Odor Classification by Neural Networks

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***Abstract*—It is important to detect an odor in the human living space and artificial electronic noses have been developed. This paper considers an array sensing system of odors and adopts a layered neural network for classification. We use all measurement data obtained from fourteen metal oxide semiconductor gas (MOG) sensors. Some sensors are not sensitive while others are sensitive. In order to classify odors, we use data from all fourteen sensors even if some of them are not sensitive so much. We will propose three methods to use the data by insensitive sensors to find the features of odors. Then, applying those features to a layered neural network, we will compare the classification results.**

***Keywords*-odor classification; odor sensors; neural networks; layered neural network; features of odor.**

I. Introduction

Recently, much research has been done about the recognition and classification of odors [1],[2],[3],[4]. It is important for human beings to obtain high quality information on odor, since it is one of our five senses. We have used these five senses to enjoy comfortable human life with communication and mutual understanding. Artificial odor sensing and classification systems through electronic technology are called an electronic nose and they have been developed according to various odor sensing systems and several classification methods [1],[2].

We have developed electronic nose systems to classify the various odors under different densities based on a layered neural network and a competitive neural network of the learning vector quantization method [5], [6],[7],[8].

From our experience, it is difficult to achieve the perfect classification even if we use many MOG sensors [9] since some of them are insensitive for some odors. This means that some sensors are actively sensitive and effective for classification. But insensitive sensors may become sensitive for other odors and we cannot take away those sensors even if they are insensitive for an odor since they could be useful for the classification of other odors.

To solve the dilemma, we use all sensors regardless of sensitive or insensitive sensors. We extract the features of odors by processing all sensors by reforming the data such that insensitive data become useful. In this paper, we propose three methods to extract the feature vectors by processing the insensitive data.

After brief survey of the electronic nose and its measurement and classification methods, we propose three methods to reform the data. The first method (Method 1) is to reverse the data belonging to an insensible group with respect to horisontal axis and enlarge the negative data. The second method (Method 2) is to rank the negative data of the method 1 and according to the ranking we assign some weights. The third one (Method 3) is to add more information about the transient property of odor data in addition to a maximum value. Finally, simulation results for odor data are discussed to see the effectiveness of the proposed methods.

II. Human Olfactory Processes

Although the human olfactory system is not fully understood by physicians, the main components of the anatomy of human olfactory system are the olfactory epithelium, the olfactory bulb, the olfactory cortex, and the higher brain or cerebral cortex as shown in Fig. 1. The process of the human olfactory system is shown in Fig. 2.

The first process of human olfactory system is to breathe or to sniff the odor into the nose as shown in Step 1 of Fig. 2. The difference between the normal breath and the sniffing is the quantity of odorous molecules that flows into the upper part of the nose. In case of sniffing, most air is flown through the nose to the lung and about 20% of air is flown to the upper part of the nose and detected by the olfactory receptors.

In case of sniffing, the most air flow directly to the upper part of the nose interacts with the olfactory receptors. The odorous molecules are dissolved at a mucous layer before interacting with olfactory receptors in the olfactory epithelium as shown in Step 2 of Fig. 2.

The concentration of odorous molecules must be over the recognition threshold. After that, the chemical reaction in each olfactory receptor produces an electrical stimulus. The electrical signals from all olfactory receptors are transported to olfactory bulb as shown in Step 3 of Fig. 2.

The input data from olfactory bulbs are transformed to be the olfactory information to the olfactory cortex as shown in Step 4 of Fig. 2. Then the olfactory cortex distributes the information to other parts of the brain and human can recognize odors precisely as shown in Step 5 of Fig. 2. The other parts of the brain that link to the olfactory cortex will control the reaction of the other organ against the reaction of that odor. When humans detect bad odors, they will suddenly expel those odors from the nose and try to avoid breathing them directly without any protection. This is a part of the reaction from the higher brain.

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Finally, the cleaning process of the nose is to breathe fresh air in order to dilute the odorous molecules until those concentrations are lower than the detecting threshold as shown in Step 6 of Fig. 2. The time to dilute the odor depends on the persistence qualification of the tested odor.

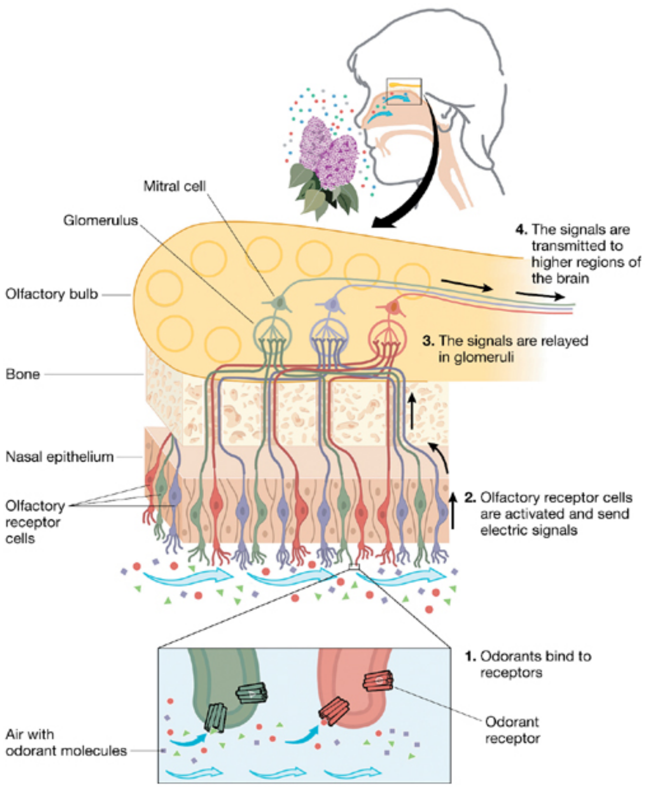

Fig. 1. Olfactory system:EMBO reports (2007).

Step 1. Sniff to bring odorous molecules to the nose

↓

Step 2. Odorous molecules are dissolved and detected by the olfactory receptors

↓

Step 3. Signals from olfactory receptors are transported to olfactory bulb

↓

Step 4. Olfactory bulb transforms the information of olfactory bulb to the information of olfactory cortex

↓

Step 5. Information of olfactory cortices is distributed to the other parts of brain and human can identify the smell

↓

Step 6. Clean the nose by breathing fresh air

Fig. 2. Process of olfactory system.

Odor delivery system → Odor sensor array

↓

Data processing ← Data recording

Fig. 3. Main parts of electronic nose systems.

III. Electronic Nose System

The electronic nose system is an alternative method to analyze odor by imitating the human olfactory system. In this section, the concept of an electronic nose is explained. Then various sensors for odors applied as the olfactory receptors are explained. Finally, the mechanism of a simple electronic nose that will be developed in this paper is described in detail by comparing the function of each part with the human olfactory process.

The mechanism of electronic nose systems can be divided into four main parts as shown in Fig. 3.

A. Odor delivery system

The first process of the human olfactory system is to sniff the odorous molecule into the nose. Thus, the first part of the electronic nose system is the mechanism to bring the odorous molecules into the electronic nose system. There are three main methods to deliver the odor to the electronic nose unit, sample flow, static system, and pre-concentration system.

The sample flow system is the most popular method to deliver odorous molecule to the electronic nose unit. Some carrier gas such as air, oxygen, nitrogen, and so on, is provided as a carrier gas at the inlet port to flow the vapor of the tested odor through the electronic nose unit via the outlet port. The mechanism to control the air flow of an electronic nose may contain various different parts such as a mass flow controller to control the pressure of the carrier gas, a solenoid valve to control the flow of inlet and outlet ports, a pump to suck the tested odor from the sampling bag in case that the tested odor is provided from outside, a mechanism to control humidity, and so on. Most commercial electronic noses contain complicated odor delivering systems and this makes the price of the electronic noses become expensive.

The static system is the easiest way to deliver odorous molecules to the electronic nose unit. The electronic nose unit is put into a closed loop container. Then an odor sample is injected directly to the container by a syringe. It is also possible to design an automatic injection system. However, the rate to inject the test odors must be controlled to obtain accurate results. Normally, this method is applied for the calibration process of the electronic nose. But, in this case, the quantity of the odor may not be enough to make the sensor reach the saturation stage, that is, the stage that sensor adsorbs

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the odor fully.

The pre-concentration system is used in case of the tested odor that has a low concentration and it is necessary to accumulate the vapor of the tested odor before being delivered to the electronic nose unit. The pre-concentrator must contain some adsorbent material such as silica and the tested odor is continuously accumulated into the pre-concentrator for specific time units. Then the pre-concentrator is heated to desorb the odorous molecule from the adsorbent material. The carrier gas is flown through the pre-concentrator to bring the desorbed odorous molecules to the electronic nose unit. By using this method, some weak odors can be detected by the sensor array in the electronic nose unit.

B. Odor sensor array

The second process of the human olfactory system is to measure various odors corresponding to various receptors in the human olfactory system. In order to realize many receptors artificially, we adopted two types of sensors. One is MOG type and the other is QCM type. The idea of the present paper is to use many sensors which are allocated in an array structure for each type of MOG and QCM types. This structure is adopted based on the human olfactory system. As we will explain in what follows, the odor sensors are not so small and a rather wide space is required to measure odors.

C. Data recording

The data recording is corresponding to temporal memory for the human olfactory system. In the latter case, after learning odors we could identify an odor suddenly, we store sensing data of odors in a computer. To read and write the data, we design an efficient data base structure.

D. Data processing

Using the data base of odors, we must apply an intelligent signal processing technique to recognize odors correctly. We pre-process the odor data for noise reduction, normalization, feature extraction, and so on. Then we use layered neural networks and competitive networks for odor classification since learning ability and robustness are important in odor classification. The most difficult and important process in the odor classification is to find excellent features which are robust for environment like temperature, humidity, and density levels of odors.

IV. Principle of Odor Sensing

Nowadays, there are many kinds of sensors that can measure odorous molecules. However, only a few kinds of them have been successfully applied as artificial olfactory receptors in commercial electronic noses. Among them, we use MOG sensors which will be explained in what follows.

A. Principle of MOG sensors

MOG sensors are the most widely used sensors for making an array of artificial olfactory receptors in electronic nose systems. These sensors are commercially available as the chemical sensor for detecting some specific odors. Generally, a MOG sensor is applied in many kinds of electrical appliances such as a microwave oven to detect the food burning, an alcohol breathe checker to check the drunkenness, an air purifier to check the air quality, and so on.

Generally, it is designed to detect some specific odor in electrical appliances such as an air purifier, a breath alcohol checker, and so on. Each type of MOG sensors has its own characteristics in the response to different gases. When combining many MOG sensors together, the ability to detect a odor is increased.

TABLE I
List of MOG sensors from the FIS Inc. used in this experiment

Sensor No.	Model number	Main Detecting Gas
1	TGS2600	Tobacco, Cooking odor
2	TGS2602	Hydrogen sulfide, VOC, Ammonia
3	TGS2610	Liquefied petroleum gas, Butane
4	TGS2611	Methane
5	TGS2620	Alcohol, Organic solvent
6,7	TGS826	Ammonia, Amine compound
8,9	TGS816	Methane, Liquefied petroleum gas, Butane
10	TGS821	Hydrogen
11	TGS832	Freon gas
12	TGS825	Hydrogen sulfide
13	TGS80	Freon gas
14	TGS822	Alcohol, Organic solvent

In order to classify the odors we adopt a three-layered neural network based on the error back-propagation method.

V. Experimental Data

We have carried out two experiments, Experiment I and Experiment II, as shown in Table II where variation means fluctuation level for each species. In Experiment I, we have measured the odors for the same kind of coffees produced in the different countries such as Colombia, Guatemala, and Ethiopia and the odors of two kinds of blend coffees such as blend coffee 1 and blend coffee 2. In Experiment I, six times of odors measurements have been repeated for each coffee. Thus, the total number of features of odors are thirty for five kinds of coffees. In Experiment II, we have measured odors of three kinds of teas, coffee, and cocoa as shown in Table II. In Experiment II, we have measured six times for each species as done in Experiment II. Thus, total number of the features in Experiemnt II is also thirty as in Experiment I. The experimental conditions for both Experinet I and II are summarized in Table III.

TABLE II
Experiment Iand II

No.	Variation	Species
I	large	Three districts cofee (Colombia, Guatemala, Ethiopia), Two blend coffees
II	small	Tea, Green Tea, Oolong tea, Coffee, Cocoa

The neural network is a layered type based on the error back-propagation method. The number of neurons for this experiment are fourteen in the input layer, thirty in the hidden layer, and three in the output layer, that is, 14-30-3 structure.

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TABLE III
ENVIRONMENTAL DATA FOR EXPERIMENT IAND II

Subject	Units
Gas flow	1[l/min]
Temperature of gas	35[°C]
Odor measurement time	12[min]
Dry air flow time	7[min]

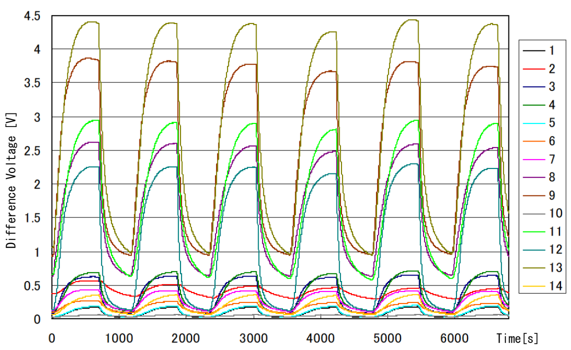

Fig. 4. Sample path of blend coffee 2 of Experiment I.

The reason why three neurons in the output layer is that three bits can represent eight neumerals where in Experimet I and Experiment II, we use five pattern for classification.

We have separated the six measurement data for each odor into three training data and three test data. The combination of the data is ${}_6C_3$=20 for each odor and total number of the test data becomes 32×10^5. Among them we have selected six thousand data for the evaluation. In Fig. 4 and Fig 5, we show the sample paths of blend coffee 2 of Experiment I and Tea of Experiment II, respectively.

We select the maximum value of each sample path as a feature of an odor for a sensor. The reason to use the maximum value is that the odor will be accumulated in the sensor for a while in the beginning and then, the molecule will be oxidized, which means that the resistance of the sensor becomes lowest. Thus, the maximum value reflects steady state of the odor. In the experiments, we have used fourteen sensors. Thus, for each odor, we have a vector of fourteen dimensions. In Fig. 6 we show the feature vectors for three coffees of Colombia, Guatemala, and blend 2 in Experinet I.

The classification results using the data measured by using fourteen sensors for Experinets I and Experiment 2 are given by Table IV and Table V, respectively.

We notice that these experimental results are not so good. Paticularly, in Experiment I it is necessary to improve the classification results. In this case, from Fig. 6 we can see that there are two groups for the feature vectors. One is sensitive for odors and the other is insensitive among fourteen sensors. Thus, if we could use the data of insensitive sensors, we could expect to improve the classification results since there exist differences of features between odors even if the fluctuation levels are not large.

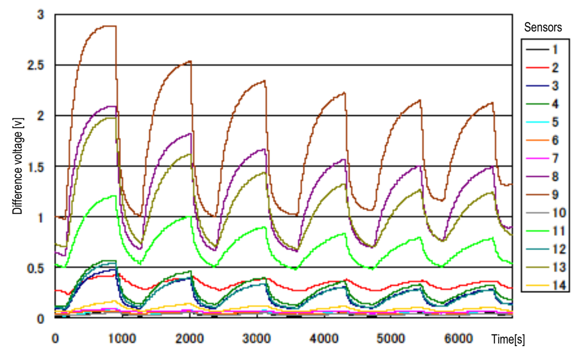

Fig. 5. Sample path of tea of Experiment II.

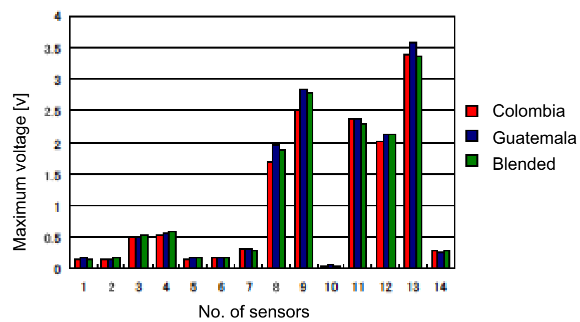

Fig. 6. Feature vectors for coffees in Experiment I.

VI. THREE METHODS FOR IMPROVING THE CLASSIFICATION RESULTS

In what follows, we will propose three methods to use the data in order to improve the classification rate.

A. Method 1

Neurons become sensitive near thresholds since the derivative of the sigmoid function becomes maximum at the threshold value. In other words, the outputs of the neurons become insensitive when the absolute value of the net input becomes very large. Thus, it is preferable to move the net input to become some regions such as [-5,5]. Thus, we propose Method 1 stated as follows. First, we make two groups for the feature vectors such that one is sensitive and the other is insensitive. In Experiment I, lower ranking group (G1) is sensors 1, 2, 5, 6, 7, and 14 and higher ranking group (G2) is sensors 3, 4, 8, 9, 11, 12, 13.

Then, reverse the sign of values in G1 (cf. Fig 7) and scale the values with negative sign such that the maximum among G2 is equal to the absolute value of the smallest value of G1 by linearly interpolation (cf. Fig 8) .

B. Method 2

This method is a ranking of the measurement data. First, separate the data into two groups, G1 and G2 as Method 1 and reverse the sign of values in G1. Then, arrange in decreasing order of absolute value and assign the value 1.4 for the first

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TABLE IV
CLASSIFICATION RESULTS FOR EXPERIMENT I. HERE, A IS COLOMBIA COFFEE, B IS GUATEMALA COFFEE, C IS ETHIOPIA COFFEE, D IS BLENDED COFFEE 1, AND E IS BLENDED COFFEE 2.

Odor data	Classification results(60.4%)						
	A	B	C	D	E	Total	Correct
A	4686	0	0	0	1314	6000	78.1%
B	1022	121	0	0	4857	6000	2.0%
C	1387	0	4067	546	0	6000	67.8%
D	956	499	2	3765	1678	6000	62.8%
E	522	0	0	0	5478	6000	91.3%

TABLE V
CLASSIFICATION RESULTS FOR EXPERIMENT II. HERE, A IS TEA, B IS GREEN TEAS, C IS OOLONG TEA, D IS COFFEE, AND E IS COCOA.

Odor data	Classification results(74.3%)						
	A	B	C	D	E	Total	Correct
A	4525	100	513	0	862	6000	75.4%
B	101	3967	0	0	1932	6000	66.1%
C	983	423	3959	635	0	6000	65.8%
D	0	283	0	5717	0	6000	95.3 %
E	629	1234	2	0	4135	6000	68.9 %

sensor, 1.3 for the second sensor, etc. in order of decreasing absolute vale. After that, scale the value in G2 in the same way by assigning values from 1.7, 1.4, 1.3, 1.1, 0.9, 0.3, 0.3. The scaled values were determined by trial and error according to the rule that G2 is more important than G1 values (cs. Fig 9

C. Method 3

This method uses additional information about the transient property. In addition to the maximum value we use the slop of the transient slope (cf. Fig. 4). In this case, we must change the number of neurons in the input layer and the neural network becomes 28-30-2.

Using those methods, we have simulated Experiment I and Experiment II. The simulation results for Experiment I by three methods are shown in Table VI, Table VII, and Table VIII, respectively. From these results, we can see Method 1 could improve the classification results by 31% compared with the result of Table IV.

Among three proposed methods, Method 1 is the best, Method 2 is medium, and Method 3 is the worst for Experiment I. This means that the slope information is not so much efficient to improve the classification results for Experiment I. The reason is that from Fig. 4 it is so sensitive to calculate the slopes from the data and rough estimated values of the slope results in worse classification results. As for Method 2, by trial and error the classification results may be improved more. But such trial is not so welcome in computation.

The simulation results for Experiment II by three methods are shown in Table IX, Table X, and Table XI, respectively. From these results, we can see Method 1 could improve the classification results by 11% compared with the result of Table V.

Among three proposed methods, Method 1 is the best, Method 3 is medium, and Method 2 is the worst for Experiment II. This means that Method 2 is sensitive to the method

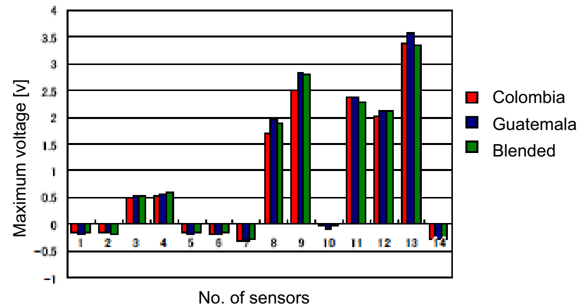

Fig. 7. Feature vectors of the sign reversed version of Experiment I.

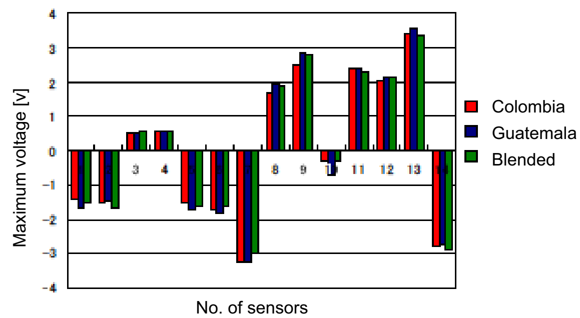

Fig. 8. Feature vectors of linearly interporated version of Experiment I.

by trial and error. Method 3 is rather stable and the result is not so bad. Therefore, Method 1 is most preferable to improve the classification results.

TABLE VI
CLASSIFICATION RESULTS BY METHOD 1 FOR EXPERIMENT I.

Odor data	Classification results (91.0%)						
	A	B	C	D	E	Total	Correct
A	5952	23	4	1	20	6000	99.2%
B	51	4793	0	214	942	6000	79.9%
C	4	0	5996	0	0	6000	99.9%
D	0	440	2	4555	1003	6000	75.9%
E	0	0	0	0	6000	6000	100%

TABLE VII
CLASSIFICATION RESULTS BY METHOD 2 FOR EXPERIMENT I.

Odor data	Classification results (87.9%)						
	A	B	C	D	E	Total	Correct
A	5949	51	0	0	0	6000	99.2%
B	1255	4445	4	296	0	6000	74.1%
C	494	0	4353	1153	0	6000	72.6%
D	0	390	0	5610	0	6000	93.5%
E	0	0	0	0	6000	6000	100%

VII. CONCLUSIONS

In this paper, a new approach to odor classification has been presented and discussed by using MOG sensors. After surveying the odor sensing and classification methods, we have examined two examples, Experiment I and Experiment II to

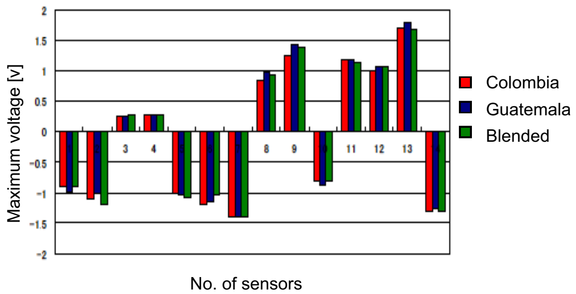

Fig. 9. Feature vectors of ranked version of Experiment I.

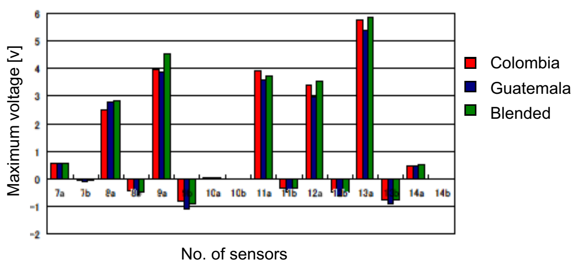

Fig. 10. Feature vectors of the scaled version of Experiment I. Here, holisontal axis simbols are sensor number+slope(a)+vertical intercept(b).

increase the classification accuracy. Basically, we have proposed three methods by using the data measured by insensitive sensors. From these results, using those data is efficient to improve the classification accuracy so much. We will search new features of odor information for classification in the future.

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TABLE VIII
CLASSIFICATION RESULTS BY METHOD 3 FOR EXPERIMENT I.

Odor data	Classification results (78.1%)						
	A	B	C	D	E	Total	Correct
A	4182	1	0	0	1817	6000	69.7%
B	2	5337	1	642	18	6000	89.0%
C	404	308	4344	944	0	6000	72.4%
D	23	1146	190	4457	184	6000	74.3%
E	881	0	0	0	5119	6000	85.3%

TABLE IX
CLASSIFICATION RESULTS BY METHOD 1 FOR EXPERIMENT II.

Odor data	Classification results (85.6%)						
	A	B	C	D	E	Total	Correct
A	4902	0	1098	0	9	6000	81.7%
B	81	5768	0	9	142	6000	96.1%
C	324	5	5421	248	2	6000	90.4%
D	0	0	450	5550	0	6000	92.5%
E	1031	94	588	260	4027	6000	67.1%

TABLE X
CLASSIFICATION RESULTS BY METHOD 2 FOR EXPERIMENT II.

Odor data	Classification results (59.7%)						
	A	B	C	D	E	Total	Correct
A	5178	754	9	0	59	6000	86.3%
B	952	3253	0	0	1795	6000	54.2%
C	504	1166	556	532	3242	6000	9.3%
D	0	347	469	5184	0	6000	86.4%
E	601	1644	0	9	3746	6000	62.4%

TABLE XI
CLASSIFICATION RESULTS BY METHOD 3 FOR EXPERIMENT II.

Odor data	Classification results (75.9%)						
	A	B	C	D	E	Total	Correct
A	4559	0	1276	93	72	6000	76.0%
B	1101	4198	0	597	104	6000	70.0%
C	743	0	3686	1571	0	6000	61.4%
D	0	15	242	5743	0	6000	95.7%
E	71	644	15	706	4564	6000	76.1%

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