were widely used in previous studies (Ebrahimi and Mollazade, 2010; Omid, 2011).

Feature Selection

Generally, feature selection techniques are used to discard redundant or unimportant features. Accordingly, feature selection improves detection accuracy for all types of classifiers (Unay et al., 2011). Feature selection can be split into two steps, feature scalar selection and feature vector selection. Feature scalar selection chooses features independently and feature vector selection chooses the best feature vector combinations using mutual correlation between features (Dua and Du, 2011).

Data normalization is often performed prior to designing a classifier. In this study, the dataset was normalized to make samples in the range of zero to 1. Then, features were ranked using scalar feature selection, which employs the Fisher's discriminant ratio criterion. A cross-correlation measure between pairs of features was also performed (Theodoridis and Koutroumbas, 2009).

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

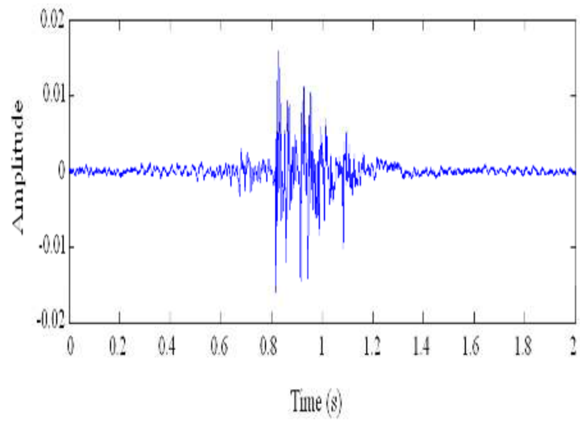

Fig. 2. Typical time domain signals of an apple

Support Vector Machine

Support vector machine (SVM) is one of the supervised learning models used for classification which has been used in different classification problems by many researchers (Unay et al., 2011). This algorithm is based on finding the hyper-plane that maximizes the margin between the two classes. There are a number of kernels such as linear, polynomial, sigmoid and radial basis function (RBF) that can be used in SVM models. The RBF is one of the most popular classical SVM kernels. This kernel is a suitable first choice for SVM classification (Felici and Vercellis, 2008).

In this study, RBF kernel was used and parameter estimation using grid search with 10-fold cross-validation was performed (Chen and Li, 2010). Different pairs of C and γ values were used. The best pair was chosen according to high cross-validation accuracy. SVM algorithm was implemented using Weka 3.7.9 data mining tool (Hall et al., 2011).

For predicting performances of SVM models, overall accuracy, Cohen's Kappa statistic and root mean square error (RMSE) were used. However, some researchers believe that Cohen's Kappa statistic is a more robust measure than overall accuracy (Unay et al., 2011).

Table 1. Statistical features and their formula used to classify apples

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	$\sigma = \sqrt{\frac{\sum_{i=1}^{N}(x_i - \bar{x})^2}{N-1}}$	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	$K = \frac{E(x_i - \mu)4}{\sigma^4}$			

RESULTS AND DISCUSSION

Destructive Results

This cultivar showed loss of hardness and juiciness assessed during two months of storage. Therefore, the storage time resulted in an increase in mealiness. According to the result of confined compression test, for the healthy group, 74.4% of the samples were greater than 40 kN/m in hardness and 5 cm^2 in juiciness. On the other hand, for the mealy group, 92.2% of the samples were lower than 40 kN/m in hardness and 5 cm^2 in juiciness.

Feature Selection

Results of scalar feature selection are shown in Table 2. According to Table 2, features are ranked in descending order. Ten highest-ranked features out of fifteen features were selected.

The highest ranked features were identified and feature vector selection was used to select the combination with maximum group classification separability. The exhaustive search method was used in this study to select the best combination of two-ten features out of ten previously selected ones. Results of feature vector selection are shown in Table 3.

SVM Model

The best pairs of C and γ were determined using grid search on the training data. Table 4 shows results of grid search for different features combination.

Table 2. Ranked features in descending order

No.	Feature
10	Moment
3	Mean
11	Sum
13	Coefficient Variation
5	STD
12	RMS
14	Crest Factor
4	Variance
7	Power
6	Energy
8	Kurtosis
15	Dynamic Range
2	Min
9	Skewness
1	Max

Classification Performance

In order to achieve the optimal performance for the SVM model, all features combinations were tested. The effectiveness of SVM model is dependent on its accuracy of prediction. Table 5 summarizes the classification accuracy results obtained by different models. The overall accuracy of seven models was over 80%. Among the seven models, the model with nine feature combination was found to be the best model.

Table 3. The best feature vectors

Feature combination	Feature No.
2	5, 10
3	3, 4, 7
4	3, 4, 7, 13
5	3, 4, 7, 10, 12
6	3, 4, 5, 7, 10, 14
7	3, 4, 7, 10, 12, 13, 14
8	3, 4, 6, 7, 10, 11, 12, 14
9	3, 4, 6, 7, 10, 11, 12, 13, 14
10	3, 4, 5, 6, 7, 10, 11, 12, 13, 14

Table 4. SVM model parameters

	C	γ
2-Feature combination	9	3.75
3-Feature combination	7.25	5.5
4-Feature combination	2	6.75
5-Feature combination	15	3.5
6-Feature combination	13	2.25
7-Feature combination	9	3.5
8-Feature combination	9.5	4.25
9-Feature combination	10.5	2.5
10-Feature combination	15	3.0

Table 6 shows the confusion matrix of data set for this method. The confusion matrix shows that this method has high accuracy of healthy apples (86.7%). As can be observed from Table 6, there is a slight difference between detection accuracy of mealy apples and healthy ones. Generally, the detection accuracy of healthy apples is slightly better than accuracy of mealy samples.

Due to overlapping values between healthy and mealy groups, incorrect selection of these two groups was done. Certainly, classification accuracies can be improved if samples with greater range of mealiness could be used (Huang and Lu, 2010).

Generally, SVM classifier was successful in assigning the apples into the right classes, but classification accuracies needed to be improved. Using more training data may further improve the performance of SVM classifier.

As mentioned previously, different nondestructive methods have been used in apple mealiness detection. In order to accurately compare our results with other reported findings, three studies were chosen that have used apple cultivars similar to those of this study because some reported methods did not have acceptable results for different cultivars (Bechar et al., 2005). Therefore, the results of this study were compared with results reported by Huang and Lu (2010), Arefi et al., (2016) and Arana et al. (2004). The mentioned methods all had overall accuracy over 80%. Therefore, they perform well in apple mealiness detection. Among these studies, the one conducted by Huang and Lu yielded the best overall accuracy (86.7%) (Huang and Lu, 2010).

Although acceptable results were obtained from previous methods in mealiness detection such as hyperspectral imaging (86.7%) and biospeckle imaging (79.8%), they are expensive and time-consuming (Arefi et al., 2015). On the other hand, acoustic methods are rapid and inexpensive. Overall accuracy of hyperspectral imaging method was slightly better than inclined plate method, while design of inclined plate is simple and inexpensive. Generally, accuracy is not the sole criterion for identifying the best method. Other criteria would be simplicity and cheapness of methods.

CONCLUSIONS

In this study, the SVM method was utilized for classification of apples into two classes, healthy and mealy. An experimental system for apple mealiness detection was developed. The proposed method provided acceptable results for apple mealiness detection in a nondestructive pattern. The analysis indicated that overall detection accuracy of this method was 85.5%.

Table 5. SVM confusion matrices for different feature vectors

Feature Vector	2	3	4	5	6	7	8	9	10
Accuracy (%)	82.78	71.67	70.56	82.78	84.45	83.89	83.34	85.56	83.89
Kappa statistic	0.66	0.43	0.41	0.66	0.69	0.68	0.67	0.71	0.68
RMSE	0.42	0.53	0.54	0.42	0.39	0.40	0.41	0.38	0.40

Table 6. Confusion matrix

		Predicted	
		Mealy	Healthy
Actual	Mealy	84.4 %	15.6 %
	Healthy	13.3 %	86.7 %

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تشخیص صوتی آردی شدن سیب براساس ماشین‌بردار پشتیبان

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کرنل تابع پایه شعاعی

چکیده آردی‌شدن، کیفیت میوه سیب را تنزل می‌دهد و این پدیده نقش مهمی در بازار میوه ایفا می‌کند. بنابراین استفاده از تکنیکی سریع و قابل اعتماد برای اندازه‌گیری و درجه‌بندی میوه‌ها ضروری است. در این تحقیق، قابلیت سیگنال‌های صوتی سیب‌های غلتان بر روی صفحه شیب‌دار به عنوان روشی نوین در تشخیص غیرمخرب آردی شدن سیب رقم رد دلیشز مورد بررسی قرار گرفت. با استفاده از آزمون مخرب فشردگی محصور، میزان آردی شدن نمونه‌ها ارزیابی شد. مدل‌های ماشین بردار پشتیبان برای طبقه‌بندی سیب‌ها در نظر گرفته شد. از کرنل تابع پایه شعاعی در مدل‌های ماشین بردار پشتیبان استفاده شد. مطابق روش جستجوی جامع، مدلی با ترکیب ۹ ویژگی به عنوان بهترین مدل انتخاب شد. نتایج نشان داد که میزان دقت کلی این روش برای تشخیص سیب‌های سالم و آردی برابر ۸۵/۵ درصد به دست آمد. نتایج حاکی از آن بود که روش مذکور از توانمندی خوبی برای تشخیص سیب‌های آردی برخوردار است.