



Data Fusion of Electronic Nose and Electronic Tongue for Discrimination of Chinese Liquors

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Abstract: The aim of this work is to improve the performance of electronic nose system and electronic tongue system by fusing the data of different sensor types, and a data fusion technique is presented in this paper. Eight different commercial brands of liquor were discriminated by using electronic nose and electronic tongue. Principle Component Analysis (PCA) was applied on the data of electronic nose and electronic tongue respectively, the classification result was not good enough. However, the result was improved by using the data fusion technique. Therefore, this technique can enhance the ability of PCA. Bayesian classifier and Bayesian classifier based on PCA were used to further classify the samples, two conclusions were proposed: compared with the single application of electronic tongue or electronic nose, the fusion technique has improved the classification accuracy; in contrast with the Bayesian classification, Bayesian classification based on PCA method has increased the classification speed trebly. *Copyright © 2013 IFSA.*

Keywords: Data fusion, Electronic nose, Electronic tongue, Chinese liquors, Bayesian classifier.

1. Introduction

Chinese liquor has a long history with special aroma and taste, which is loved by a vast number of consumers. And as is known, liquor is a great invention of our ancestors. Liquors' production and consumption play an important role in the national economy. Recently, some adulterated liquors have appeared in the markets, which are harmful to health. With the improvement of living standard, people increasingly pay attention to the quality of liquors. The discrimination of Chinese liquors is a very complicated task since innumerable chemical compounds are present in them. Therefore, many researchers have been working on this issue for a long time.

At present, the methods of liquors detection include sensory analysis of people, chemical

analysis, electronic nose analysis and electronic tongue analysis. Sensory analysis is completed by experienced professionals. Although the professionals have been trained strictly, they would be influenced by various factors like individual variability, decrease in sensitivity due to prolonged exposure, infection, and adverse mental state at times. The chemical analysis, a classical method, has been applied widely. Such as the technique of solid-phase micro-extraction (SPME) has been used to discriminate wine aroma [1], the gas chromatography (GC) has been taken to evaluate the aroma of wine [2, 3], and the capillary liquid chromatography has been chosen to determinate ochratoxin A in wines [4]. However, the chemical analysis is quite complex, and most of the chemical analysis instruments are so heavy that they are inconvenient to use. As electronic nose and electronic tongue, they

are new detection means. Nowadays many of commercial electronic nose and electronic tongue equipments have appeared. For electronic nose, PEN3 of German AIRSENSE, FOX4000 and Heracles II of French Alpha MOS, and ODP2 of German Gerstel are more popular. In this paper, we constructed the electronic nose since the high price of the commercial instruments. For electronic tongue, the representative instruments include ASTREE and ASTREE II of French Alpha MOS, TS-5000Z of Japanese INSENT and Chinese Smartongue. According to the report of the foreign research institutions, the electronic nose and electronic tongue systems have become mature increasingly. They were applied in many fields, such as food industry [5, 6], medical [7, 8], environment [9, 10], agriculture [11, 12] and so on.

With the development of science, more and more people would prefer to use electronic nose or electronic tongue to evaluate the quality of liquor [13, 14]. Applications of electronic nose and electronic tongue related to Chinese liquors analysis are focused on the discrimination of samples. Data analysis and pattern recognition in particular, are an important part of any system. Pattern recognition can be divided into two categories: linear pattern recognition and non-linear pattern recognition. Nonlinear pattern recognition methods namely artificial neural network (ANN), probabilistic neural network (PNN), back propagation neural network (BPNN) and support vector machine (SVM) have been used in various applications [15, 16]. Linear pattern recognition includes principal component analysis (PCA), linear discriminant analysis (LDA) and cluster analysis (CA). And they also have been commonly used in both electronic nose and electronic tongue systems [17, 18].

In fact, some substances have two characteristics: aroma and taste. Using electronic nose or electronic tongue single can only provide partial information of the samples, which may cause inaccuracy of the classification. Since some characters can not be measured by one sensor might be measured by the others, the probability of correct classification could be increased. So it is expected that in instrumental Chinese liquors quality analysis fusion of electronic nose and electronic tongue data will improve the liquors classification. Multi-sensor data fusion has several advantages compared with one sensor: fault tolerance, complementarity and economy, and most importantly, it can be suited with identical or dissimilar sensors to provide information about the same measured. Thus it has been used in a lot of domains, such as automation technology [19], robotics [20], and remote sensing technique [21] and so on.

In this paper, we fuse the feature data of electronic nose and electronic tongue. At first, we use PCA to process the data, and obtain the distribution of Chinese liquors. Then Bayesian classifier and Bayesian classifier based on PCA were applied to classify the samples. In this work, 8 different Chinese liquors were tested to verify the performance of this method in the experiment.

2. Measurement Systems

The measurement equipment consists of two kinds of sensor: MOS sensors for electronic nose system; ion specific electrodes for electronic tongue system. For the two systems, they are attached to a common personal computer. Fig. 1 shows the block diagram of the equipment.

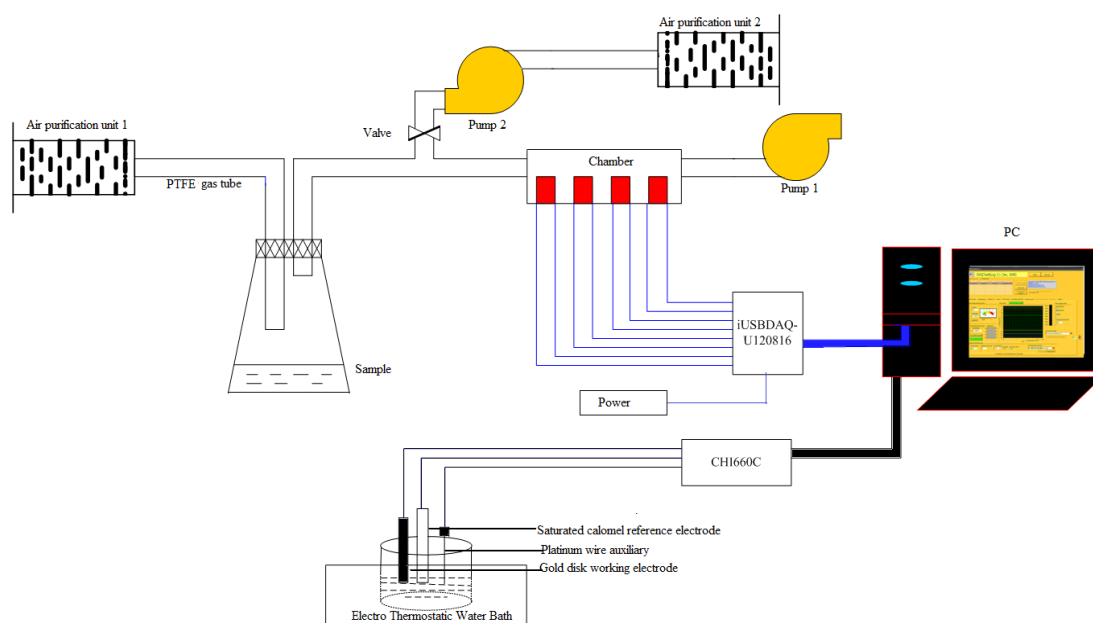


Fig. 1. Block diagram of measurement equipment.

2.1. Electronic Nose

2.1.1. The Hardware of Electronic Nose

Electronic nose system includes three main parts: gas supply, modulating and transmitting unit; sensor array and the chamber unit; power and data acquisition unit.

The first unit is divided into two stages: injection and cleaning. The air is filtered by active carbon to obtain zero gas. In the injection phase, pump1 is used to suck the sample gas compounds into chamber and valve is closed. In the cleaning phase, open both pumps. Since the flow rate of pump2 is higher than pump1, the waste gas flow direction at the inlet is inverted.

An electronic nose system has been specially made with an array of 8 MOS sensors: TGS-832, TGS-831, TGS-830, TGS-826, TGS-825, TGS-821, TGS-822 and TGS-813. Table 1 lists all the sensors. They have a number of good features, such as high sensitivity, high stability and long life. The sensing element for such sensors is tin dioxide (SnO_2), which

has low conductivity in zero gas. And the conductivity of the sensors is depending on the concentration of odor molecules in the chamber. The higher the concentration is, the higher the output voltage is. Fig. 2 shows the circuit of MOS sensor. V_H is heater voltage, which is required for an external 5.0 ± 0.2 V AC or DC power supply. V_C is circuit voltage, which needs a DC power supply and the value must lower than 24 V. R_L is load resistance, and the value must greater than or equal to $0.45 \text{ k}\Omega$. The volume of chamber is 1012.5 ml ($13.5 \times 12.3 \times 6 \text{ cm}^3$). The chamber is made of cardboard which is covered by Polytetrafluoroethene (PTFE) inside. PTFE is a thermoplastic polymer, which is a white solid at normal atmospheric temperature. Its melting point is 327°C (621°F), coefficient of friction is 0.05 to 0.10 and density is 2.2 g cm^3 [22]. PTFE's resistance to van der Waals forces means that little substance can stick on its surface, which was chosen as the material for chamber. And in the electronic nose system, all of the gas tube is also PTFE.

Table 1. Characters of 8 MOS sensors.

Number	Sensor name	Sensitive gas	Detection range(mg L-1)
1	TGS-832	R-134a	100-3000
2	TGS-831	R-21, R-22	100-3000
3	TGS-830	R-113, hydrogen and alcohol	100-3000
4	TGS-826	Ammonia	30-300
5	TGS-825	Hydrogen sulfide	5-100
6	TGS-821	Hydrogen	30-1000
7	TGS-822	Alcohol	50-5000
8	TGS-813	Methane, propane and butane	500-10000

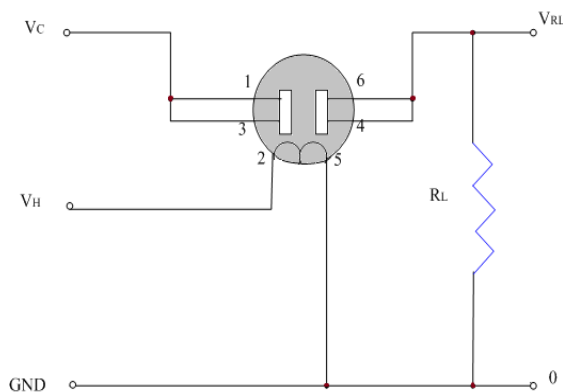


Fig. 2. Circuit of MOS sensor.

In the third unit, we choose WD-5 power to supply DC +5 V and +10 V, it was purchased from Qidong computer factory. IUSBDAQ-U120816,

which is developed by HYTEK Automation, was used to acquire signals. It can change analog signals to digital signals, and transmit to the computer. Its features can be listed as follows:

- USB 2.0/1.1 full speed interface;
- USB bus powered;
- 8 single-ended, 12-bit analog inputs;
- 0-5 V analog input range;
- Up to 32k samples/second throughput with single channel up to 13k samples/second for streaming mode.

2.1.2. The Software of Electronic Nose

Measurement system is based on LabVIEW, which is made up of four modules: login module, data acquisition module, data preprocessing

module and pattern recognition module. Table 2 details such modules.

The system, combined LabVIEW with Matlab, is more powerful. According to the needs of user,

developer can modify the program easily. For the pattern recognition modular, user can select the most appropriate method for special measured object.

Table 2. Modules for electronic nose system.

First order modules	Second order modules	Function
Login modular	User logon User login	User can log on the system when user name and password are correct Supply new user login function.
Acquisition module	Data acquisition Data store	Eight channel data acquisition and real-time data waveform display According to user requirements, the data can be stored in disk with specified format (e.g. .txt and .xls.)
Data preprocessing module	Feature extraction Normalization	Extract features from the data Normalize the features from the data
Recognition module	Algorithms	PCA, BP, Bayes, RBF, and KNN and so on

2.2. Voltammetric Electronic Tongue

For the voltammetric electronic tongue system, the sensor array is composed of a gold disk working electrode, a platinum wire auxiliary electrode and a saturated calomel reference electrode. The CHI660C electrochemical workstation is also an important part of the electronic tongue system, and it was bought from Shanghai Chenhua Instrument limited Company.

3. Experiments

3.1. Sample Collection

8 commercial Chinese liquors were purchased at a local supermarket to use as testing samples. Their names, types, raw materials, total acidities and location were copied from the liquor bottle labels. Table 3 lists all of these. The eight liquors can be divided into mild aromatic Chinese liquors and strong aromatic Chinese liquors.

Table 3. Samples for Chinese liquors.

Number	Brand	Alcohol content	Type	Raw material	Location
1	Aoxi Beijing Erguotou	56 %	Mild aromatic Chinese spirits	Water, sorghum, wheat	Beijing
2	Fangzhuang Erguotou	56 %	Mild aromatic Chinese spirits	Water, sorghum	Daxing District, Beijing
3	Hengshui Laobaigan	50 %	Mild aromatic Chinese spirits	Water, sorghum	Fucheng Country, Hengshui City
4	Hongxing Erguotou	46 %	Mild aromatic Chinese spirits	Water, sorghum	Huairou District, Beijing
5	Luzhou Laojiao	45 %	Strong aromatic Chinese liquors	Water, sorghum wheat	Luzhou City, Sichuan Prov.
6	Niulanshan Erguotou	56 %	Strong aromatic Chinese liquors	Water, sorghum rice, corn	Shunyi District, Beijing
7	Chuncheng Yingbin	45 %	Mild aromatic Chinese spirits	Water, sorghum	Yushu City, Jilin Prov.
8	Zhongde Beijing Erguotou	50 %	Strong aromatic Chinese liquors	Water, sorghum, wheat	Baoding City, Hebei Prov.

3.2. Measurement Using the Electronic Nose

Measurements are taken using the dynamic headspace technique. The laboratory conditions for gas-sensing measurements is under $20^{\circ}\pm 2^{\circ}\text{C}$ and $65\pm 5\%$ relative humidity. The measurements in a flow of zero gas continue to 30 min, at the same time, we have to observe the sensors signal and to make sure the final values of all the sensors were equilibrated. In the process of dynamic headspace sampling, 20 ml Chinese liquors were put into an airtight flask of 100 ml, and then the headspace of the flask is continuously swept into the chamber by zero gas flow for detection. The response time of the sensors was approximately 4 min. In the injection phase, the flow of the pump1 was set to 0.5 L min^{-1} . After that, open both pumps, and the flow of pump2 was set to 1 L min^{-1} , so the zero gas can clean the chamber and the gas tube, and the cleaning phase lasted 20 min. Not until the sensors equilibrated, can a new measurement be initiated.

Each measurement was repeated 25 times, 80 % of the total data of each class were used to train the model of Bayesian classifier, and 20 % measurements were used as the testing data set in data analysis.

3.3. Measurement Using the Electronic Tongue

The electronic tongue setup is three sensors that work on the liquid samples. The sensors don't respond to a particular constituent of the aqueous solution but to the whole for all the constituents of a particular solution [23]. Due to the present of different compounds and ions, the response of the tongue is multivariate. Before the measurements, the saturated calomel reference electrode was soaked in alcoholic solution for 5 min, and then all the electrodes were rinsed by a lot of deionized water. In the measurements, 50 ml sample was poured into beaker of 50 ml. Electro Thermostatic Water Bath was taken to keep the samples at 30°C .

The electronic tongue is based on cyclic voltammetry, and this technique is chosen for better sensitivity. The parameters set as follows:

- Initial voltage = 1.3 V;
- High voltage = 1.3 V;
- Low voltage = -0.6 V;
- Initial P/N=N;
- Scan rate= 0.5 V s^{-1} ;
- Segment=2;
- Sample interval= 0.001 V ;
- Quiet time = 2 s;
- Sensitivity = $1\text{e-}6\text{ A V}^{-1}$.

4. Data Analysis

Usually, data analysis can be divided into 3 steps. They are signal pre-processing, feature extraction and classification.

4.1. Signal Pre-Processing

In this section, baseline manipulation was applied to decrease the effects of sensor drifts for electronic nose system. There are many methods for the baseline manipulation, such as relative, logarithmic and differential methods and so on. In this paper, we use relative method to solve the aforesaid issue. It can be expressed as

$$V = V_S - V_0 \quad (1)$$

Here V_S is the stable voltage of gas sensors for sample, V_0 is the voltage of gas sensors for reference gas. Since the Electro Thermostatic Water Bath was used for experiments of electronic tongue, we consider the experiment condition is stable. In other worlds, the sensors drift can be neglected in electronic tongue system.

4.2. Feature Extraction

Feature extraction is the second step of data analysis. Signals of both electronic nose system and electronic tongue system contain hundreds of measures and usually overlapping regions with nonstationary characteristic. Thus, in order to avoid redundancies in the information and achieve proper mathematical models, the complex signals should be reduced. In a sense, when choosing the features from the two datasets, we shouldn't only focused on making compatible the nature of the two distant signals for each sensor and on facilitating the computation, but also on retaining the relevant information from each signal type [24]. In this section, we choose the maximum values of every sensor as features for the electronic nose system. For the electronic tongue, seven representative features were extracted from the cyclic voltammogram of each experiment. And we choose the currents corresponding to 1.3 V, 1 V, 0.7 V, 0.4 V, 0.1 V, -0.2 V and -0.5 V respectively.

4.3. Theory Method

4.3.1. Principle Component Analysis (PCA)

PCA is a dimensionality reduction method, which, as a pre-processing technique, was used widely. The basic idea of PCA is to extract most significant parameters (principle components) which contain most important information. Through a linear transformation, original parameters can be changed to a new set of uncorrelated and optimized ones. In this paper, we use PCA to demonstrate the distribution of 8 Chinese liquors, but it can not be used to classify text samples correctly.

4.3.2. Data Fusion Based on Bayesian Classification Method

In order to discriminate the 8 Chinese liquors, we designed a Bayesian classifier. It is known that Chinese liquor testing is a difficult job for its two features: aroma and taste. One kind of sensors provides incomplete information about a property that needs to be evaluated. So it is necessary to fuse the data from multiple sensors, which has an important advantage that it can provide information about the same measured with identical or dissimilar sensors [25]. The fused matrix of data obtained from electronic nose and electronic tongue is given as

$$\begin{bmatrix} x_{11} & x_{12} & \dots & x_{1m} \\ x_{21} & x_{22} & \dots & x_{2m} \\ \dots & \dots & \dots & \dots \\ x_{(k*n)1} & x_{(k*n)2} & \dots & x_{(k*n)m} \end{bmatrix},$$

where x is the feature of one sensor for one class, k is the number of experiment times for one class, n is the number of classes and m is the number of features (the total number of features for both systems). Before the data are fused, we have to normalize the data to ensure that they are in the same order of magnitude.

In actual classification problems where samples are not fully separable, but it is realistic to determine the optimum classification rate by the determination of the Bayesian error. In order to assign a pattern y to n classes w_i ($i = 1, 2, \dots, n$), decision boundaries or decision surfaces should be found.

We consider that data from each sensor is independent, so the conditional probability can be calculated by

$$p(y | w_i) = \prod_{j=1}^m p_j(x | w_i), \quad i = 1, 2, 3, \dots, n, \quad (2)$$

where w_i is the class, n is the number of classes, m is the number of features, and $y = [x_1, x_2, \dots, x_m]$ is a pattern vector which corresponds to the fused data, x is a one-dimensional variable and $p(x | w_i)$ is the probability density function for each feature. However, in the case of multivariate class-conditional probability density, the conditional probability can be expressed as

$$p(y | w_i) = \frac{1}{(2\pi)^{m/2} \sqrt{|\Sigma|}} \exp\left[-\frac{1}{2}(y - \bar{\mu})^T \Sigma^{-1}(y - \bar{\mu})\right], \quad (3)$$

where Σ is the covariance matrix, $\bar{\mu}$ is the vector mean, $|\Sigma|$ is the determinant of the covariance matrix and Σ^{-1} is the inverse of the matrix.

According to the Bayesian decision theory

$$p(w_i)p(y | w_i) > p(w_k)p(y | w_k), \quad (4)$$

$$k, i = 1, 2, \dots, n; k \neq i$$

the pattern y is assigned to a class w_i . In the inequality, $p(y | w_i)$ is the conditional probability, $p(w_i)$ is prior probability, which can be calculated by

$$p(w_i) = \frac{N_i}{N}, \quad (5)$$

where N_i is the number of class i , and N is the total number of samples.

According to equation (1), $p(w_i)p(y | w_i)$ can be replaced as

$$p(w_i)p(y | w_i) = p(w_i) \frac{1}{(2\pi)^{m/2} \sqrt{|\Sigma|}} \exp\left[-\frac{1}{2}(y - \bar{\mu})^T \Sigma^{-1}(y - \bar{\mu})\right] \quad (6)$$

In order to find the class of y , we only need to find the max value of equation (6). And the probability of error for n classes is given as

$$p(e | y) = \min[p(w_1 | y), p(w_2 | y), \dots, p(w_n | y)] \quad (7)$$

5. Results and Discussion

According to equation (1), we can obtain the pre-processed signals. Fig. 3 shows the pre-processed signals of the eight samples. Each color represents a response of one sensor.

Fig. 4 shows the experimental results of the electronic tongue system. Curves with different colors represent different brands of liquors.

As previously mentioned, we choose maximum values as the features. There are 8 MOS sensors in the electronic nose system, so the number of features is 8 in each sample. As for the electronic tongue, the current values corresponding to 7 voltage values in the voltammograms are chosen as the features. Fig. 5 shows the features of electronic nose system, and Fig. 6 shows the features of electronic tongue system

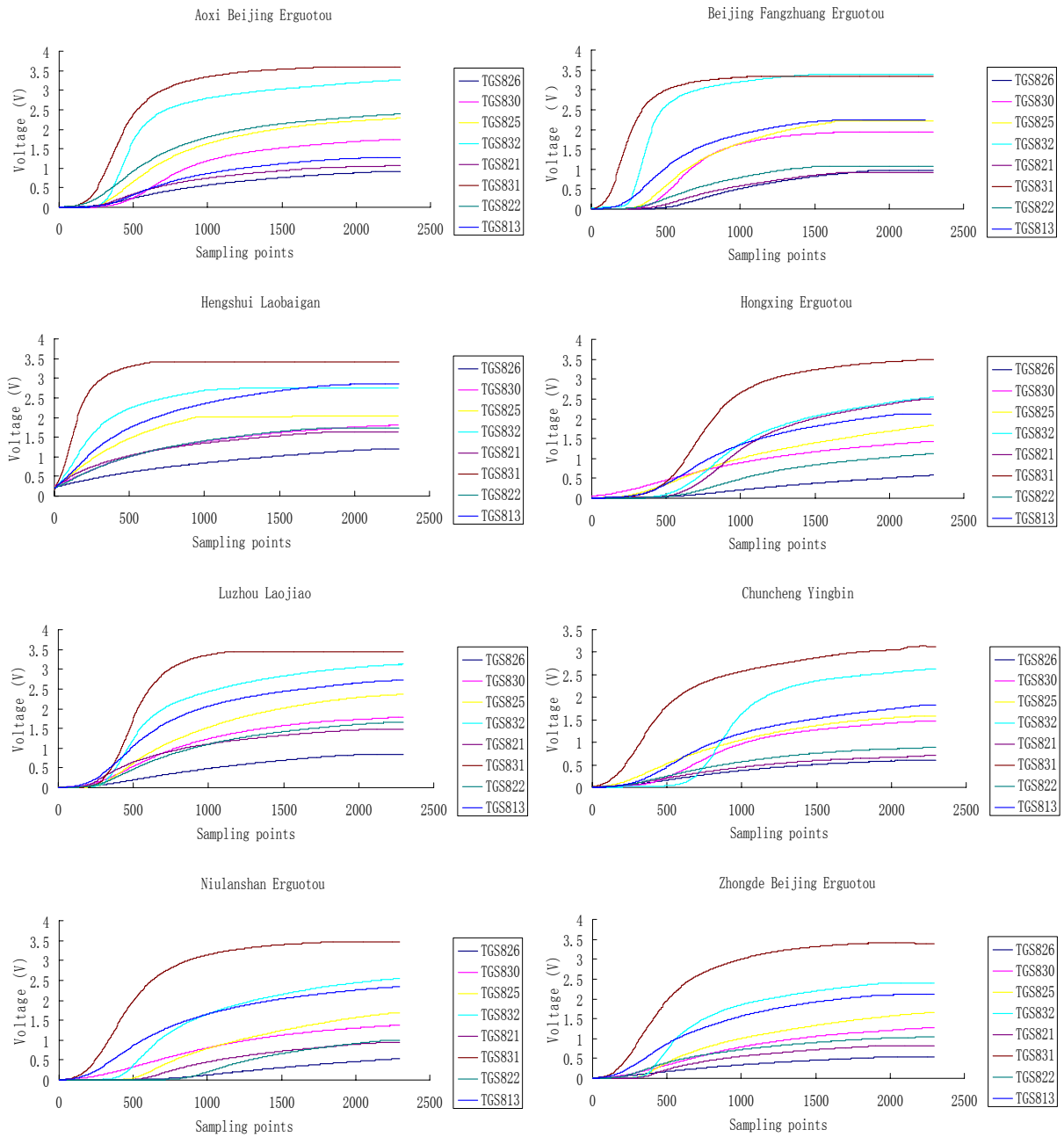


Fig. 3. Pre-processed signals of 8 samples.

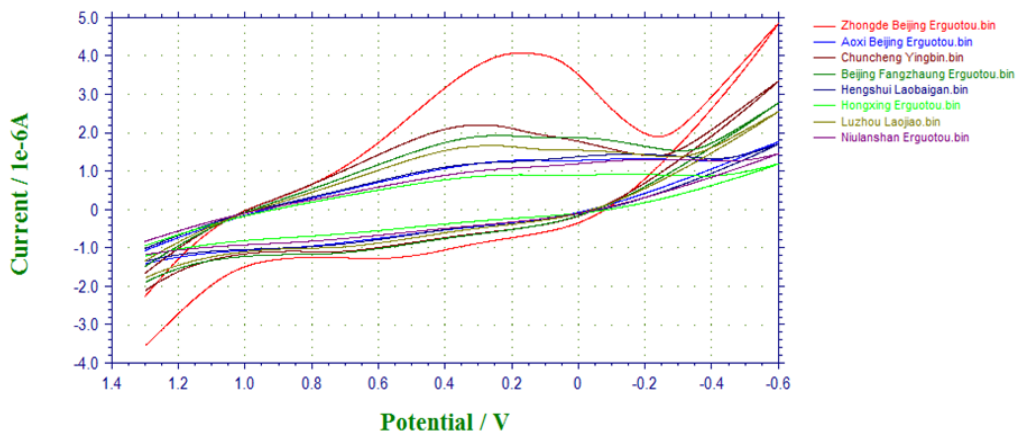


Fig. 4. Signals of electronic tongue.

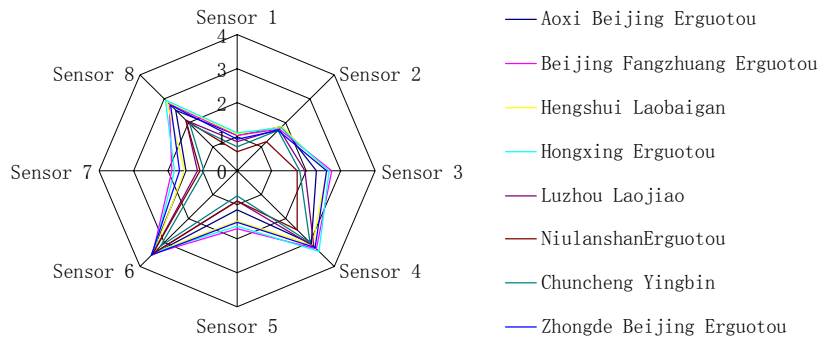


Fig. 5. Radar graph of electronic nose.

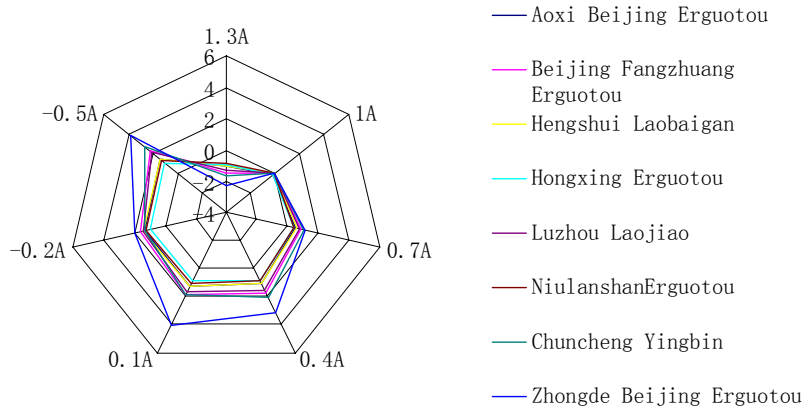


Fig. 6. Radar graph of electronic tongue.

5.1. Principle Component Analysis

Sensors, in electronic nose system or electronic tongue system, have cross-sensitivity toward liquors. Thus, there exist collinear variables among multiple characteristic variables, which could be solved with the help of principal component analysis (PCA). PCA is a linear, unsupervised and pattern recognition technique, which is used for analyzing and reducing the dimensionality of numerical datasets in a multivariate problem [26]. In this paper, PCA was performed on the aforementioned 8 datasets, and some of the PCs were extracted as the input of pattern recognition. In brief, it could extract useful information and eliminate the redundant information.

Fig. 7 shows the score plots of each sample with the first PC and second PC. Fig. 7(a), for the dataset of electronic nose, shows that PC1 can explain 78.15 % of the variance, and PC2 can explain 15.23 % of the variance. Fig. 7(b), for the data set of electronic tongue, shows that PC1 can explain 96.05 % of the variance, and PC2 can explain 2.1073 % of the variance. Fig. 7(c), for the fused data sets of two systems, PC1 can explain 79.45 % of the variance, and PC2 can explain 13.82 % of the variance. Besides that, we can see that the 8 groups of different Chinese liquors can not be separated well in both Fig. 7(a) and Fig. 7(b), but the classification

effect was improved when fuse the data set of electronic nose and electronic tongue.

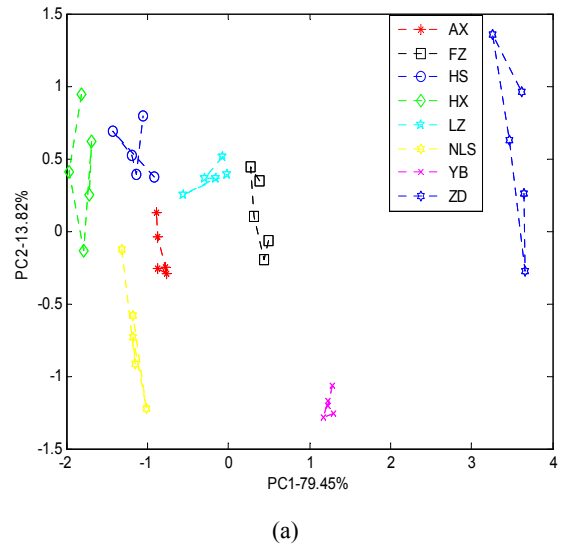


Fig. 7(a). PCA plots for 8 Chinese liquors. PCA plot of electronic nose system. Where ‘AX’ is ‘Aoxi Beijing Erguotou’; ‘FZ’ is ‘Beijing Fangzhuang Erguotou’; ‘HS’ is ‘Hengshui Laobaigan’; ‘HX’ is ‘Hongxing Erguotou’; ‘LZ’ is ‘Luzhou Laojiao’; ‘NLS’ is ‘Niulanshan Erguotou’; ‘YB’ is ‘Chuncheng Yingbin’; ‘ZD’ is ‘Zhongde Beijing Erguotou’.

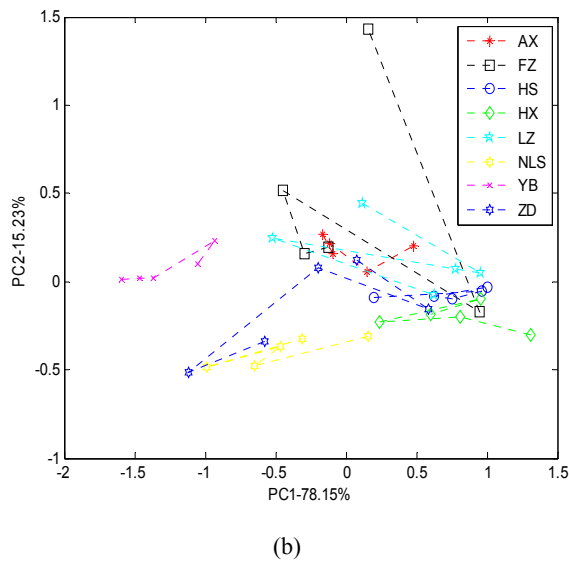


Fig. 7(b). PCA plots for 8 Chinese liquors. PCA plot of electronic tongue system. Where ‘AX’ is ‘Aoxi Beijing Erguotou’; ‘FZ’ is ‘Beijing Fangzhuang Erguotou’; ‘HS’ is ‘Hengshui Laobaigan’; ‘HX’ is ‘Honxing Erguotou’; ‘LZ’ is ‘Luzhou Laojiao’; ‘NLS’ is ‘Niulanshan Erguotou’; ‘YB’ is ‘Chuncheng Yingbin’; ‘ZD’ is ‘Zhongde Beijing Erguotou’.

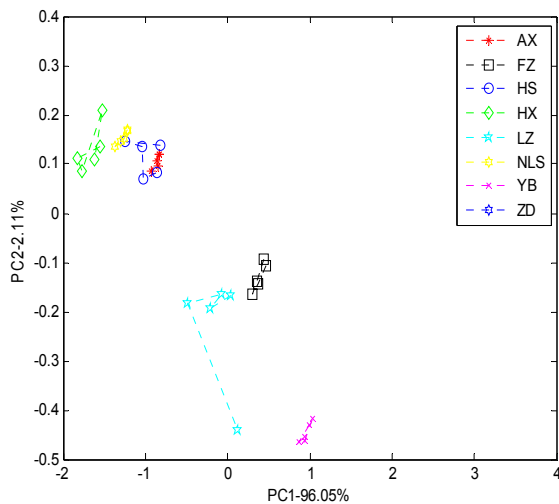


Fig. 7(c). PCA plots for 8 Chinese liquors. PCA plot of data fusion. Where ‘AX’ is ‘Aoxi Beijing Erguotou’; ‘FZ’ is ‘Beijing Fangzhuang Erguotou’; ‘HS’ is ‘Hengshui Laobaigan’; ‘HX’ is ‘Honxing Erguotou’; ‘LZ’ is ‘Luzhou Laojiao’; ‘NLS’ is ‘Niulanshan Erguotou’; ‘YB’ is ‘Chuncheng Yingbin’; ‘ZD’ is ‘Zhongde Beijing Erguotou’.

5.2. Bayesian Classifier

The geometrical explorations of these plots by PCA only give the data cluster trend. The aim of this work is to discriminate Chinese liquors by means of two datasets with the help of the classification tool.

Therefore, it is crucial to choose the suitable classification tool to develop a discrimination model.

In this work, Bayesian classifier was designed to discriminate the samples.

Using equation (2), we can get $p(y | w_i)$ as

$$p(y | w_i) = \prod_{j=1}^m \frac{1}{\sqrt{2\pi\sigma_j^2}} e^{-(x-\mu_j)^2/2\sigma_j^2} \quad (8)$$

For the electronic nose system, m is 8; as for electronic tongue system, m is 7; and m is 15 for the fusion of electronic nose and electronic tongue. Where σ_j is the standard deviation of the training samples for each feature of each class, and μ_j is mean of the distribution. And in this paper, the prior probabilities for the 8 class are equal, which means that $p(w_1) = p(w_2) = \dots = p(w_8) = \frac{1}{8}$.

can get the error probability by equation (7). Table 4 shows the result on error probability for Chinese liquors with 8 different classes.

According to equation (4), sample classification is performed. The percentage of classification error was calculated dividing the number of times that the classifier was wrong by the total number of the text samples. And the wrong classifier was contrasted with the true class asset prior. Table 5 shows the classification error.

Table 4. Error probability with different sensor system.

Sensor system	Error Probability
Electronic nose	8.33 %
Electronic tongue	6.50 %
Combine system	2.93 %

Table 5. Percentage error calculation for Bayesian classifier.

Features	Type	Error Probability	Times (ms)
Aroma	univariate	25 %	25.858
Taste	univariate	10 %	19.304
Total	Multivariate	7.5 %	18.224

From Table 4 and Table 5, we can observe that the probability of error and classification error both were improved with the fused data. However, there is a disagreement between them, which could be explained by the possible differences the “true statistic” values of priors and likelihoods and the estimated. If the sample size is large enough, the error difference in the classification can be avoided according to the Central Limit Theorem requirements.

5.3. Bayesian Classifier Based on PCA

As previously mentioned, the Bayesian classification based on PCA is taking PCA method to pre-process the raw data, and the principle components can be obtained. Then using the principle components build the training set for the Bayesian classifier. Through the above method, the percentage of classification error can be calculated also. Table 6 shows the percentage error calculation for Bayesian classifier based on PCA.

Table 6. Percentage error calculation for Bayesian classifier based on PCA.

Features	Type	Error Probability	Times (ms)
Aroma	univariate	20 %	7.283
Taste	univariate	10 %	5.672
Total	multivariate	2.5 %	4.987

Table 5 and Table 6 show that the classification results of Chinese liquors almost the same by using electronic nose and electronic tongue system singly, but the classification accuracy is obviously improved for the fusion data. Compared with the application of Bayesian classifier, the classification time was significantly shortened by using the Bayesian classifier based on PCA.

6. Conclusions

The concept of data fusion was applied to classify the Chinese liquors. A Bayesian classifier and a Bayesian classifier based on PCA considering a multivariate eight-class problem were incorporated for data fusion. The results show that data fusion improves the classification and reduces the error. Compared with the Bayesian classifier without PCA, the Bayesian classifier based on PCA method has the advantages of fast classification and recognition. That because PCA can reduce the dimensionality of numerical datasets in a multivariate problem for the particular process. In some circumstance, PCA could be applied to improve computational speed.

In summary, different sensor modalities can provide different information of samples, so fusing all the information can enhance the classification performance. This paper has shown that discrimination of 8 different Chinese liquors can be improved by applying data fusion. It can be extrapolated to other substances which have aroma and taste two features. There are a variety of material have aroma and taste two features in the real word. In order to detect the material, it is necessary to fuse the two features.

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