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Recognition of Odor Characteristics based on BP Neural Network

Wu Lei*[1], Fang Jiandong[2], Zhao Yudong[3]
[1,2]College of Information Engineering, Inner Mongolia University of Technology, Hohhot 010080, P.R.China
[3]Inner Mongolia Agriculture and Animal Husbandry Information Center, Hohhot 010011, P.R.China
*Corresponding author, e-mail:wlmango@163.com[1], zhaoyvdong@163.com[3]

Abstract

This paper introduces the basic principle and calculation steps of BP neural network algorithm for recognition of odor characteristics. Using the PEN3 electronic nose collects the volatile components of milk. Simulation of BP neural network algorithm in MATLAB condition, and compared with the partial least squares identification algorithm which is in the software of electronic nose. It is verified that the odor characteristic parameters with nonlinear and little differences could be better identified by BP neural network.

Keywords: *BP neural network, electronic nose, odor, recognition.*

1. Introduction

The sense of smell is an effective way to understand the information of the external smell. Due to the influence by the odor component complexity and subjectivity of the sense organs, the smell still con't is expressed by specific terms. In recent years, with the rapid development of sensor technology and computer technology, the research of electronic nose system has been paid more attention by scientists and developed rapidly. Electronic nose system consists of two parts, the semiconductor gas sensor array and pattern recognition system. Pattern recognition is one of the key researchs of electronic nose system. It plays an important role in the realization of the function of electronic nose system [1-3].

In the process of actual production and life, the electronic nose can't completely take the place of the biological nose [4]. One of the reasons is that most of the existing electronic nose pattern recognition algorithms are based on statistical models. This technique is based on the statistical distribution of the observed features with significant differences [5], and most of the data processing is linear structure, such as partial least squares analysis. Therefore, for the odor data with little differences and nonlinear structure it is difficult to make accurate identification.

Artificial neural network is one of the typical methods of nonlinear data processing. The method is mainly a kind of algorithm to imitate the human brain thinking engineering. It can solve the recognition problem that the distribution of the sample is unknowing [6-8]. This paper designs a model based on BP neural network algorithm to identify odor characteristics. A case study on the odor characteristics of milk with different quality, through compared with partial least squares algorithm of electronic nose software, it is verified that the odor characteristic parameters with nonlinear and little differences could be better identified by BP neural network.

2. BP Neural Network

2.1. Definition and Structure

Multi layer feed forward artificial neural network based on error back propagation algorithm is called BP neural network or BP neural network model. BP network can learn and store a large number of input-output mode mapping relationship, and no need to reveal and describe the mathematical equations of the mapping relationship. Its learning rule is to use the steepest descent method, by back propagation to constantly adjust the network weights and threshold, which makes the sum of network's error square is minimum. The topology structure of

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BP neural network model includes input layer, hidden layer and output layer. The interconnection between layer and layer, each layer between nodes is not connected. The numbers of input layer nodes usually take the dimensions of the input vector, the number of output layer nodes usually take the dimensions of the output vector, the number of hidden layer nodes there is no definite standard, through repeated trial, then get the final result. Figure 1 is a three layer BP neural network structure model.

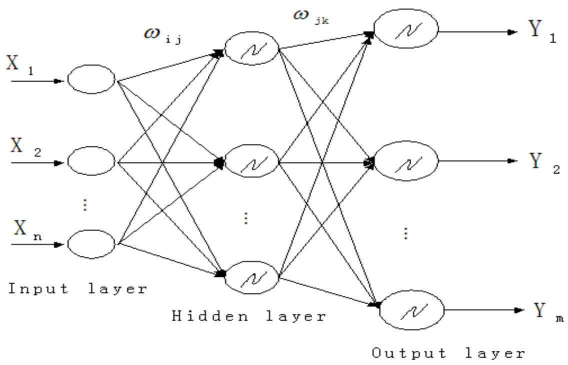


Figure 1. The three layer BP neural network structure model

In Figure 1, $X_1, X_2, \cdots X_n$ are the input values and $Y_1, Y_2, \cdots Y_m$ are the predictive values of BP neural network, ω_{ij} and ω_{jk} are BP neural network weights. As can be seen from Figure 1, the BP neural network can be regarded as a nonlinear function, the network input values and the predictive values respectively represent this function's independent variables and dependent variables. When the input nodes are n , the output nodes are m, the BP neural network is expressed the function mapping relation which is from n independent variables to m dependent variables [6].

2.2. Algorithm Steps and Flow Chart

BP algorithm is a kind of supervised learning algorithm. The main idea is: input learning samples, using the back-propagation algorithm of the network, weights and deviations are repeated adjustment and training, make the output vectors and expected vector as close as possible. When the error sum of squares of the network output layer is smaller than the specified error, training is complete, save the network weights and deviations. Specific steps are as follows [6]:

The first step: Weights initialization. According to the system input and output sequence (x, y) determine the network input layer's node number n, the hidden layer's node number l , the output layer's node number m, initialize the input layer, hidden layer and output layer connection weights between neurons ω_{ij} and ω_{jk} ,and initialize hidden layer's threshold a, output layer's threshold b , given the learning rate and the excitation function of neurons.

The second step: The hidden layer output calculation. According to the input variable X, the connection weights of input layer and the hidden layer ω_{ij} and the hidden layer's threshold value a , calculate the hidden layer's output H .

$$H_j = f(\sum_{i=1}^{n} \omega_{ij} x_i - a_j) j = 1, 2, \cdots, l \qquad (1)$$

In the formula, l is the number of hidden nodes; f is the incentive function of the hidden layer. This function has many kinds of expression forms, and this paper selected function is:

$$f(x) = \frac{1}{1+e^{-x}} \tag{2}$$

The third step: Calculate the output layer. According to the hidden layer's output $\boldsymbol{H}$, connection weights $\boldsymbol{\omega_{jk}}$ and threshold $\boldsymbol{b}$, calculate the BP neural network's predictive output $\boldsymbol{O}$.

$$O_k = \sum_{j=1}^{l} H_j \omega_{jk} - b_k \qquad k = 1, 2, \cdots, m \tag{3}$$

The fourth step: Calculate the error. According to the network's forecast output O and expected output $\boldsymbol{Y}$, the network's prediction error is calculated.

$$e_k = Y_k - O_k \qquad k = 1, 2, \cdots, m \tag{4}$$

The fifth step: Update the weight. According to the network's prediction error $\boldsymbol{e}$, update the network's connection weights $\boldsymbol{\omega_{ij}}$ 、$\boldsymbol{\omega_{jk}}$.

$$\omega_{ij} = \omega_{ij} + \eta H_j(1 - H_j)x(i)\sum_{k=1}^{m} \omega_{jk} e_k \qquad \mathrm{i} = 1, 2, \cdots, l \tag{5}$$

$$\omega_{jk} = \omega_{jk} + \eta H_j e_k \qquad j = 1, 2, \cdots, l; \qquad k = 1, 2, \cdots, m \tag{6}$$

In the formula, η is the learning rate.

The sixth step: Update the threshold. According to network's prediction error $\boldsymbol{e}$, update network node's threshold $\boldsymbol{a, b}$.

$$a_j = a_j + \eta H_j(1 - H_j)\sum_{k=1}^{m} \omega_{jk} e_k \qquad \mathrm{j} = 1, 2, \cdots, l \tag{7}$$

$$b_k = b_k + e_k \qquad k = 1, 2, \cdots, m \tag{8}$$

The seventh step: Judge whether the iteration of the algorithm is over. If not over, return to the second step.

The flow chart of BP neural network algorithm is shown in Figure 2.

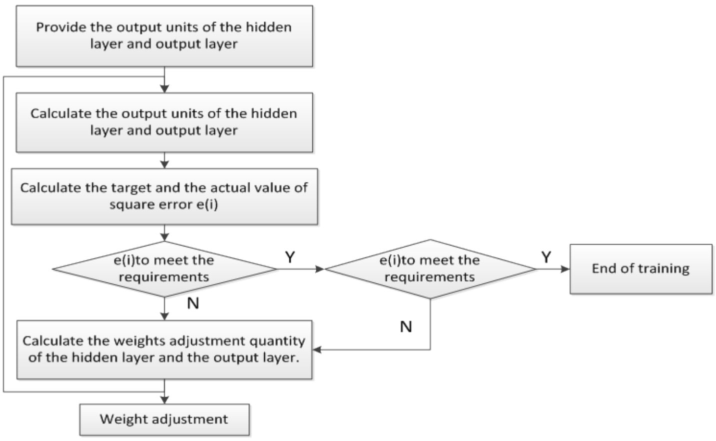


Figure 2. Flow chart of BP algorithm

3. Odor Signal Acquisition
3.1. Experiment Equipment
This paper uses the PEN3 electronic nose system to collect the odor data. PEN3 electronic nose is an analytical instrument which is compose of a set of composite chemical sensors and identification software. The hardware structure of the system includes sensor array, sampling and cleaning channel, data acquisition system and computer. The sensor array consists of 10 metal oxide sensors; each sensor sensitive to the odor molecules is different. When the odor contacted with the surface of the sensor, the redox reaction occurs, thereby affecting the circuit structure of the sensor. After sample stand for a certain time, the top empty volatile gas through a built-in pump, it is adsorbed from the entrance to the sensor channel, through the sensor array is excluded from the exports. Figure 3 shows the response curve of ten sensors in the measurement process. Data processing and pattern recognition based on the ratio of G to G0. G is the resistance value of the sample headspace volatiles through the sensor. G0 is the resistance value of the reference gas through the sensor [9-11].

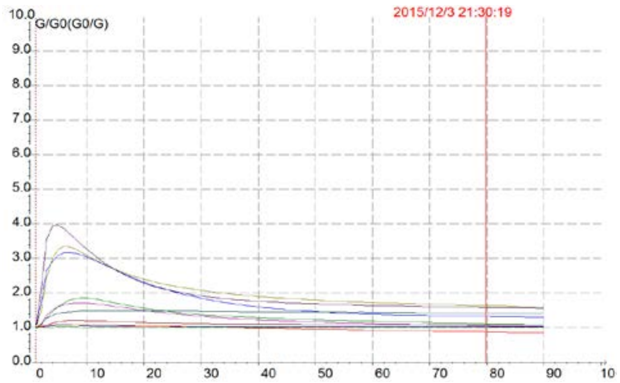


Figure 3. Electronic nose response signal

3.2. Experimental Materials
Laboratory temperature is 25 degrees Celsius, the same quality of milk were stored for one day, two days, three days, four days, five days. Take the same quality of fresh milk and five different days of milk into the test tube.

3.3. Experimental Methods
The laboratory temperature of 25 degrees Celsius, Fresh milk and five kinds of stored with different number of days of milk each take out 10ml put in the test tube. Each type of milk samples was prepared 50 replicate samples. After standing for 10min, the top empty volatile gas through a built-in pump, it is adsorbed from the entrance to the sensor channel, through the sensor array is excluded from the exports. The detection time is 150s, sensor cleaning time is 60s. Analysis of the signal in a steady state, the signal of the 80s is used as the time point of the electronic nose analysis. Table 1 shows the relative conductivity values of the six groups of samples in ten sensors. Due to the limitation of this paper length, here are only the results of three duplicate samples.

4. Result Analysis
4.1/ Partial Least Squares Analysis of Electronic Nose Software
Partial least squares(PLS) regression is a multivariate statistical data analysis method, which by minimizing the error sum of squares of a set of data to find the best matching function.It uses the most simple method to obtain some unknown truth value, and the sum of error square is minimum [6]. PLS is one of the commonly used pattern recognition algorithms for electronic nose. Figure 4 is the partial least squares analysis milk's quality in the software of electronic nose. Can be seen from the figure the milk of all kinds of quality's PLS value, through the comparison of their size can be judged the test sample’s quality. Randomly selected each

samples of 10%, 20% and 40% for the template, and the rest for the test samples, the results of the experiment as shown in Table 2.

Table 1. The electrical conductivity of milk with different storage days in 80s

Resistance / Quality		R(1)	R(2)	R(3)	R(4)	R(5)	R(6)	R(7)	R(8)	R(9)	R(10)
Fresh	Sample1	1.096	1.095	1.034	0.887	1.016	1.427	1.628	1.039	1.749	1.410
	Sample2	1.079	1.151	1.029	0.836	1.011	1.191	1.505	0.955	1.064	1.369
	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
	Sample50	1.089	1.163	1.035	0.866	1.016	1.258	1.507	0.980	1.598	1.450
One day	Sample1	1.097	1.044	1.038	0.934	1.017	1.557	1.618	1.058	1.605	1.460
	Sample2	1.037	1.090	1.030	0.862	1.012	1.185	1.538	0.932	1.524	1.373
	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
	Sample50	1.079	1.112	1.035	0.870	1.017	1.182	1.499	0.925	1.486	1.438
Two days	Sample1	1.143	2.222	1.054	1.017	1.026	2.155	3.220	1.254	3.275	1.636
	Sample2	1.080	1.098	1.031	0.885	1.014	1.244	1.523	0.961	1.551	1.407
	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
	Sample50	1.090	1.134	1.038	0.891	1.019	1.280	1.505	0.974	1.561	1.483
Three days	Sample1	1.089	1.366	1.050	1.082	1.028	2.318	1.763	1.275	1.651	1.653
	Sample2	1.090	1.402	1.051	1.176	1.028	2.476	1.788	1.344	1.714	1.675
	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
	Sample50	1.090	1.406	1.052	1.165	1.026	2.331	1.727	1.305	1.699	1.709
Four days	Sample1	1.111	1.293	1.049	0.977	1.026	1.795	1.756	1.168	1.810	1.610
	Sample2	1.110	1.348	1.048	0.931	1.023	1.678	2.013	1.092	2.036	1.607
	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
	Sample50	1.091	1.153	1.041	0.869	1.023	1.311	1.563	0.970	1.551	1.509
Five days	Sample1	1.094	1.081	1.037	0.915	1.019	1.480	1.630	1.039	1.627	1.460
	Sample2	1.082	1.120	1.034	0.883	1.016	1.297	1.561	0.979	1.545	1.434
	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
	Sample50	1.089	1.134	1.039	0.893	1.020	1.313	1.482	0.979	1.498	1.500

Table 2. Experimental results

The numeber of template sample	20% of the total sample	40% of the total sample	80% of the total sample
The number of training sample	10	20	40
The number of test sample	40	30	10
PLS accuracy rate(%)	21%	34%	53%
BP accuracy rate(%)	35%	46%	90%

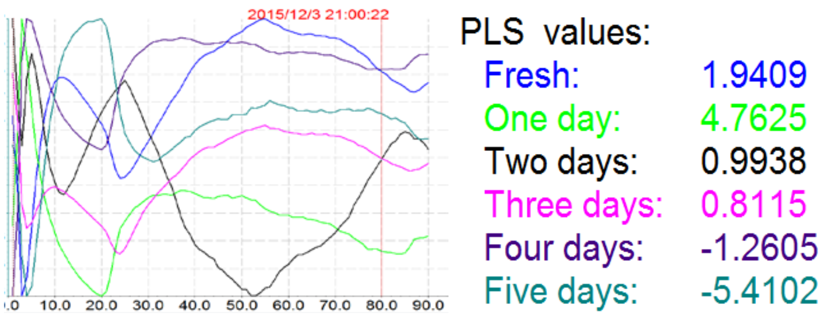
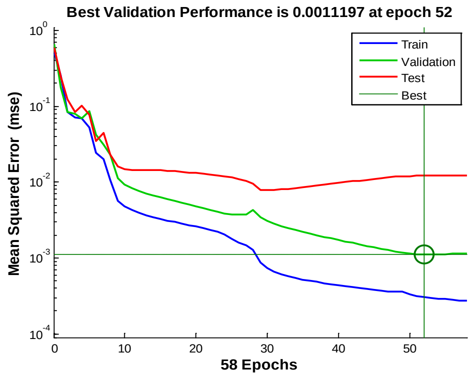


Figure 4. Partial least squares analysis

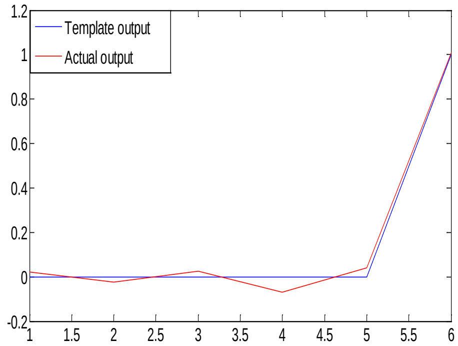
4.2. BP Neural Network Analysis

The structure of BP neural network is determined according to the characteristics of system input and output data. The electronic nose has 10 sensors to measure the odor characteristic parameter, so the odor input signal has 10 dimensions. There are six kinds of different quality of milk, so the output signal has 6 dimensions. According to the trial to determine, the number of nodes in the hidden layer is 9 best. So the structure of the BP neural network is 10-9-6. Selected each samples of 10%, 20% and 40% for the template, and the rest for the test samples.

Figure 5 is the mean square error and the predictive odor signal of the test sample for fresh milk. Mean square error is the mean squared difference between the output and the target that is the e value. The best verification performance more close to 0 indicates that the training model is better. It can be seen from the figure that the training model of BP neural network is reasonable; the best verification performance is 0.0011197 in the fifty-second training. In the picture of predictive odor signal, the dotted line in the figure represents the target output category; the solid line shows the actual output category. From the figure can be seen the actual output and the target output is basically consistent.



(a) Mean square error



(b) Predictive odor signal

Figure 5. BP neural network analysis

The identification results for all test samples are shown in Table 2. As can be seen from the data in Table 2, the more number of training samples is the higher recognition rate of the algorithm. Under the condition of the same training sample number, the recognition rate of BP neural network algorithm is higher. To sum up, for the identification of odor characteristics with nonlinear data structure and little difference, the recognition accuracy of BP neural network is higher than the partial least square algorithm.

5. Conclusion

Using the method of this paper, BP neural network algorithm is used to identify the characteristic of odor. The recognition accuracy can reach 90%. Compare with the partial least squares analysis which is in the electronic nose software, BP neural network algorithm recognition accuracy is much higher than the partial least squares algorithm. And the recognition accuracy will increase with the increase of the number of training samples. Therefore, for the identification of odor characteristics with nonlinear data structure and little difference, neural network can more accurately and effectively identify the odor characteristics.

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References

[1] Liu Hong-xiu, Luo De-han. Odour Recognition Algorithms for Machine Olfaction System. *Chinese journal of sensors and actuators.* 2006; 19(6): 2518-2522.
[2] Wang Wei-wei, Zhang Sai-nan. Electronic nose system based on PCA and BP hybrid neural network algorithm.*Transducer and Microsystem Technologies*. 2013; 33(4): 90-92.

[3] De Han, Yawen Shao. Discrimination of Chinese Herbal Medicine by Machine Olfaction. *TELKOMNIKA Telecommunication Computing Electronics and Control.* 2013; 11(2): 630-636.
[4] Shi Zhibiao, Huang Shengquan, Fan Xuebing, Li Yang. Study on Electronic Nose Based on Biologic Olfaction. *China Mechanical Engineering*. 2007; 18(23): 2810-2812.
[5] QIN Shu-ji, Xu Chun-hua, WANG Zhan-shan. Effect of Artificial Neural Network on Performance of Electronic Nose. *Journal of Tongji University.* 2005; 33(6): 804-808.
[6] Gao Tian, Wang Qi. Target Recognition Algorithm Based on BP Networks and Invariant Moments. *TELKOMNIKA Telecommunication Computing Electronics and Control*. 2013; 11(2): 969-974.
[7] Hong Xue-zhen, Wei Zhen-bo, Hai Zheng, Wang Jun. Application of Electronic Nose and Neural Network in Beef Freshness Detection. *Modern Food Science and Technology.* 2014; 30(4): 280-285.
[8] Hanaa T, EI-madany, Faten H Fahmy. Spacecraft power system controller based on neural network. *Acta Astronautica.* 2011; 69(7-8): 650-657.
[9] Gao Li-ping, Wang Jun, Cui Shao-qing, et al. Evaluation of fresh juice of strawberries at different degrees of ripeness using electronic nose and electronic tongue. *Journal of Zhejiang University.* 2012; 38(6): 715-724.
[10] Zhou Hongbiao, Zhang Yulin, Ding Youwei, Liu Jiajia. Application of adaptive probabilistic neural network in Chinese liquor E-Nose. *CAAI Transactions on Intelligent Systems.* 2013; 8(2): 177-182.
[11] Olunloyo VO, Ibidapo TA, Dinrifo RR. Neural network-based electronic nose for cocoa beans quality assessment. *Agricultural Engineering International: CIGR Journal.* 2012; 13(4): 1-17.