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The Quantitative Analysis to Inferior Oil with Electronic Nose Based on Adaptive Multilayer Stochastic Resonance

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Abstract: This study makes the three acryl glycerin polymers, oxidation three acryl glycerins, and low carbon number fatty acid as inferior oil feature index. Using double steady state stochastic resonance signal-to-noise ratio analysis methods make the quantitative analysis to inferior oil. This paper analyzes the stochastic resonance. Introduces the principle detection system structure based on adaptive multilayer stochastic resonance algorithm in inferior oil quantitativeanalysis; and make adaptive double stochastic resonance model and inferior oil as example, give the simulation and numerical analysis of this model of the system. The results show that the system can obtain more accurate quality the proportion of the inferior oil information. At the same time, this method can effectively solve the semiconductor gas sensors of the baseline drift problem. The method of stochastic resonance has a lot of application prospect in improving the system performance.

Key words: Electronic noses, inferior oil, quantitative analysis, stochastic resonance

INTRODUCTION

Due to the global market competition is becoming increasingly intense, and there are more and more countries joined the WTO. This move on the part of the country's economic produce severe impact, especially in the country which food and consumer products production cost is high and human cost are creeping up. In order to seek improper profits, some manufacturers will use the technique of spoofing to cheat the consumer. In recent years in the cooking oil product mix with inferior oil in order to make the cost of incident lower has happened. In fact, with the appearance of the food or simple equipment to identify the quality of the cooking oil is extremely difficult, so it is necessary to establish a set of standard reliable identification method (Gambarra-Neto *et al*., 2009).

Whether inferior oil (special), hogwash oil (ShaoShui oil) or Fried oil, as second oil, all must experience high temperature, or air contact, or light irradiation, so food plant oil is subjected to the high level of oxidation. Oil storage experiments have confirmed that oxidation three glycerins and three bmi acylation glycerin polymers can reflect fresh degree. Compared with Long-term storage of aerobic grease and fresh oil, there are significant differences on the content of three acyl glycerin polymer and acid oxidation three glycer (Martin-Polvillo *et al*., 2004).At present our country of cooking oil testing technology has certain hysteresis. Therefore developed a set of electronic nose system to detect the spoofing degree of the cooking oil have important value. By using nonlinear stochastic resonance two steady state systems to process signal detection of cooking oil, it not only can be used to extract the cooking oil's feature information of the spoofing degree, but also can overcome the baseline drift problem of the gas sensor.

STOCHASTIC RESONANCES

Stochastic resonance principles: In linear system, the signal will be fuzzy as the noise become bigger and bigger, which means that the signal-to-noise ratio will be weakened as noise increasing. However, the influence of nonlinear system noise is not the case. For example, in the double steady state system joins the noise and the signal. When the noise gets large signal served only to strengthen, if the signal-to-noise ratio in the appropriate noise intensity.

This is the so-called stochastic resonance. This phenomenon is not only a physical system, in the chemical, biological systems also have been found. So in the past twenty years, the SR theme in all areas of has been attracted the attention of many research teams (Mitaim and Kosko, 1998; Deng *et al*., 2007; Harmer *et al*., 2002).

When the system modulated by a periodic signal and high noise, use Langevin's equation to express the stochastic resonance system.

$$\frac{dX}{dt} = aX - bX^3 + A\cos(\Omega t) + \xi(t) \qquad (1)$$

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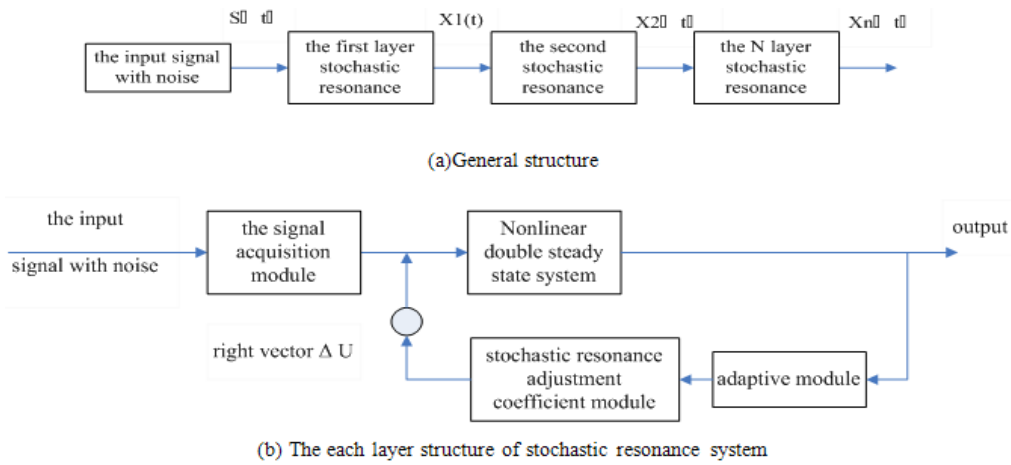

Fig. 1: Ructure of adaptive multilayer stochastic resonance algorithm

In the formula $\xi(t)$: is the Gaussian white noise which noise intensity is D, $\Omega(t)$ is the periodic signal, the amplitude is A.The most common effect evaluation method of stochastic resonance is use the ratio SNR (signal-to-noise) to measure SR system resonance effect; it's defined by Fauve and Heslot. SNR can get from the power spectrum of output signal frequency domain .For a sine signal, the PSD (power spectral density) in the background noise, there is a peak near the sine frequency. SNR is the ratio of the signal frequency spectrum and the background noise. Along with the noise intensity increased, the spectrum peak which power spectrum in the signal frequency spectrum also increases (Dietrich *et al.*, 2011; Jung and Hanggi, 1991; Gammaitoni and Hanggi, 1998). Using mathematical to express SNR as:

$$SNR = 10\log_{10}(\frac{S(w_x)}{B(w_x)}(dB) \quad (2)$$

Says for the integral approach

$$SNR = 10\log[\lim_{\Delta\omega\to 0}\int_{\Omega-\Delta\omega}^{\Omega+\Delta\omega} S(w)dw] / B(w)(db) \quad (3)$$

S (ω) is the signal power spectral density; B (ω) is the size of noise strength in the signal frequency area.

Adaptive multilayer stochastic resonance models: For stochastic resonance system its coefficient a, b, noise intensity D plays an important role in the stochastic resonance resonates system (Pulak *et al.*, 2010; Pian *et al.*, 2008). But in practical applications, because can't know in advance of the characteristics of measured signal like frequency and amplitude. So the general stochastic resonance system can't meet the actual needs of electronic nose signal detection. It is to put forward new requirements to make use of stochastic resonance system for electronic noses signal processing: stochastic resonance system should have adaptive function, which means that according to the different signal for detecting, automatic control their own parameters in order to achieve the stochastic resonance, and extraction the feature information of the measured signal.

When based on stochastic resonance inferior oil detection system can't distinguish the voltage of the weak signal detection, if the maximum peak of the signal-to-noise ratio still without obvious difference, which means that the system for weak signal enhancement have not reached a satisfactory effect, in order to further improve the inferior oil examination ability, we can make the stochastic resonance system for many levels league. Through the use of each layer of stochastic resonance system to process signal, increase the weak signal transmission in every layers. This means that make the output of a layer of the stochastic resonance system as the input of the next layer of stochastic resonance system, to further improve output SNR (Asfaw *et al.*, 2011; Hui-Long *et al.*, 2007; Yong-gang *et al.*, 2007). The structure of adaptive multi-layer stochastic resonance algorithm is shown in Fig. 1.

EXPERIMENT PRINCIPLE

Electronic nose system: Electronic nose is one of the applications in bionics; it used the gas sensor array to make a specific identification and analysis for gas molecules. It has been widely used in many fields, including food surveillance (Li *et al.*, 2007), medical test (Kateb *et al.*, 2009), environmental monitoring (Romain *et al.*, 2005), and explosives detection (Jehuda, 2002).

Figure 2 is the electronic noses detection system structure schemes, including data collection, regulate units and transmission units, sensor array and the gas chamber,

Table 1: Gas sensor array

Sensor Numbers	Sensor Model	Sensitive Gas
1	TGS-822	Alcohol, Methylbenzene, Dimethylbenzene
2	TGS-813	Methane,Propane, Butane
3	TGS-821	Hydrogen
4	TGS-830	Halogen
5	TGS-831	Freon
6	TGS-832	Oxygen
7	TGS-825	Sulfide
8	TGS-826	Ammonia

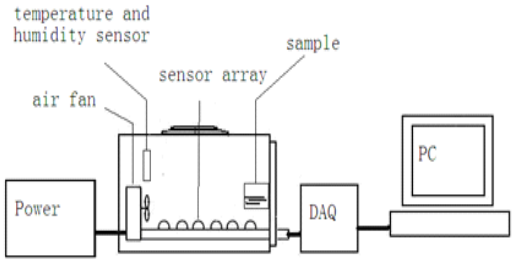

Fig. 2: Electronic nose detection system structure

and gas supply power device three parts. Data collection, regulate and transmission units used by the HYtek Automation iUSBDAQ-U120816, sensor array and the gas chamber part includes eight selected semiconductor gas sensors.

The sensor arrays are formed by eight kinds of semiconductor gas sensors from Figaro Company. The sensor characteristics are shown in Table 1.

Inferior oil testing experiment: The system uses the TGS-8 series of six metal oxide gas sensors come from Figaro company, the specific model are TGS822, TGS813, TGS821, TGS830, TGS831, TGS832. The experiment equipment used the signal regulating circuit of divider-type. Through the sensor voltage reflects the gas concentration. This article chooses the experiments oil which buy from the supermarket. The inferior oil use for this experiment are repeated use gold dragon fish soybean oil; Random buy bulk oil A, bulk oil B, bulk oil C as the test object. Draw respectively 0, 6, 12, 18, 24, 30 mL of the inferior oil in 30, 24, 18, 12, 6 and 0 mL of the gold dragon fish in soybean oil and blend. So we have a 0, 20, 40, 60, 80 and 100% of the inferior oil. Use the quantitative liquid sampling methods, sample volume set at 5 mL. The system selects the time between the data rapidly increasing and slow decrease to collect the data. Generally, after the sample put into a container 2 min later, the significant changes a lot. In order to avoid the impact of environment on the test results, we carried out intermittent testing for two weeks from 2011.4.15-2011.4.29 in the university lab. Before each sample being measured, use built-in fan make the sensor come to usual.Then make use of electronic noses system to test the

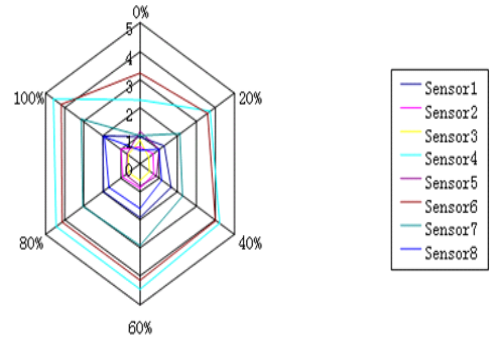

Fig. 3: The radar map of the experiment e oil with spoofing oil

sample, each sample test three times repeat and get an average. We make 0, 20, 40, 60, 80, and 100% of the inferior oil as an experimental samples input stochastic resonance model and make data processing. We make the bulk oil A, bulk oil B, bulk oil C as the test set to verify its quantitative analysis.

RESULTS

The response of the sensor array: When gas comes into the system, the sensor typical reaction can be divided into three stages. In the first stage, the sensor resistance keeps in its baseline Rbase. When the gas is released into the surface of the sensor, the sensor reacts. And its resistance increases rapidly on the rise time. Later, sensor resistance gradually increases to the balance of its final value the Rmax. This is the second stage. As long as the gas also to maintain the same concentration, sensor resistance will be remained in its equilibrium value Rmax. When the air is removed, the sensor resistance drastic decline in the down time, and then toward to the original baseline Rbase slowly decreases. Finally, sensor resistance will slowly back to its original baseline values, this is the third stage. Here we mainly analyze the second phase. Figure 3 is the analysis of oil.

Test sample of stochastic resonance analysis: We make 6 kinds of oil samples as the testing data input SNR analysis system, using the adaptive module adjust the parameter make the system to achieve stochastic resonance condition. Use the multilayer stochastic resonance cascade system to make the maximum signal-to-noise ratio separate. Make it is convenient for the recognition and classification. 6 kinds of oil of resonance SNR curve is shown in Fig. 4.

Stochastic resonance signal-to-noise ratio analysis method is a new signal feature extraction technology. Signal feature extraction is a very important technology for the electronic nose system, the traditional method mainly have the principal component analysis, factor

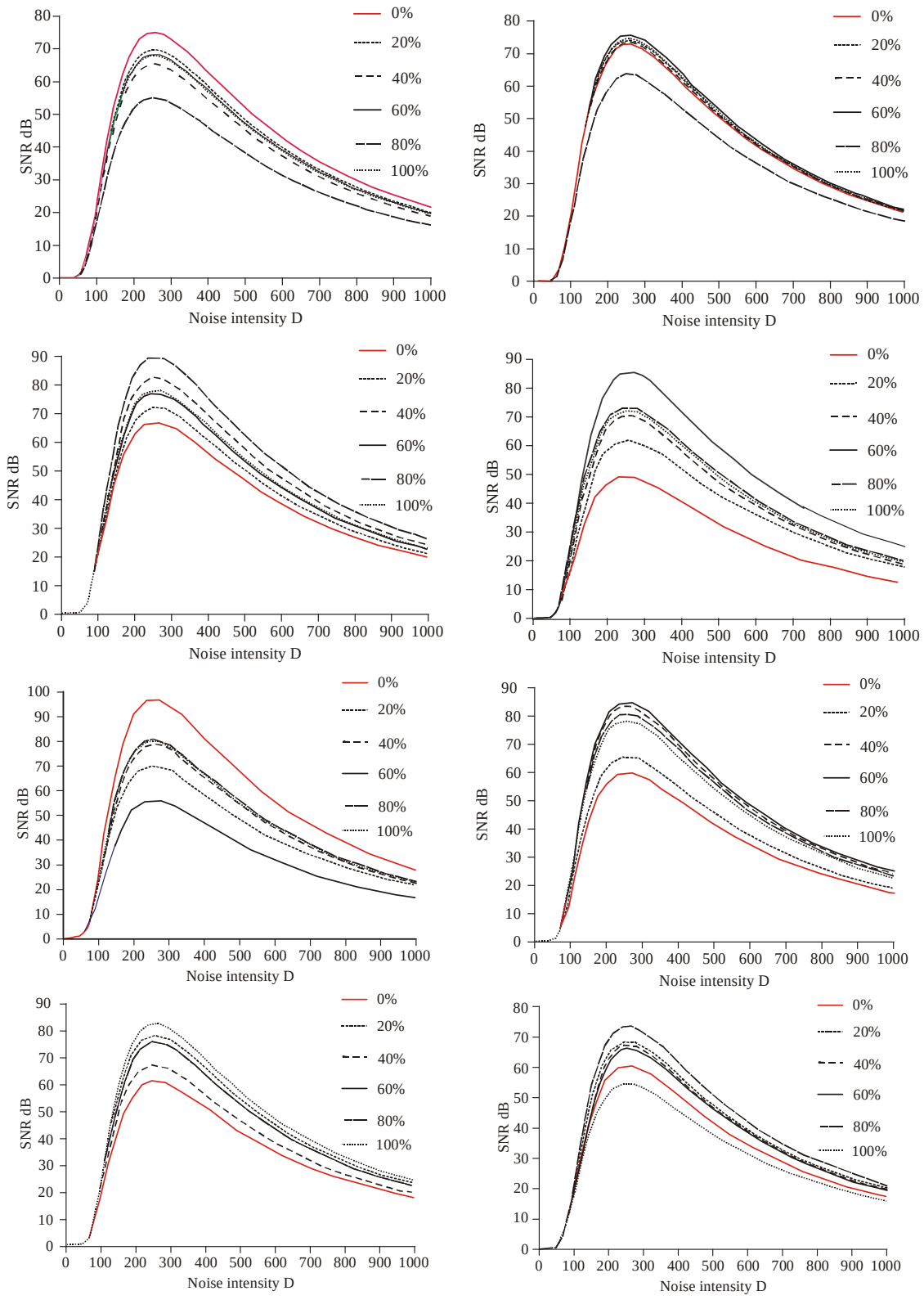

Fig.4: The output of the stochastic resonance system

Table 2: the error rate of clustering method

	SR-FCM	FCM
Best error rate	0%	0%
Average error rate	0%	10%

Table 3: clustering performance analysis

	SR-FCM	FCM
Average running time	16.321	34.875
The average number of evaluation function	9120	15600

analysis (Ronny and D'Aspremont, 2010; Madireddi and Ravi, 2011), artificial neural network (Jouan-Rimbaud *et al.*, 2007), etc. The principal component analysis applies only to data set which most of the dimension are related to the clustering task. Factor analysis in the calculation of the factor score by using least square method may make the result rejected. Artificial neural network as the input data have more cases may appear low training speed and low efficiency, reduce the forecast accuracy and need to multiple learning (Heinsalu *et al*., 2009). In addition, the gas sensors of semiconductor type because of the working temperature is higher than 400 degrees, long time work are easy to happen the baseline drift phenomenon. This is a problem for the enose technology development .The solution method is that before every time detects the gas, the sensor is cleaned and standardized. These factors not only reduce the instrument testing precision, but also increase the complexity of the instrument operation (Walaa *et al.*, 2009; Hanying *et al.*, 2005).

FCM: We deal with the response signal of the sensor array with stochastic resonance method. And use the peak value of the signal-to-noise ratios to make FCM cluster analysis. The FCM based on the matlab language. We make a compared between FCM and SR-FCM about the clustering accuracy. The convergence is shown in Fig. 5, the error rate is shown in Table 2, and its performance is shown in Table 3. Due to the stochastic resonance system can effectively achieve the data dimension reduction and can eliminate noise signal for the influence of the sensor. So SR-FCM clustering algorithm is superior to the FCM clustering algorithm.

PLS test results: Make the PLS analysis to golden arowana soybean oil mixed with different proportion of inferior oil. Make the corresponding sensor of the peak value of signal-to-noise ratio as the independent variable and the inferior oil content as the fitting target. The analysis results are shown in Fig. 6. The fitting correlation coefficient is 0.9842, fitting effect is good. And make the testing data which the sample oil ratio is 20 and 40% as the blind kind. Use the established linear curve make forecast, the obtained recognition discrimination in the

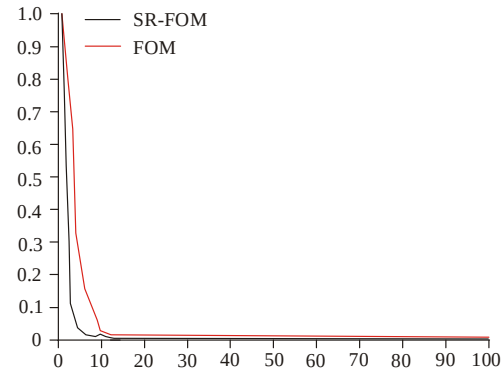

Fig. 5: Algorithm convergence

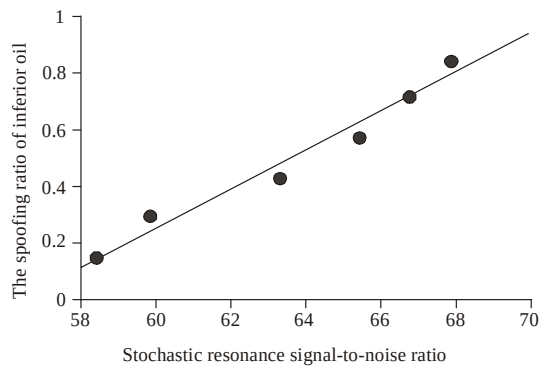

Fig. 6: The PLS to different proportion of adulteration sample oil

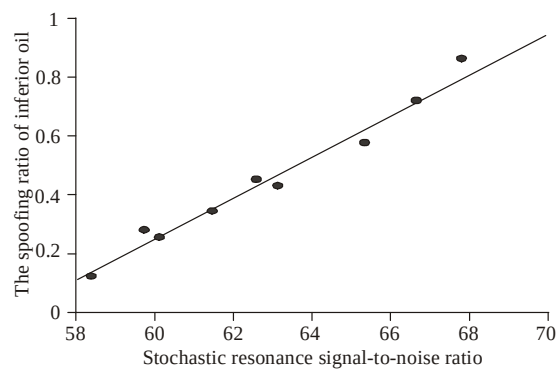

Fig. 7: The PLS to different proportion of adulteration bulk oil

average of the results were respectively 19.15 and 41.82% and the results of the actual error within 5%.Fig. 7 is the result of analysis PLS between sample oil data and the data of bulk oil A, bulk oil B, bulk oil C data, as can be seen from the figure that the measured data of bulk oil A close to the contains 20% of inferior oil, bulk oil B approximately close to the contains 30% of inferior oil, bulk oil approximately close to the contains 40% of inferior oil. These results have the same conclusion with

the PCA, conductivity measurement, the measurement of the acid value and peroxide value.

CONCLUSION

This study developed a set of the electronic nose system based on semiconductor gas sensor array and nonlinear double steady state stochastic resonance. The experiment test inferior oil for cooking oil. Because the detected signal contains the information of inferior oil concentration which is weak is presented. We design a scheme which is based on adaptive multilayer stochastic resonance system to detect inferior oil. Adopt double steady state stochastic resonance method to inferior oil will convert the difference between sensor response signals to the output curve characteristics of SNR, this method can effectively overcome semiconductor type of gas sensor long time work under high temperature caused by the baseline drift phenomena. And use this system make FCM identify to the 6 kinds of oil. The results show that the electronic nose system can distinguish with cooking oil contains different concentrations of inferior oil. Detection method is simple, intuitive, fast, and before clustering analysis the experimental data do not need any processing, have high application value. For quantitative analysis provides a good direction.

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