Advance Journal of Food Science and Technology 12(6): 337-342, 2016
DOI:10.19026/ajfst.12.2970
ISSN: 2042-4868; e-ISSN: 2042-4876

Submitted: November 30, 2015 Accepted: February 3, 2016 Published: October 25, 2016

Research Article

Nondestructive Classification and Recognition of Litchi Varieties Using Bionic Electronic Nose

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Abstract: In order to apply the bionic electronic nose in classifying the litchi into different classes, there were five different litchi varieties tested by the proposed methods in this study. Firstly, Physical differences of the 5 litchi varieties were compared in this study. Secondly, the response curves from the electronic nose (PEN3) were recorded for all the samples of the five litchi varieties. Variance Analysis (VA) was used for best characteristic value selection. Finally, via different pattern recognition techniques, including the Principal Component Analysis (PCA), the Linear Discrimination Analysis (LDA), the Probabilistic Neural Network (PNN), the Support Vector Machine (SVM) and the loading analysis (Loadings), it is found that PCA and LDA have a poor performance in classifying litchi varieties. The classification accuracy of the PNN model with training set and test set were 100 and 84%, respectively. As to the SVM model, the classification accuracy of training set and test set were 100 and 92%, respectively. According to the Loadings results, the sensors R3, R5, R8 and R1 can be chosen for developing special and simple instruments for the detection of litchi volatiles. The test results has demonstrated the feasibility and effectiveness of using bionic electronic nose for discriminating and classifying litchi varieties, which provides a new method for rapid and nondestructive classification of litchi varieties.

Keywords: Artificial olfactory, bonic electronic nose, classification and recognition, litchi, variety

INTRODUCTION

Litchi, a typical subtropical fruit, is rich in nutrient elements, taste delicious and has high officinal value (Zan *et al*., 2009). As a main producer of litchi, China ranks the first place of the world in both the acreage and the yield of litchi. Including early-maturing litchi, mid-maturing litchi and late-maturing litchi, there are more than 60 varieties of litchi in China, such as Feizixiao, Guiwei, Nuomici, Gualü *et al*. and Lee *et al*. (2007). The ripe litchi fruit has a spherical shape with reddish brown shell and white flesh. The morphological characteristics of different litchi varieties such as shape, size and color *et al*. are similar, which can hardly be classified by naked eyes. Thus, it is significant to find an effective method to discriminate the litchi varieties. There are several existing classification and recognition methods of litchi varieties, such as the sensory evaluation method (Chen *et al*., 2013; Falasconi *et al*., 2005), the electronic tongue detection method (Qiao *et al*., 2012a, 2012b), the gas chromatographic method (Hou *et al*., 1987) and the liquid chromatography method (Xu and Yang, 2004). As a simple and visualized detection method, the sensory evaluation method using human sense to distinguish varieties of litchi artificially has the disadvantages of low efficiency and labor-intensive. The machine detection methods such as the electronic tongue detection method, the gas chromatographic method and the liquid chromatography method, overcome the disadvantages of sensory evaluation method to some extent. However, these machine detection methods have a higher requirement for the measured samples and more complicated operations, which usually need extract the juice of litchi fruit for testing. Besides, they cannot meet the non-destructive and rapid testing requirements. Thus, all the existing classification methods are unable to meet the needs of practical production.

As a biomimetic simulation of biological olfactory means of detection, electronic nose system is mainly composed of sampling and cleaning channel, an array of gas sensors and appropriate identification device, which can analyze and recognize complex smells and most of volatiles quickly (Anonymous, 2009). Electronic nose have the following advantages: simple

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equipment and operation; rapid analysis; independent test results without influence by subjective factors; and non-destructive detection. Currently, electronic nose has been applied in many research fields-, such as: environmental monitoring (Baby *et al*., 2000; Bourgeois *et al*., 2003), medical treatment and health care (Shnayder *et al*., 2009), food quality detection (Saevels *et al*., 2004; Zheng *et al*., 2009), biological pathogens detection (Falasconi *et al*., 2005; Olsson *et al*., 2002) and so on. However, the application of electronic nose on litchi varieties classification has not been reported yet. In 2013, Guo *et al*. (2013) detected 105 kinds of volatiles from dried litchi fruit and proved that the type and content of different varieties of litchi volatiles are significant different, which provides a theoretical basis for the application of bionic electronic nose on classification of litchi varieties.

This study explores the feasibility of using electronic nose for litchi varieties classification and recognition through an experiment, in which 5 varieties of litchi were chosen for testing. Firstly, physical difference of litchi varieties based on hardness and sugar content is analyzed. Then, with the bionic electronic nose, Variance Analysis (VA) is employed to determine the optimal characteristic value for pattern recognition. At last, the Principal Component Analysis (PCA), the Linear Discrimination Analysis (LDA), the Probabilistic Neural Network (PNN), the Support Vector Machine (SVM) and the loading analysis (Loadings) are used for pattern recognition, aiming to explore the feasibility of an electronic nose on the use of litchi varieties classification and recognition.

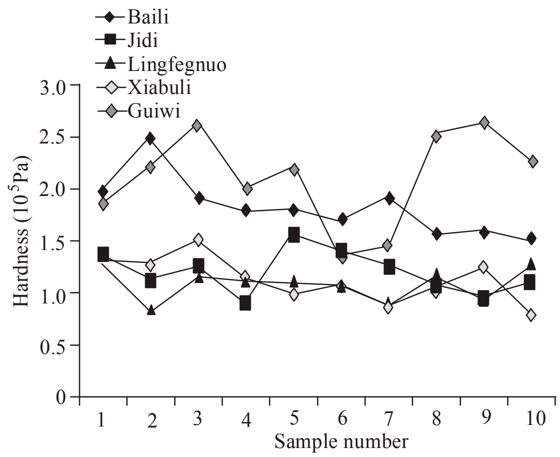

Fig. 1: Hardness of each litchi sample

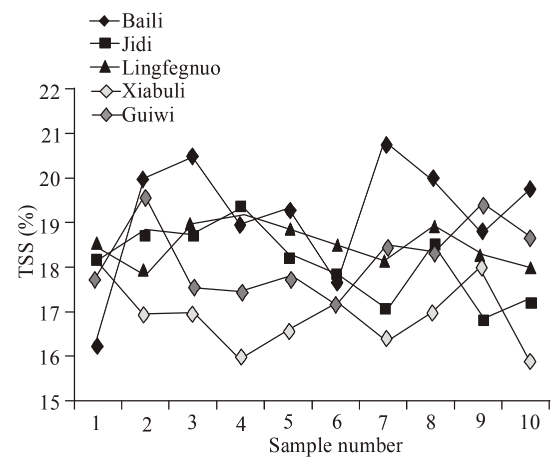

Fig. 2: Total soluble solid of each litchi sample

MATERIALS AND METHODS

Experimental materials: Five varieties of ripe litchi were chosen for sampling in this experiment, including Baili, Guiwei, Xiabuli, Jidi, Lingfengnuo, which were planted on the orchard of South China Agricultural University. The selected litchi fruits have a similar size and maturity and were sent to laboratory for experiment immediately. There were 18 litchi samples of each variety (5 litchi varieties×18 litchi samples = 90 samples in total) taken for sampling and analysis by electronic nose. Another 20 litchi samples of each variety (5 litchi varieties×20 litchi samples = 100 samples in total) were taken for the analysis of physical difference. Each litchi sample for sampling was placed in a 200 mL beaker with double-layer plastic film sealed. Before sampling, every sample was kept in an indoor environment (The temperature is (31±1)°C, the humidity is (79±1)%) for 1 hour. All the beakers were cleaned by ultrasonic cleaning instrument and dried in shade before use.

Physical indexes difference between different litchi varieties: Total soluble solid (TSS) and hardness are the important indicators to detect fruit flavors (Wu *et al*., 2012; Zhang *et al*., 2012). When operating the hardness measurement, the litchi samples were peeled and then the probe of sclerometer was pricked into the sample vertically for 0.5 cm depth to record average value of the hardness of 3 repeated detections. The TSS of litchi fruit was measured after peeling the litchi sample as well. Then, litchi juice was collected using a clean gauze and beaker while stirring with a clean glass rod. The average value of the 3 repeated detections was used to represent the sample's sugar content value. The hardness value and sugar content value of 5 litchi varieties are shown in Fig. 1 and 2. It can be seen that there are overlaps between the hardness and sugar content values of the five litchi varieties and the fluctuation of hardness value and sugar content value for a single litchi variety is significant. Therefore, It is unable to classify the litchi varieties well relying on physical indicators only. It is necessary to find some new means for litchi variety classification.

Experimental electronic nose: An experimental electronic nose (PEN3, Airsense Analytics GmbH and

Table 1: Response feature of sensor array

Number in array	Sensor name	Object substances for sensing
R 1	W1C	Aromatics
R 2	W5S	Nitrogen oxides
R 3	W3C	Ammonia and aromatic molecules
R 4	W6S	Hydrogen
R 5	W5C	Methane, propane and aliphatic non-polar molecules
R 6	W1S	Broad-methane
R 7	W1W	Sulfur-containing organics
R 8	W2S	Broad-alcohols
R 9	W2W	Aromatics, sulfur-and chlorine-containing organics
R 10	W3S	Methane and aliphatics

Germany) is used for sampling of litchi volatiles. This electronic nose system is mainly composed of sampling and cleaning channel, an array of gas sensors and an appropriate identification device. The array of gas sensor contains 10 metallic oxide sensors. Each sensor is sensitive to a different type of volatile and the whole electronic system is able to recognize complex volatiles. The response features of each sensor are given in Table 1. The operating parameters of electronic nose are set as: sampling interval is 1 s; flush time is 90 s; zero point trim time is 10 s; measurement time is 80 s; pre-sampling time is 5 s; and injection flow is 300 mL/min.

Variance analysis for characteristic value selection: Appropriate characteristic value should not only contain enough information of samples, but also simplify the data analysis. There were many feature extraction methods for sampling signal via electronic nose. In this study, to figure out the best characteristic value, 4 common feature extraction methods are used for comparison:

The average differential value (K_{mean}):

$$K_{\text{mean}} = \frac{1}{n-1}\sum_{z=1}^{n-1}\frac{x_{z+1}-x_z}{\Delta t}$$

where n is the amount of the test points (n = 80), xz is the z-th response value of a sample and $\triangle$t is the time difference of adjacent test points ($\triangle$t = 1 s).

The maximum value (Y_{max}):

$$Y_{\text{max}} = \text{Max}\,[Y_z]$$

where, Y_z is the z-th response value of a sample.

The average value (Y_{mean}):

$$Y_{\text{mean}} = \frac{1}{80}\sum_{i=1}^{80} x_i$$

where xi is the i-th response value of a sample.

The steady value (Y_t).

$$Y_t = Y_{75}$$

Table 2: Variance analysis for different features of five litchi varieties

Characteristic value	F value	P value
Average differential value	14.15	3.366×10-11
Maximum value	8.97	4.183×10-7
Average value	9.34	2.154×10-7
Steady value	1.19	3.147×10-1

where Y_{75} is the 75-th response value of a sample

The results of variance analysis for 4 features were given in Table 2. In variance analysis, F value (F-statistics) and P value are important indicators of difference. Larger value of F indicates more significant difference and vice versa. In addition, the difference is proved to be significant if the P less than 0.05, where as it is not significant (Yu *et al*., 2007). According to Table 2, except steady value selection method, the other 3 feature selection methods show significant difference for 5 litchi varieties, Using the average differential value as the characteristic value, the difference reached the most significant state (F = 14.15) and its effect of classification is the best. Thus, the average differential value was chosen as the characteristic value in this experiment.

Pattern recognition methods:

Principal component analysis and linear discriminant analysis: PCA is a most widely used and common processing method for data analysis. It is an unsupervised technique, which is able to reduce the dimensionality of raw data and provide a means of visualizing the complicated data for easy interpretation. LDA is a supervised technique aiming at reducing dimensionality and preserving as more discriminatory information as possible. This method can maximize the ratio of between-class variance to within-class variance in any given data set to guarantee maximal separation (Gupta *et al*., 2015).

Probabilistic neural network: The Probabilistic Neural Network (PNN) includes input layer, hidden layer, summation layer and output layer, which can achieve high accuracy by taking place of nonlinear algorithm with linear algorithm. It has been widely used in pattern classification (Kim *et al*., 2008).

Support vector machine: The Support Vector Machine (SVM) overcomes some deficiencies of traditional machine learning methods and has been widely spread in the world (Shi *et al*., 2009). SVM has a better generalization, which can guarantee that the local optimal solution is exactly the global optimal solution and solve the learning problem with a smaller number of samples.

RESULTS AND DISCUSSION

PCA for litchi variety: The results of principal component analysis (PCA) for 5 litchi varieties classification were shown in Fig. 3. The contribution rate of the first Principal Component (PC1) is 98.69%, the contribution rate of the second principal component (PC2) is 1.19% and the total contribution of PC1 and PC2 is 99.88%. The data of Xiabuli does not overlap others, which means it can be classified. However, the distance between data points of Xiabuli and Baili is small, which may lead to confusion in practical classification. The data points of Baili, Guiwei, Jidi and Lingfengnuo overlap with each other, which cannot be classified.

LDA for litchi variety: The results of linear discrimination analysis are shown in Fig. 4. It can be seen that, the contribution rate of the first linear discrimination (LD1) is 50.57%, the contribution rate of the second linear discrimination (LD2) is 37.15% and the total contribution of LD1 and LD2 is 87.72%. The data of Xiabuli, Baili and Lingfengnuo does not overlap with others, so that that can be classified in this method. However, the data points of Lingfengnuo and Jidi are very close, which may risk in confusion in practical classification. Guiwei and Jidi cannot be classified, due to the overlap of data points. Based on the results, compared with the performance of PCA on litchi varieties classification, LDA is more effective.

PNN for litchi variety: To apply the Probabilistic Neural Network (PNN) for the classification of 5 litchi varieties in this experiment, there are 18 samples of each litchi variety (5 litchi varieties × 18 litchi samples = 90 samples) used for analysis. 13 samples of each variety are selected randomly as the training set and the remaining 5 samples of each variety are used as the test set. Hence, there are 65 training samples and 25 test samples. To optimize the PNN network model, the spread of the optimal range is set as [1×10^{-3}, 2×10^{-3}, 3×10^{-3}, 4×10^{-3}, 5×10^{-3}, 6×10^{-3}, 7×10^{-3}, 8×10^{-3}, 9×10^{-3}, 1×10^{-2}]. The PNN model with highest accuracy of the training set and the test set can be chosen as the best one for analysis, which is set at spread = 1×10-3 in this study. Using this model for classification, the training set's classification accuracy is 100% and the test set's classification accuracy is 84%. The results demonstrate the effectiveness of PNN in classifying litchi varieties.

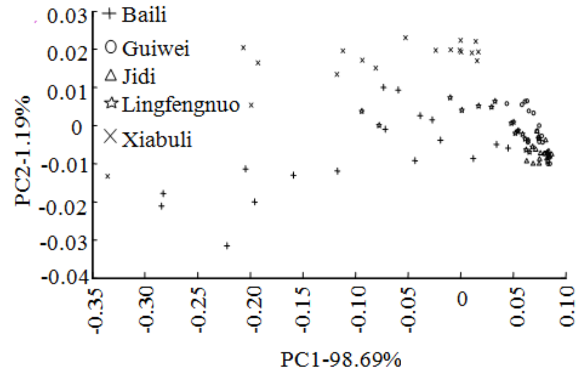

Fig. 3: PCA for different litchi varieties

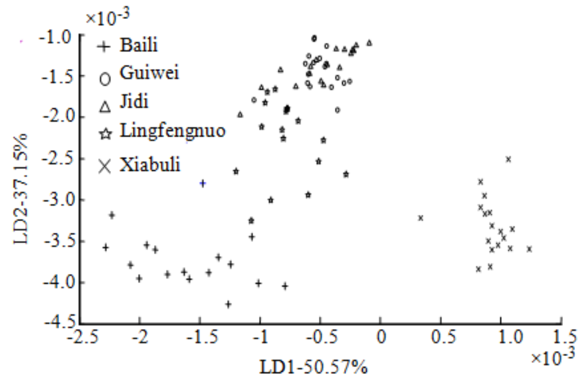

Fig. 4: LDA for different litchi varieties

SVM for litchi variety: When employing the Support Vector Machine (SVM) for classification, the same training set and test set as the PNN analysis are used. Before establishing classification model, appropriate kernel function should be chosen. The common used kernel functions are the linear kernel, the polynomial kernel, radial basis function kernel and sigmoid kernel. The selection of kernel function has great influence on the performance of SVM model. By comparing the properties of available functions, radial basis function kernel is determined as the kernel function to establish SVM classification model. In addition, considering the influence of the parameters of kernel function on SVM model, the parameters of kernel function, including the penalty coefficient, C and the regularization coefficient, γ, need to be optimized. After a set of trials, the SVM model is established with C is 71 and γ is 0.06. Using this model for classification, the training set's classification accuracy is 100% and the test set's classification accuracy is 92%. The results indicate that SVM has good classification effect for litchi varieties.

Loadings for litchi volatile: Loading is a correlation coefficient of Principal Component (PC) and corresponding original variables, used to reflects the closeness of each PC or variable and judge the

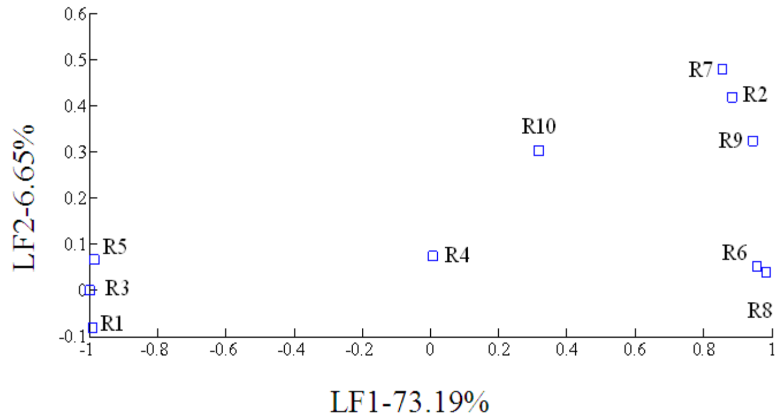

Fig. 5: Loading results for volatiles of litchi

contribution and correlation of each sensor to PC1 and PC2 (Li *et al*., 2013; Liu *et al*., 2010). The results from loading analysis are shown in Fig. 5. The contribution rate of the first loading factor (LF1) is 73.19%, the contribution rate of the second loading factor (LF2) is 6.65% and the total contribution rate of LF1 and LF2 is 79.84%. To evaluate the contribution of each sensor on litchi volatiles identification, the value D_{Ri} (the sum of LF1's contribution and LF2's contribution) is used for measurement. Larger D_{Ri} indicates greater contribution of each sensor to identify litchi volatiles.

$$D_{Ri} = |x_{Ri}| \times C_{LF1} + |y_{Ri}| \times C_{LF2}$$

where Ri is the number of sensors i (i = 1, 2, 3, … , 10), x_{Ri} is the sensor's (Ri) loading value in LF1, y_{Ri} is the sensor's (Ri) loading value in LF2, C_{LF1} and C_{LF2} are the respective contribution rate of LF1 and LF2.

The contribution values of sensor R1 to R10 for litchi volatiles recognition are 0.742, 0.674, 0.731, 0.006, 0.730, 0.702, 0.658, 0.722, 0.713, 0.235, respectively. Thus, the sensors that are mainly sensitive to litchi volatiles are R3, R5, R1 and R8. The sensitive materials of each sensor are shown in Table 1, which reflects that the main components of the Litchis' volatiles are Ammonia and aromatic molecules (R3), Methane, propane and aliphatic non-polar molecules (R5), Broad alcohols (R8), Aromatics (R1). The results also provide a reference for sensors selection when developing specialized Litchi identification devices in the future.

CONCLUSION

This study, proposed a new way for litchi variety classification and recognition. TSS and hardness detection results have demonstrated that litchi varieties cannot be classified based on the two physical indexes only. Then, an electronic nose with different analytical methods was applied to classify the litchi varieties. The result of VA shows that the average differential value of each sensor's response curve is the best choice to act as the characteristic value. Both classification effects of PCA and LDA were poor. However, using PNN model for classification, the classification accuracy of training set and test set are 100% and 84%, respectively. Using SVM model for classification, the classification accuracy of training set and test set are 100% and 92%, respectively. Both PNN and SVM can classify litchi varieties effectively. Furthermore, the results from loading analysis suggest that the sensors R3, R5, R8 and R1 can be chosen for developing specialized litchi identification devices in the future. In summary, the feasibility of applying electronic nose on litchi varieties classification is proved in this study. It provides a novel method for nondestructive examination of litchi varieties.

ACKNOWLEDGMENT

This research has received financial support from Natural Science Foundation of China (31571561) and College Outstanding Young Teacher Training Program in Guangdong Province (Y92014025).

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