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Research Article

Electronic Nose Monitoring the Maillard Reaction Flavors of Sesame Oil from Different Production Processes

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Abstract: The objective in this study was to evaluate the capacity of electronic nose to monitoring the effect of different Maillard reaction processes on natural flavors of sesame oil, using a specific Electronic Nose device (PEN3). The flavors were prepared by Maillard reaction using chemical constituents from water extract of Lentinus and other precursors. The optimum conditions of reaction process was determined by using orthogonal test design, then an Electronic Nose (PEN3)was used to characterize and classify eight different flavors from different reaction process and sesame oil from market. This method firstly sampled aroma composition emanating from the flavors by PEN3 systems and then obtained response values of PEN3. Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA) were used in order to investigate whether the electronic nose was able to distinguish among different Maillard Reaction Production (MRP). The loadings analysis was used to identify the sensors responsible for discrimination in the current pattern file. The results of this study showed that the basic components added with lysine, xylose and glycerin, heated in glycerine bath at 140°C for 120 min, was a novel flavors with sesame oil flavor and taste. The electronic nose PEN 3 can discriminate successfully different MRPs using both PCA and LDA analysis. But, it was not able to detect a clear difference in the sample of similar aroma with sesame oil using PCA analysis. Some sensors have the highest influence in the current pattern file for electronic nose PEN 3. A subset of few sensors can be chosen to explain all the variance. This result could be used in further studies to optimize the number of sensors.

Keywords: Electronic nose, linear discriminant analysis, monitoring, principal component analysis, thermal process flavors

INTRODUCTION

The electronic noses (e-noses) are analytical instruments which are capable to recognize simple or complex mixtures of organic vapors after an appropriate training period. They are typically array of sensors used to detect and distinguish odors precisely in complex samples and at low cost (Peris *et al*., 2009). The sensor array consists of broadly tuned (non-specific) sensors that are treated with a variety of odor-sensitive biological or chemical materials. An odor stimulus generates a characteristic fingerprint (or smell print) from the sensor array. Patterns or fingerprints from known odors are used to construct a database and train a pattern recognition system so that unknown odors can subsequently be classified and identified (Pearce *et al*., 2003). The system makes e-noses very useful for fast quality control applications in the food and chemical industry. Environmental, safe and even medical applications are also possible. In fact, in the past decade, many established papers have already described the use of electronic noses, such as several reports on electronic sensing in environmental control, medical diagnostics and the food industry (García-Martínez *et al*., 2011; Yu and Jun Wang, 2007; Hai and Wang, 2006; Schaller *et al*., 1998) and some authors reported positive applications of electronic nose technology to the discrimination of different fruits quality and many experiments were performed, such as testing mandarin (Gomez *et al*., 2007), peaches (Molto *et al*., 1999; Brezmes *et al*., 2000), melons (Benady *et al*., 1995), blueberries (Simon *et al*., 1996), apples (Brezmes *et al*., 2000, 2001; Saevels *et al*., 2003), pears (Oshita *et al*., 2000; Correa *et al*., 2001) and bananas (Llobet *et al*., 1999). Often the sensitivity of electronic noses is similar to that of human noses but humans are specially gifted in sensing specific compounds (e.g., thiols, biogenic compounds, pyrazines, thiazoles, some aldehydes (Doleman and Lewis, 2001)). The biological sensitivity can go down to ppt levels with a response time in the order of milliseconds whereas instruments barely go under ppb levels with a response time in the order of seconds (Table 1) (Ampuero and Bosset, 2003).

The Maillard Reaction (MR) or nonenzymatic glycation is the reaction of reducing sugars with amino

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Table 1: Detection threshold levels of human olfactory systems and electromic noses

Volatile compound	Reported human threshold (ppm)	Electronic nose threshold (ppm)	Type of electronic nose
Ethly acetate[a]	7-17[b]	5-25	Fox 3000 (12 MOS)
Butyric acid[a]	0.4-10[b]	<1	Fox 3000 (12 MOS)
Diacetyl[a]	$(4\text{-}15)\times10^{-3}$ [b]	$(50\text{-}100)\times10^{-3}$	Fox 3000 (12 MOS)
n-hexanal[a]	$(10\text{-}50)\times10^{-3}$	$(10\text{-}50)\times10^{-3}$	Fox 3000 (12 MOS)
Methional[a]	$(2\text{-}50)\times10^{-3}$	$(10\text{-}50)\times10^{-3}$	Fox 3000 (12 MOS)
Furanola[a]	$(20\text{-}40)\times10^{-6}$ [b]	$(50\text{-}100)\times10^{-6}$	Fox 3000 (12 MOS)
n-nonane[c]	0.2-7	<0.2	20 CP composite
n-octane[c]	3-9	0.6	20 CP composite
n-heptane[c]	7-13	<2	20 CP composite
n-hexane[c]	13-30	<10	20 CP composite
n-pentane[c]	20-50	40	20 CP composite
l-pentanol[c]	0.13-1.3	<0.06	20 CP composite
l-butanolc[c]	0.20-1.3	0.3	20 CP composite
l-butanol[d]	0.70	-	Aromascan (32 CP)
l-butanol[d]		-	Fox 3000 (12 MOS)
l-butanol[d]		+	6 taguchi (SnO_2)
l-propanol[c]	0.9-1.9	1.3	20 CP composite
Ethanol[c]	5-500	2.0	20 CP composite
Methanol[c]	13-600	3.0	20 CP composite
Acetone[d]	141	-	Aromascan (32 CP)
Acetone[d]		+	Fox 3000 (12 MOS)
Acetone[d]		+	6 taguchi (SnO_2)
Ethanethiol[d]	0.1×10^{-3}	-	Aromascan (32 CP)
Ethanethiol[d]		-	Fox 3000 (12 MOS)
Ethanethiol[d]		-	6 taguchi (SnO_2)

acids and amino groups of peptides or proteins. This reaction produces a variety of early, intermediate and advanced compounds. The advanced compounds of protein-sugar reactions are referred to as advanced glycation end products or AGEs and melanoidins (more concrete, melanoproteins) (Chellan and Nagaraj, 1999). Highly glycated proteins produced by such reactions give rise to fewer safety issues than chemically modified food proteins (Pan and Melton, 2007), so the glycated proteins through the MR can be added as functional ingredients into foods in order to improve emulsion and gelation and alter flavor, appearance and texture (Honda and Huroda, 1999; Nakamura *et al*., 1992). Many studies have reported beneficial effects associated with advanced Maillard Reaction Products (MRPs), including antioxidative (Chang *et al*., 2011; Gu *et al*., 2010; Lertittikul *et al*., 2007; Sun *et al*., 2004), antimicrobial (Sant'Anna *et al*., 2011; Li *et al*., 2011; Rufián-Henares and Morales, 2006, 2008), antihypertensive (Rufián-Henares and Morales, 2007a, b and c), anticarcinogenic and antimutagenic properties (Kolpe *et al*., 2002; Yen and Tsai, 1993).

The Maillard reaction, a well-known non-enzymatic browning reaction involving a reducing sugar and an amino acid, may produce colored or colorless reaction products depending on the stage of the reaction as well as other factors such as pH, type of reactants, temperature, water activity, etc. Condensation reactions between amino acids and lipid oxidation products may also form MRP and the role of lipids in the Maillard reaction is similar to the role of reducing sugars (Hidalgo and Zamora, 2000). A group of compounds in the final products of the reaction includes high molecular weight melanoidins, which are furan ring and nitrogen containing brown compounds. Little is known about their physical, chemical and physiological properties because of their complex structures. This complexity in MRP structures limits the determination of antioxidant activity for each compound in the whole group of MRP.

Sesame oils have a mild odor and a pleasant taste and, as such, is a natural salad oil requiring little or no winterization. It is used as a cooking oil, in shortening and margarine, as a soap fat, in pharmaceuticals and as a synergist for insecticides (Ampuero and Bosset, 2003). It is very popular as cooking oil in many Asian countries and more expensive than other edible vegetable oils. Sesame oils are non-water soluble; therefore have limitations in application of food industry. The objectives in this study were:

- To prepare the flavors with sesame oil by Maillard reaction using chemical constituents from water extract of Lentinus and other precursors
- To evaluate the capacity of the electronic nose for monitoring the flavors with sesame oil, using a specific Electronic Nose device (PEN 3) based on a 10-sensor array and suitable pattern recognition techniques
- To study Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA) techniques to obtain whether the electronic nose would be able to distinguish different aroma
- To identify each sensor responsible for discrimination in the current pattern file, using loading analysis

MATERIALS AND METHODS

Materials: Lentinus edodes fruitbody obtained from Hangzhou City Huadan Agricultural Products Limited

Table 2: Factors and levels for orthogonal test

	Level			
Variable	1	2	3	4
A, reaction time/min	100	120	140	160
B, reaction temperature/°C	140	160		
C, moisture content/%	35	45		
D, pH	6	7		
E, absolute alcohol/day	5	10		

Company. Xylose, lysine and the other solvents/chemicals used were of analytical grade and obtained from Shanghai Chemical Reagent Co., Ltd. (Shanghai, China).

Preparation of Maillard Reaction Products (MRPs): Lentinus edodes fruitbody (100 g) was homogenized in 3000 mL of distilled water. The homogenate was stirred for 2 h at 60°C and then filtered through Whatman No. 1 paper. The filtrate was concentrated to 400 mL using a rotary evaporator at 60°C under low pressure and obtained Lentinus Edodes Extract (LEE). Xylose and lysine were mixed (1:1 ratio) and dissolved in LEE and adjusted pH with 0.5 mol/L citric acid solution. The substrate concentration was adjusted to 35 and 45% (w/v) with glycerol. The solution was transferred to a 250 mL three-neck round-bottom flask and heated under refluxing in an oil bath with magnetic stirring at 40 rpm. The reaction conditions were showed at Table 2. An orthogonal L_8 (4×2^4) test design in the Maillard reaction mode was used for optimization the reaction conditions. After heating, the sample was immediately placed in an ice bath to cool down. The heated mixtures were termed as Maillard Reaction Products (MRPs).

Sensory evaluation: Sensory evaluation was performed in the Department of Food Science at the China JiLiang University (Hangzhou, Zhejiang). MRPs sample of 0.5 mL was diluted with 50 mL of de-ionised water. In preparation for the sensory evaluation, MRP diluents were individually presented in covered small porcelain tubes to each panelist. The judges were not informed of the experimental approach and the samples were blind-coded with random numbers. Panelists were instructed to smell the MRP diluents and pause for 30 s between samples. A 10-point hedonic scale, from 9 (excellent, extremely acceptable) to 0 (poor, extremely unacceptable), was employed to evaluate each MRP diluent sample on flavor. The sensory attributes of MRP diluent were compared with those of the commercial sesame oil products (Taitaile purchased from Wumei supermarket). MRP diluent samples receiving overall scores of more than 4 were considered acceptable, while a score between 3 and 4 was considered the borderline of acceptability. The overall acceptance of the MRP diluents was also evaluated by those consumers using a 10-point hedonic scale. At least 20 panelists participated in this study.

Electronic nose data acquisition and analysis: Experiments were performed with a Portable E-Nose (PEN 3) operating with the Enrichment and Desorption Unit (EDU). The system was from Win Muster Airsense (WMA) Analytics Inc. (Schwerin, Germany). PEN 3 consists of a sampling apparatus, a detector unit containing the array of sensors and pattern recognition software (Win Muster v.1.6) for data recording. The sensor array is composed of 10 different Metal Oxide Semiconductor (MOS) type chemical sensor: MOS1 (aromatic), MOS2 (broad range), MOS3 (aromatic), MOS4 (hydrogen), MOS5 (arom-aliph), MOS6 (broadmethane), MOS7 (sulphur-organic), MOS8 (broad-alcohol), MOS9 (sulph-chlor), MOS10 (methane-aliph). In Fig. 1 shows schematic diagram of the electronic-nose measurements and gas flow of PEN 3 during the experiments.

Table 3 lists all used sensors and their main applications. This table contains current known or specified reaction.

Each sample was placed into an airtight glass tube with a volume of 50 mL (concentration chamber). The glass tube was then closed and the headspace inside it was equilibrated for 1 h. Preliminary experiments showed that after 0.5 h of equilibration the headspace reached a steady state and experiments were conducted after 0.5 h of equilibration. One luer-lock needle (20 g) connected to a Teflon-tubing (3 mm) was used to perforate the seal (plastic) of the vial and to absorb the air accumulated inside it, during the measurements. The sample gas was inhaled into the sensor chamber (whose volume was about 150 mL) by pump 1 through the inlet at a rate of 400 mL/min. After that, zero gas (air

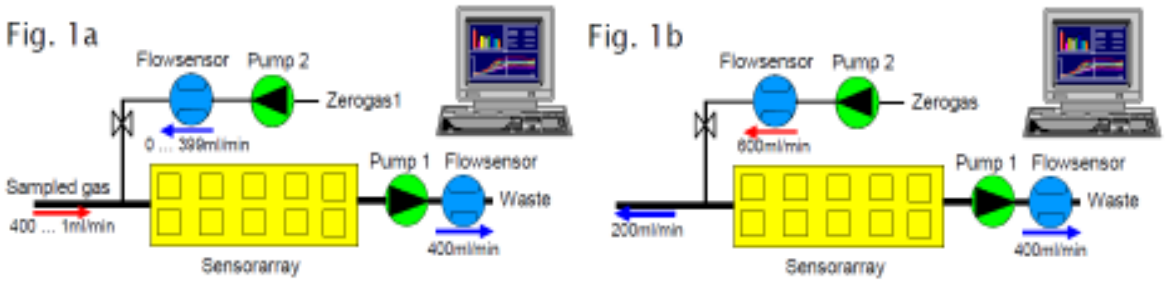

Fig. 1: Gas-flow diagrams of the electronic nose

Table 3: Sensors sensitivity of individual sensors within the sensor array of the PEN 3 e-nose

Number in array	Sensor-name	General description	Reference
1	W1C	Aromatic compounds	Toluene, 10 ppm
2	W5S	Very sensitive, broad range sensitivity, react on nitrogene oxides, very sensitive with negative signal	NO_2, 1 ppm
3	W3C	Ammonia, used as sensor for aromatic compounds	Benzene, 10 ppm
4	W6S	Mainly hydrogen, selectively, (breath gases)	H_2, 100 ppb
5	W5C	Alkanes, aromatic compounds, less polar compounds	Propane, 1 ppm
6	W1S	Sensitive to methane. Broad range, similar to No. 8	CH_3, 100 ppm
7	W1W	Reacts on sulfur compounds, H_2S 0.1 ppm. Otherwise sensitive to many terpenes and sulfur organic compounds, which are important for smell, limonene, pyrazine	H_2S, 1 ppm
8	W2S	Detects alcohol's, partially aromatic compounds, broad range	CO, 100 ppm
9	W2W	Aromatics compounds, sulfur organic compounds	H_2S, 1 ppm
10	W3S	Reacts on high concentrations >100 ppm, sometime very selective (methane)	CH_3, 10 CH_3, 100 ppm

filtrated by active carbon) was pumped by pump 2 from its port at the backside of the instrument into the electronic nose at a rate of 600 mL/min. A part of the zero gas was sucked into the sensor chamber by pump 1 to flush the sensors at the rate of 400 mL/min. The rest of the zero gas was expelled from the inlet to rinse the sample line at a rate of 200 mL/min. Since the property of the sensors would change as time goes by, the ethyl acetate was used as a calibration gas, which should be inhaled into the sensor chamber periodically to supervise the aging procedure of the sensor array. The operation temperature of the sensors was 300°C and the interior temperature of the cavity was 110°C. The schematic diagram of this electronic nose system is shown in Fig. 1.

When a measurement is completed, a stand-by phase is activated (60 sec). The purpose is to clean the circuit and return sensors to their baseline. Clean air enters the circuit, crosses the measurement chamber first, the empty concentration chamber afterwards and pushes the remaining volatiles out of the circuit.

Sensors were held at the temperature of 20°C and 50-60% RH during all experiments, the temperature was maintained constant with an accuracy of ±1°C. When the sensors are exposed to volatiles, the computer records the resistance changes that the sensors experience during the measurement phase. When the measurement was completed, the acquired data was properly stored for later use. The set of signals of all sensors during measurement of a sample is a pattern. Pattern of multiple measurements dealing with the same problem are stored in a Pattern File and act as the Training Set. The pattern data were recorded, checked visually and analyzed using SAS 8.0.

By using this zero-gas and comparing it to the signals from the analyzed sample gas the effect of the possible drift of the sensor itself is reduced (differential measuring technique). With the zero-gas the sensor array is kept clean to achieve a long lifetime and stability.

Electronic nose measurement: The temperature of the tubes was set at 40°C by a thermostatic bath and after a headspace generation time of 0.5 h, the samples were injected in a random order. The measurement time was 60 sec and upon injecting the sample, data were acquired every second. The flushing time was 300 sec and that was enough to desorb the volatiles from the sensors and enable the signals to return to the baseline.

Since the conductivity of the sensors will change as the sample gas blows over, the data obtained are the changing ratio of conductivity between G and G_0 (the conductivity of the sensors when the sample gas or zero gas blows over). As the sample gas of the headspace is pumped away and the air pressure in the vial dropped down, the signal reverted to the baseline gradually.

It is important to notice that the signals changed as time went on. That is the result is not only from variation of volatiles in the headspace but also from the variation of air pressure. Since the procedure of sampling was the same all the time, as for the same samples, the signals have no significant difference at the same time point. As the sample gas in the headspace was pumped out, the air pressure of the vials dropped down. Thus, more volatiles were expected to evaporate into the headspace. And then we could check the discriminating capability of the electronic nose under different condition of air pressure.

Principal component analysis, linear discriminant analysis and loadings analysis: Pattern recognition algorithms and data processing techniques are a critical component in the implementation, development and successful commercialization of Electronic Nose (EN) systems. There are a large amount of pattern recognition techniques available. In order to select the appropriate pattern recognition algorithm for EN application, it is important to understand the fundamental nature of the data being analyzed. Statistical and non-parametric analysis techniques are the most known and commonly used to analyze EN data.

Classical statistical methods, using a probability model, were first developed and used in the field of applied mathematic, now called chemometrics. Several mathematical methods could be applied to the multi-component analysis of odors. Categorization of classifiers, can be made based on certain features, such

as supervised or unsupervised, model based on model-free and qualitative or quantitative analysis. Discriminant Function Analysis (DFA) is a parametric learning classifier, which can be used for both qualitative and quantitative analysis. There are many ways of performing DFA, but the classical approach is Loading Discriminant Analysis (LDA). Principal Components Analysis (PCA) is a non-parametric projection method and pattern recognition technique used for analyzing, classifying and reducing the dimensionality of numerical datasets in a multivariate problem and is often used to implement a linear supervised classifier, in conjunction with discriminant analysis. This method permits extraction of useful information from the data and exploration of the data structure, the relationship between objects, the relationship between objects and variables and the global correlation of the variables. The main features of PCA are the coordinates of the data in the new base (scores plot) and the contribution to each component of the sensors (loads plot). The score plot is usually used for studying the classification of the data clusters, while the loads plot can provide information on the relative importance of the array sensors to each principal component and their mutual correlation. This technique has been widely used for researcher to display the response of an EN to simple and complex odors and it provides qualitative information for EN pattern recognition file.

Using the Principal Component Analysis (PCA) the measured data, previously trained will be transformed into 2D or 3D coordinates. This is carried out through the data reduction that extracts the most important information from the database as a result. The results of training phase can be displayed in a two dimensional view. PCA is based on a linear project of multidimensional data into different coordinates based on maximum variance and minimum correlation. Training pattern from measurements of similar samples will be located close to each other after transformation. Hence, the graphical output can be used for determining the difference between groups and comparing this difference to the distribution of pattern within one group.

The Linear Discriminant Analysis (LDA) is the first step of the Discriminant Function Analysis (DFA). The LDA calculates the discriminant functions and is similar to the PCA-a 2 or 3 dimensional display of the training set data. The difference between PCA and LDA is that PCA does not consider the relation of a data point to the specified classes, while the LDA calculation uses the class information that was given during training. The LDA utilizes information about the distribution within classes and the distances between them. Therefore, the LDA is able to collect information from all sensors in order to improve the resolution of classes.

The loadings analysis is well correlated to the PCA. Using this analysis, the sensors can be investigated for their responsibility for the discrimination given by the trained patterns. Sensors, located near the center of the diagram (0, 0), have a minor responsibility for the distribution of pattern in the PCA plot. They may be switched off because they may have a negative influence on the pattern resolution, when particular normalizations are selected. The loadings analysis helps to identify the sensor responsible for discrimination in the current pattern file. The sensor may be switched off (the response signal not used) for analysis if it has no positive influence on the identification process.

The sum of displayed variances is higher; the further principal components also contain discriminant information using PCA and LDA.

The loadings analysis is well correlated to the PCA. Using this analysis the sensors can be investigated for their responsibility for the discrimination given by the trained patterns. Sensors, located near the center of the diagram (0, 0) have a minor responsibility for the distribution of pattern in the PCA plot. They may be switched off because they may have negative influence on the pattern resolution, when particular normalizations are selected. The Loadings analysis will help to identify the sensors responsible for discrimination in the current pattern file. Single sensors may be switched off for analysis as long as they have no positive influence on the identification process.

RESULTS

Analysis of the orthogonal test: To the best of our knowledge, various parameters play a great role in the optimization of the experimental conditions for the development of a Maillard reaction method. Reaction time, reaction temperature, moisture content, pH, number of absolute alcohol are generally considered to be the most important factors that (to) affect the flavor of MRP. The investigated levels of each factor were selected depending on the preliminary experiment results of the single-factor. In the present study, all selected factors were examined using an orthogonal L_8 (4×2^4) test design. The total evaluation index was used to analysis by statistical method (Table 4). The analysis results of orthogonal test, are presented in Table 2. In the orthogonal test, k is the sum of score of every level and by comparing to k, the optimal level of variables can be confirmed. R = max {$k1$, $k2$, ..., kn} - min {$k1$, $k2$, ..., kn} and R scales the effect of variables on the result. High R value of variable means that this variable has strong effect on the result. Although the maximum score of MRP was 7.80±0.37, we cannot choose the corresponding reaction conditions as the best technology. In view of orthogonal analysis, we adopt statistical software to calculate the values of K, k and R.

Table 4: Analysis of L_8 (4×2^4) test results

No.	A, reaction time /min	B, reaction temperature /°C	C, moisture content /%	D, pH	E, absolute alcohol/day	Score
1	1 (100)	1 (140)	1 (35)	1 (6)	1 (5)	5.60±0.31
2	1 (100)	2 (160)	2 (45)	2 (7)	2 (10)	6.20±0.28
3	2 (120)	1 (140)	1 (35)	2 (7)	2 (10)	7.30±0.45
4	2 (120)	2 (160)	2 (45)	1 (6)	1 (5)	7.80±0.37
5	3 (140)	1 (140)	2 (45)	1 (6)	2 (10)	6.90±0.41
6	3 (140)	2 (160)	1 (35)	2 (7)	1 (5)	5.30±0.19
7	4 (160)	1 (140)	2 (45)	2 (7)	1 (5)	5.80±0.33
8	4 (160)	2 (160)	1 (35)	1 (6)	2 (10)	4.90±0.26
k_1	5.90	6.40	5.78	6.30	6.12	
k_2	7.55	6.05	6.68	6.15	6.32	
k_3	6.15					
k_4	5.35					
R	2.20	0.35	0.90	0.15	0.20	

R: The result of extreme analysis

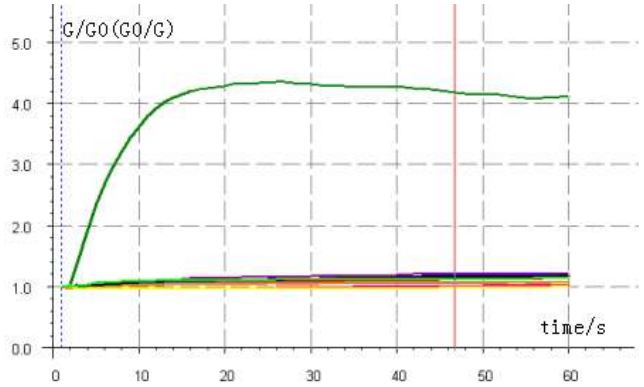

Fig. 2: Ten sensors responses to sesame oil aroma

The factors influence the score of MRP were listed in a decreasing order as follows: A>C>B>E>D according to the R value. So the maximum score of the MRP was obtained when reaction time, reaction temperature, moisture content, pH, number of absolute alcohol were $A_2C_2B_1E_2D_1$ (120 min, 45%, 140°C, 10 day and pH 6), respectively. According to the R value and the result of analysis of variance table (data not shown), we can find the reaction time was found to be the most important determinant of the score of MRP. However, two levels of four other factors can be overlooked in the score. In order to save the cost of production and time for industrialization, we make the optimum technology as follows: $A_2C_2B_1E_1D_2$ (120 min, 45%, 140°C, 5 day and pH 7). Through confirmatory test, we get the high score of MRP, with a score of 7.93±0.27%.

Electronic nose response to MRP aroma: Figure 2 shows a typical response of ten sensors during measuring sesame oil. Each curve represents a different sensor transient. The curves represent sensor conductivity of one sensor of array against time due to electro-valve action when the volatiles from the sesame oil reach the measurement chamber. In that transition, the clean airflow reached the measurement chamber is substituted by airflow, which comes from the concentration chamber, closing a loop circuit between both chambers. It can be seen that, after an initial period of low and stable conductivity (when only clean air is crossing the measurement chamber), conductivity increases sharply and then stabilizes after 30 sec. The each sensor signal generally stabilizes and was considered to use in analysis of electronic nose. In this research, the signal of each sensor at response 47 sec was used in analysis of electronic nose.

Figure 3 shows the response value of each sensor in Cartesian coordinate for an example at 47 sec. As the first example, the polar graphs of the responses of the sensors to the 8 group samples of Maillard reaction and sesame oil are shown in Fig. 3. These graphs were constructed using the changes of relative resistance and representing the peak height of each sensor as a radial vector. The response of the sensors was highly reproducible. Each formula (with different MRP) produced similar radar chart shapes (Fig. 3 (1 to 8)), which were clearly similar shape (Fig. 3 (9)) from sesame oil, particularly Fig. 3 (3 and 4) which the highest score from the orthogonal test. The analysis for sesame oil and different MRP showed that all the ten sensors had a clear response, particularly the 2^{th} sensor (sensitive to nitrogene oxides), the 6^{th} sensor (sensitive to broad-methane) and the 8^{th} sensor (sensitive to broad-alcohol). While, it was hard to discriminate MRPs from sesame oil on radar maps, which indicated that it was necessarily aid to PCA or LDA to classify these formulas.

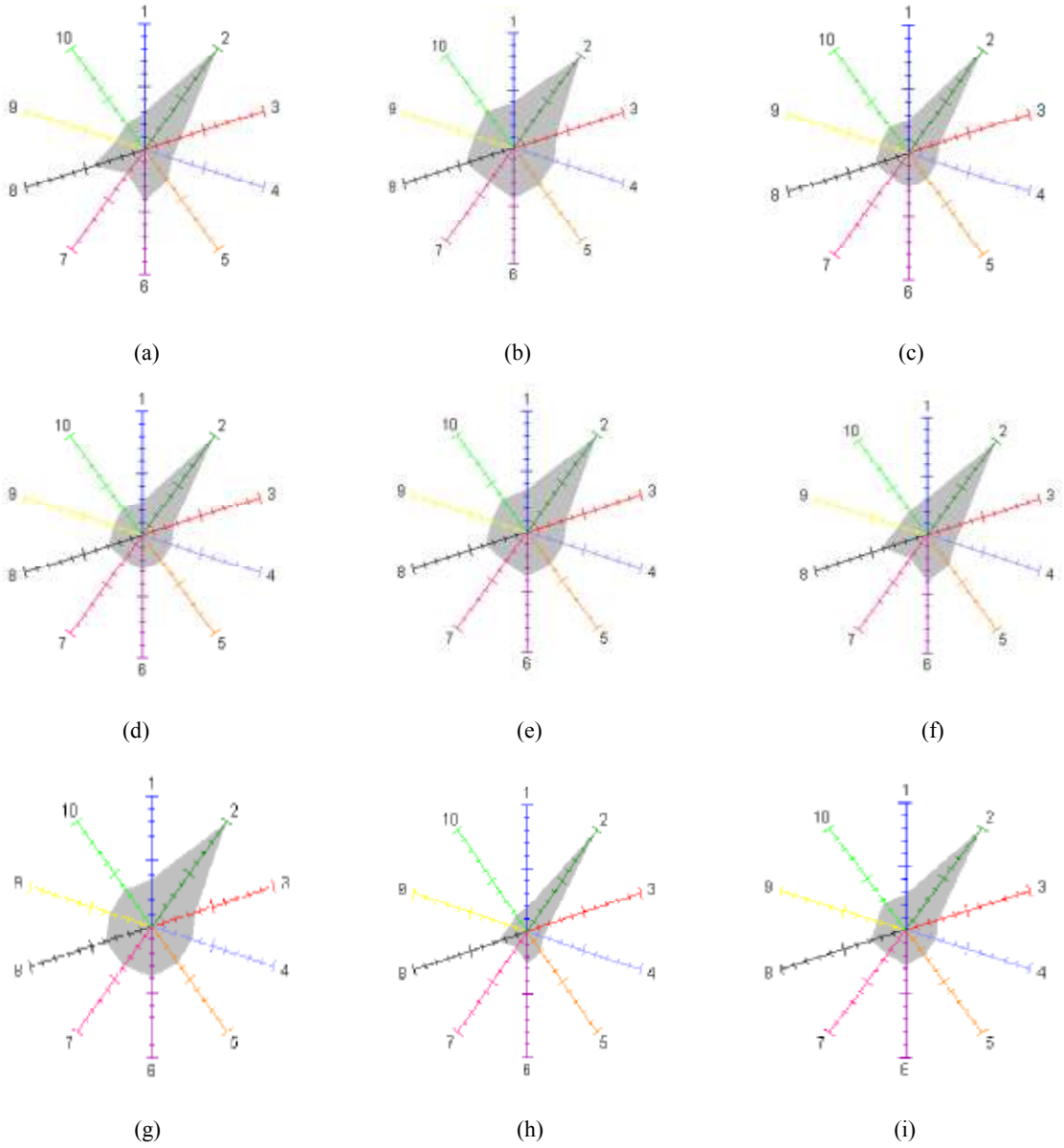

Fig. 3: Radar maps of sesame oil and different MRP by PEN3 electronic nose at the 47rd second

Classification of MRPs using PCA and LDA: In order to investigate whether the electronic nose was able to distinguish among different process, PCA and LDA analysis were applied in this study. The analysis was carried out using the signal stability at 47 sec in sesame oil.

PCA and LDA analysis results are shown in Fig. 4 and 5. Two figures show that analysis results on a two-dimensional plane, Principal Component 1 (PC1) and Principal Component 2 (PC2) in Fig. 4 and first and second linear discriminant LD1 and LD2 in Fig. 5.

PCA is a linear combinatorial method, which reduces the complexity of the data-set. The inherent structure of the dataset is preserved while its resulting variance is maximized. PCA has been performed to describe the aroma changes for different reaction process. Figure 4 shows that the score plot inside the rotundity and represent the variation around each process data (Maillard reaction) in the space. The processed data shows a shift erratic of the different process date along the first principal component, PC1, which explains 92.94% of the total variance with value 99.79%. The second Principal Component (PC2) explains 6.85% of the variation and shows no particular trend with reaction process date. There were a clear separation between the 3rd samples, the 4th sample, the sesame oil with other groups of samples, showed that this two samples had the similar aroma with sesame oil. In spite of the clear separation that was achieved among different groups using the Analysis (PCA), this two

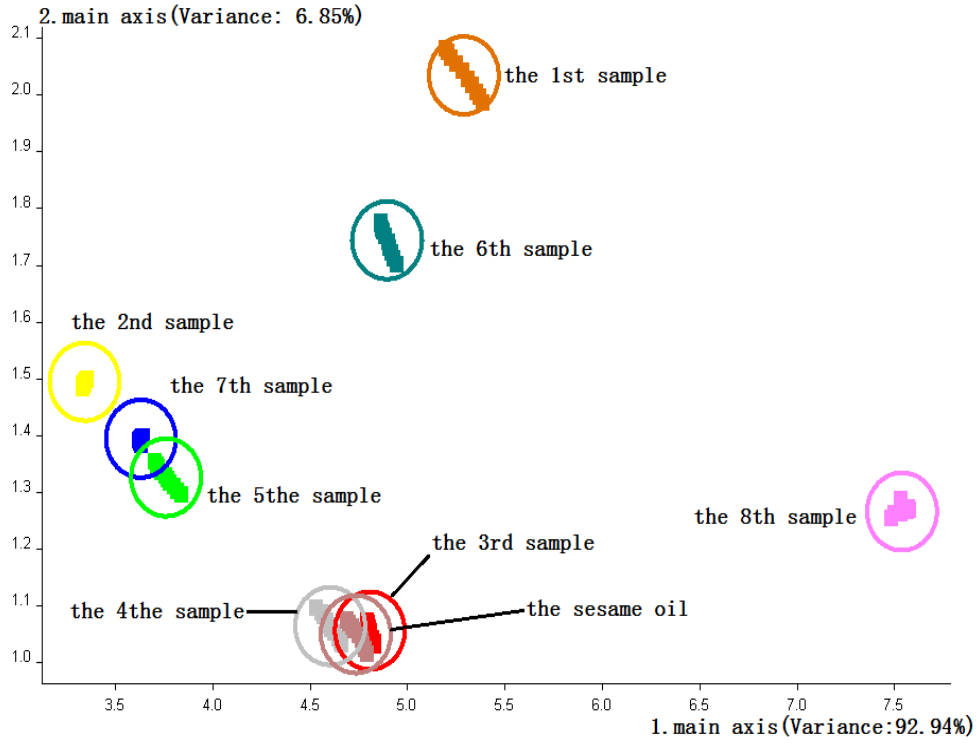

Fig. 4: PCA analysis for MRPs

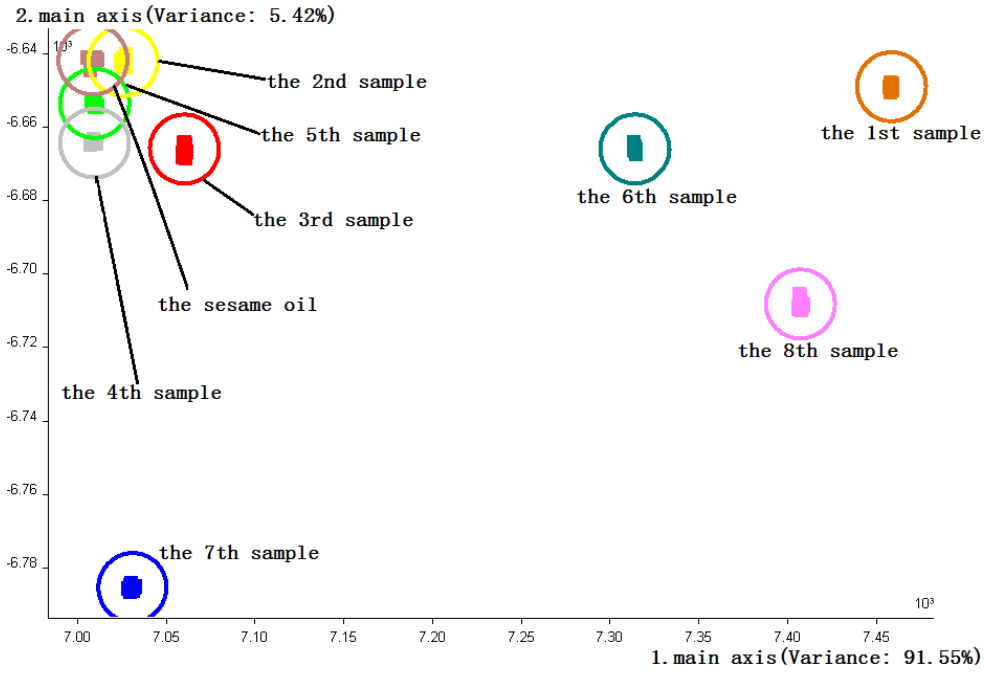

Fig. 5: LDA analysis for MRPs

groups of the 3rd samples and the 4th sample overlap each other. The system has not enough resolution to different Maillard reaction process.

When the LDA analysis (Fig. 5), using the same data of nine groups (Maillard reaction process and the sesame oil date), the MRPs were distinguishable from each group. In this plot about 96.98% of the total variance of the data is displayed. LDA function 1 (LD1) and function 2 (LD2) accounted for 91.55 and 5.42% of the variance, respectively. In spite of the clear location among all the classes by Maillard reaction using the analysis (LDA), but a small overlap joint was achieved

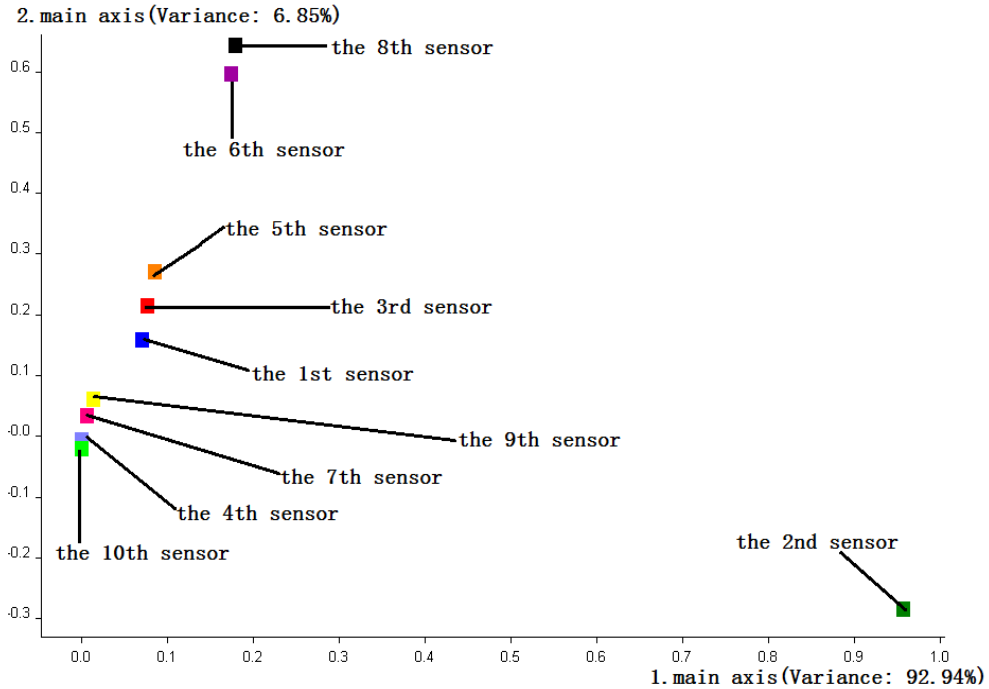

Fig. 6: Loading analysis related to PC1 and PC2 for the total variance in 99.79%

between the 2nd group, the 4th group and the 5th group, meaning that this three groups of Maillard reaction production do not differ much. This may be the reason that the score was approximative by organoleptic test.

Loading analysis: The loading analysis will help to identify the important of sensors responsible for discrimination in the current pattern file. Single sensors may be switched off for analysis if they have rather smaller influence on the identification process. Sensors with loading parameters near to zero for a particular principal component have a low contribution to the total response of the array, whereas high values indicates a discriminating sensor.

The loading analysis was performed, a loading plot of the loading factors associate to PC1 and PC2 for MRPs shown in Fig. 6. It was also shown that the relative importance of the sensors in the array. The loading factor associates to first and second principal components for each sensor is represented. There are sensor groups that have almost identical loading parameters and they might be represented by just one sensor. Figure 6 shows that the sensors 2, 6 and 8 have higher influence in the current pattern file, while the sensors 1, 3, 4, 5, 7, 9 and 10, respectively have low influence. This is identical with the result in Fig. 3. The sensors 4, 7, 9 and 10, respectively have similar loading factor and so could be represented by just one sensor.

Sensors with loading parameters near to dilution factor for a particular principal component have also a low contribution to the total response of the array. Hence, nearly a subset of few sensors can be chosen to explain all variance. This result could be used in further studies to optimize the number of sensors.

CONCLUSION

Optimum process of Maillard reaction with the natural flavors of sesame oil was as follow, the basic components added with lysine, xylose and glycerin, heated in glycerine bath at 140°C for 120 min, was a novel flavors with sesame oil flavor and taste. The obtained results prove that the electronic nose PEN 3 based on 10 metal oxide semiconductor sensors can differ successfully the MRPs with flavors of sesame oil and have been demonstrated that electronic nose technology has excellent sensitivity and selectivity for differentiating the MRPs. Principal component analysis and linear discriminant analysis were used to investigate whether the electronic nose was able to distinguishing among different the MRPs. The loadings analysis was used to identify the sensors responsible for discrimination in the current pattern file. The results prove that the electronic nose was not able to detect a clear difference in the similar aroma with sesame oil of the 3rd and the 4th sample using PCA analysis, but it achieves a clear separation in this two samples using LDA analysis.

Sensors 2, 6 and 8 have the highest influence in the current pattern file. Hence, nearly a subset of few sensors can be chosen to explain all the variance. This result could be used in further studies to optimize the number of sensors.

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