Intelligent Classification of Odor Data Using Neural Networks

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***Abstract*—Metal oxide semiconductor gas (MOG) sensors and quartz crystal microbalance (QCM) sensors are used to measure several kinds of odors. Using neural networks to classify the measured data of odors, artificial electronic noses have been developed. This paper is to consider an array sensing system of odors and to adopt a layered neural networks for classification. Furthermore, we consider mixied effect of odors for classification accuracy. For simplicity, we will treat the case that two kinds of odors are mixed, since more than two becomes too complex to analyze the classification efficiency. In order to consider the mixed effect, we use as the test data two out of four kinds of odors. An acceptable result, although not perfect, has been achieved for the classification of mixed odors, by using aht lruered neural network.**

***Keywords*-odor classification; odor sensors; sensor array; mixed odors; neural networks.**

I. INTRODUCTION

The problem of recognition and classification of odors are important to achieve the high quality of information like human being since the smell is one of 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][3][4].

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].

Based on the experience, we have developed a new measurement system such that precise evaluation of the odor can be done with many sensors and by controlling dry air flow rate, temperature, and humidity. Furthermore, we have attached a sensing system with both Metal oxide semiconductor gas (MOG) sensors array and quartz crystal microbalance (QCM) sensors array.

After brief survey of the electronic nose and its measurement and classification methods, we consider the electronic nose accuracy when two odors are mixed after each of the original odors has been classified precisely by using a neural network. We will consider the classification of mixed odors based on the sensing data by using QCM sensors. The QCM sensors are more sensitive than MOG sensors to some kinds of odor and the environmental condition for sensing odors. Using many QCM sensors, we will try to separate the mixed odors into the original odors based on the neural network classifier.

II. HUMAN OLFACTORY PROCESSES

Although the human olfactory system is not fully understood by physicians, the main components about 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 first process of human olfactory system is to breathe or to sniff the smell into the nose, as shown in Step 1 of Fig. 1. 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. 1.

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. 1.

The input data from olfactory bulbs are transformed to be the olfactory information to the olfactory cortex, as shown

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in Step 4 of Fig. 1. Then the olfactory cortex distributes the information to other parts to the brain and human can recognize odors precisely, as shown in Step 5 of Fig. 1. 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 smell. When human detects bad smells, human will suddenly expel those smells from the nose and try to avoid breathing them directly without any protection. This is a part of the reaction from the higher brain.

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. 1. The time to dilute the smell depends on the persistence qualification of the tested smell.

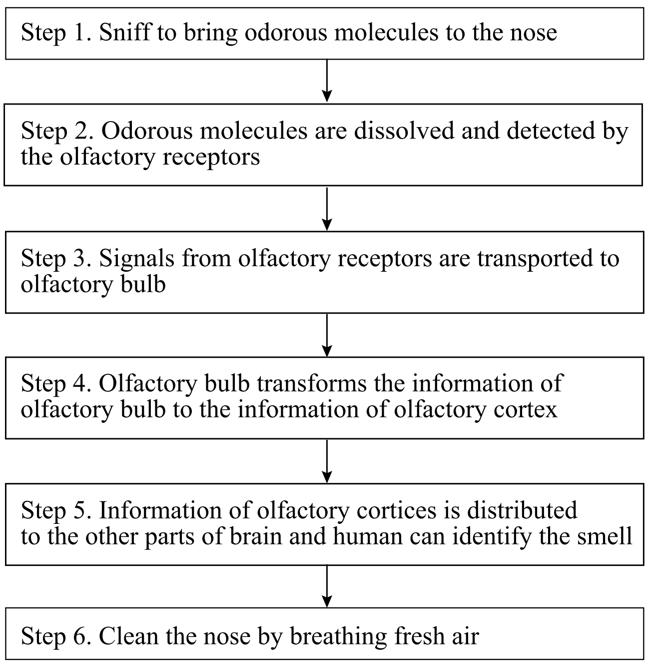

Fig. 1. Olfactory system.

III. ELECTRONIC NOSE SYSTEM

The electronic nose system is an alternative method to analyze smell 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 main four parts as shown in Fig. 2.

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.

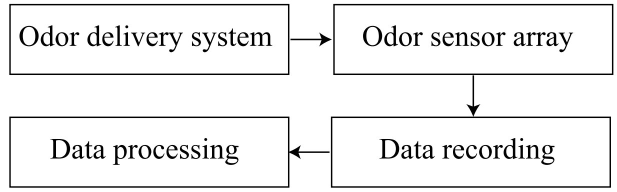

Fig. 2. Main parts of electronic nose systems.

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 smell 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 the smell fully.

The pre-concentration system is used in case of the tested smell 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 smells 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 n [8] and the other is QCM type p [7]. 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, which results in a large space 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 make reading and writing the data, we make an efficient structure of data base.

D. Data processing

Using the data base of odors, we must apply an intelligent signal processing technique to recognize odors correctly. We make pre-processing the odor data such as noise reduction, normalization, feature extraction, etc. Then we use neural networks for classification of odors. Basically, we use a 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. We show two types of odor sensors which are major for odor sensing. One is a MOG sensor and the other is a QCM sensor, 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 smells. Generally, an 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.

The picture of some commercial MOG sensors are shown in Fig. 3. Various kinds of metal oxides, such as SnO_2, ZnO_2, WO_3, TiO_2 are coated on the surface of a semiconductor. But, the most widely applied metal oxide is SnO_2. These metal oxides have a chemical reaction with the oxygen in the air and the chemical reaction changes when the adsorbing gas is detected. The scheme of chemical reaction of an MOG sensor when adsorbing with the CO gas, is shown as follows:

$$\frac{1}{2}\mathrm{O}_2 + (\mathrm{SnO}_{2-x}) \rightarrow \mathrm{O}^{-}\mathrm{ad}\ (\mathrm{SnO}_{2-x}) \quad (1)$$

$$\mathrm{CO} + \mathrm{O}^{-}\mathrm{ad}\ (\mathrm{SnO}_{2-x}) \rightarrow \mathrm{CO}_2 + (\mathrm{SnO}_{2-x}) \quad (2)$$

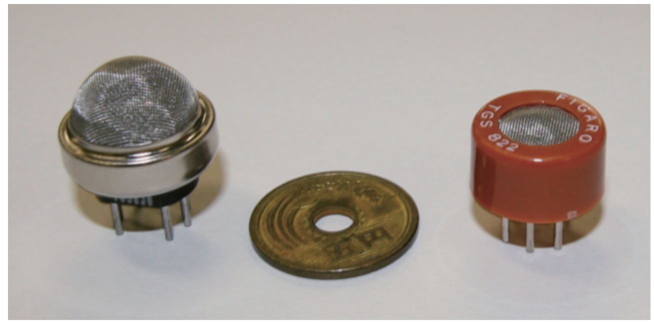

Fig. 3. MOG sensors.

When the metal oxide element on the surface of the sensor is heated at a certain high temperature, the oxygen is adsorbed on the crystal surface with the negative charge as shown in Fig. 4. In this stage, the grain boundary area of the metal oxide element forms a high barrier as shown in the left hand side of Fig. 4.

Then, the electrons cannot flow over the boundary and this makes the resistance of the sensor become higher. When the deoxidizing gas, e.g., CO gas, is presented to the sensor, there is a chemical reaction between negative charges of oxygen at the surface of the metal oxide element and the deoxidizing gas as shown in (1). The chemical reaction between adsorbing gas and the negative charge of the oxygen on the surface of MOG sensor reduces the grain boundary barrier of the metal oxide element as shown in the right hand side of Fig. 4. Thus, the electron can flow from one cell to another cell easier. This makes the resistance of MOG sensor lower by the change of oxygen pressure according to the rule of (2). Thus, (1) means that CO_2 is reduced and (2) means that CO is oxidized.

The relationship between sensor resistance and the concentration of deoxidizing gas can be expressed by the following equation over certain range of gas concentration:

$$R_s = A[C]^{-\alpha}$$

where R_s =electrical resistance of the sensor, $A =$ constant, $C =$ gas concentration, and α =slope of R_s curve. The electric

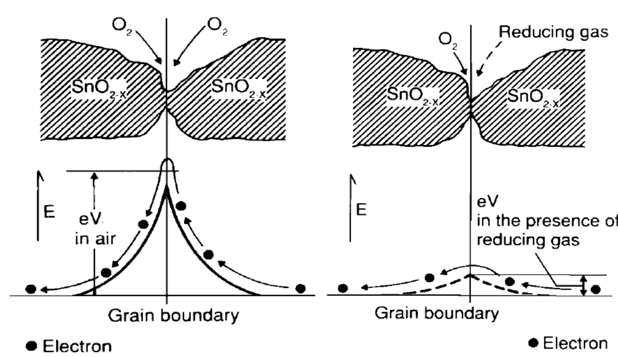

Fig. 4. Principle of MOG sensor [8].

circuit for the MOG sensor is shown in Fig. 5. Electrical voltages are provided to the circuit (V_c) and the heater of the sensor (V_h). When the MOG sensor is adsorbed with oxygen and the deoxidizing gas, the resistance of the sensor (R_s) is changed. Thus, we can measure the voltage changes (V_{out}) while the sensor is adsorbing the tested odor.

MOG sensors need to be operated at high temperature, so they consume a little higher power supply than the other kinds of sensors. The reliability and the sensitivity of MOG sensors are proved to be good to detect volatile organic compounds (VOCs), combustible gas, and so on [8]. However, the choices of MOG sensors are still not cover all odorous compounds and it is difficult to create an MOG sensor that responds to one odor precisely. Generally, most commercial MOG sensors respond to various odors in different ways. Therefore, we can expect if we use many MOG sensors to measure a smell, the vector data reflect the specific properties for the smell. Generally, it is designed to detect some specific

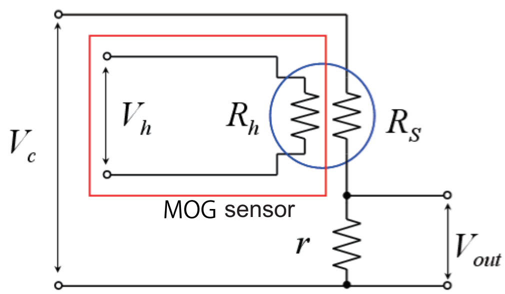

Fig. 5. Principle of MOG sensors.

smell 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 smell is increased. The main part of the MOG sensor is

TABLE I
LIST OF MOG SENSORS FROM THE FIS INC. USED IN THIS EXPERIMENT.

Sensor Model	Main Detecting Gas
SP-53	Ammonia, Ethanol
SP-MW0	Alcohol, Hydrogen
SP-32	Alcohol
SP-42A	Freon
SP-31	Hydrocarbon
SP-19	Hydrogen
SP-11	Methane, Hydrocarbon
SP-MW1	Cooking vapor

the metal oxide element on the surface of the sensor. When this element is heated at certain high temperature, the oxygen is adsorbed on the crystal surface with the negative charges. The reaction between the negative charge of the metal oxide surface and deoxidizing gas makes the resistance of the sensor vary as the partial pressure of oxygen changes [8]. Based on this characteristic, we can measure the net voltage changes while the sensors adsorb the tested odor.

B. Principle of QCM sensors

QCM sensors have been well-known to provide a very sensitive mass-measuring devices in Nano-gram levels, since the resonance frequency will change upon the deposition of the given mass on the electrodes. Synthetic polymer-coated QCM sensors have been studied as sensors for various gasses since a QCM sensor is coated with a sensing membrane works as a chemical sensor. The QCM sensors are made by covering the surface with several kinds of a very thin membrane with about 1 μm as shown in Fig. 6.

Since the QCM sensor oscillates with a specific frequency depending on the cross section corresponding to three axis of the crystal, the frequency will change according to the deviation of the weight due to the adsorbed odor molecular (odorant). The membrane coated on QCM sensor has selective adsorption rate for a molecular and the frequency deviation show the existence of odorants and their densities. Odorants and membranes are tight relation while it is not so clear whose materials could be adsorbed so much.

In this paper, we have used the following materials as shown in Table II. The reason why fluorine compounds are used here is that the compounds repel water such that pure odorant molecular could be adsorbed on the surface of the membrane. To increase the amount of odorants to be adsorbed it is important to iron the thickness of the membrane. In Table II, we have tried to control the density of the solute in the organic solvent. The basic approach used here is a sol-gel method. The sol-gel process is a wet-chemical technique used for the fabrication of both glassy and ceramic materials. In this process, the sol (or solution) evolves gradually towards the formation of a gel-like network containing both a liquid phase and a solid phase. Typical precursors are metal oxides and metal chlorides, which undergo hydrolysis and polycondensation reactions to form a colloid. The basic structure or morphology of the solid phase can range anywhere from discrete colloidal particles to continuous chain-like polymer networks.

TABLE II
CHEMICAL MATERIALS USED AS THE MEMBRANE WHERE E:ETANOL, W:WATER, DA:DILUTE NITRIC ACID, EA:ETHYL ACRYLATE, MTMS:TRIMETHOXY SILANE, PFOEA:PERFLUOROOCTYLETHYL ACRYLATE.

Sensor number	Materials of membrane
Sensor 1	E(4ml), DA(0.023ml),
Sensor 2	W(3.13ml), E(4ml), EA(0.043ml), MTMS
Sensor 3	W(3.13ml), E(4ml), EA(0.014ml), MTMS, PFOE
Sensor 4	W(3.13ml), E(4ml), EA(0.015ml), MTMS, PFOE
Sensor 5	W(0.30ml), E(4ml), EA(0.043ml), MTMS, PFOE
Sensor 6	W(0.05ml), E(3.0ml), EA(0.043ml), MTMS, PFOE
Sensor 7	W(0.30ml), E(3.2ml), EA(0.043ml), MTMS, PFOE
Sensor 8	No membrane

V. ODOR SENSING SYSTEM

Generally, odor sensors are designed to detect some specific odor in electrical appliances such as an air purifier, a breath alcohol checker, and so on. Each of odor sensors such as MOG sensors or QCM sensors has itself characteristics in

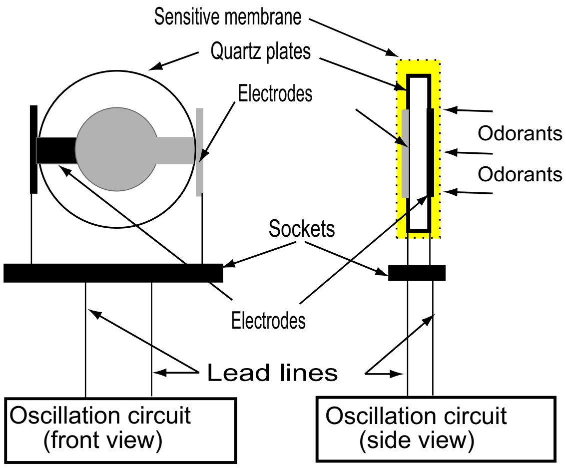

Fig. 6. Principle of QCM sensors. The odorants attached on a sensitive membrane will make the weight change of quartz plane. Thus, the original frequency of the crystal oscillation will become smaller according to the density of odorants.

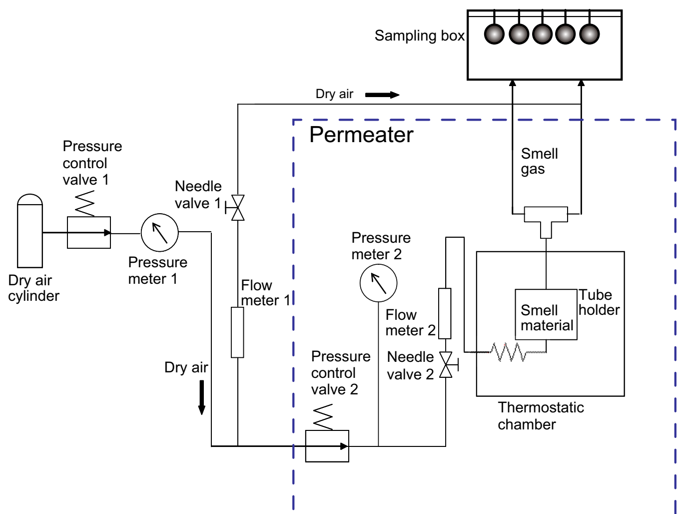

Fig. 7. Odor sensing systems. The air will be emitted from the dry air cylinder. Air flow is controlled by pressure control valves 1 and 2. By using the needle valve 2, more precise flow rate of the dry air can be achieved and the thermostatic chamber in the permeater can control the temperature of the dry air. Finally, the air is pull in the sampling box where the MOG sensors and/or QCM sensors are attached on the ceiling of the box.

the response to different odors. When combining many odor sensors together, the ability to detect an odor is increased. An electronic nose system shown in Fig. 7 has been developed, based on the concept of human olfactory system. The combination of odor sensors, listed in Tables I and II, are used as the olfactory receptors in the electronic nose.

VI. Classification Method of Odor Data

In order to classify the odors we adopt a three-layered neural network based on the error back-propagation method as shown in Fig. 8.

The error back-propagation algorithm which is based on a gradient method is given by the following steps.

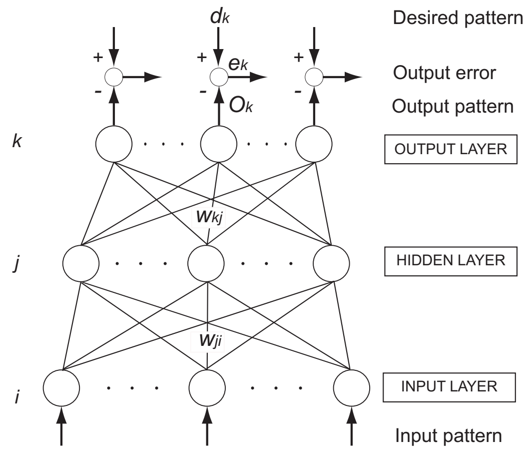

Fig. 8. Three layered neural network with the error back-propagation. The neural network consists of three layers, that is, an input layer i, a hidden layer j, and an output layer k. When the input data $x_i, i = 1, 2, \dots, I$ are applied in the input layer, we can obtain the output O_k in the output layer which is compared with the desired value d_k which is assigned in advance. If the error $e_k = d_k - O_k$ occurs, Then, the weighting coefficients w_{ji}, w_{kj} are corrected such that the error becomes smaller based on an error back-propagation algorithm.

Step 1. Set the initial values of $w_{ji}, w_{kj}, \theta_j, \theta_k$, and $\eta (> 0)$.
Step 2. Specify the desired values of the output $d_k, k = 1, 2, \dots, K$ corresponding to the input data $x_i, i = 1, 2, \dots, I$ in the input layer.
Step 3. Calculate the outputs of the neurons in the hidden layer and output layer by

$$\begin{aligned} \text{net}_j &= \sum_{i=1}^{I} w_{ji} x_i - \theta_j, O_j = f(\text{net}_j), f(x) = \frac{1}{1+e^{-x}} \\ \text{net}_k &= \sum_{j=1}^{J} w_{kj} O_j - \theta_k, O_k = f(\text{net}_k). \end{aligned}$$

Step 4. Calculate the error e_n and generalized errors by

$$\begin{aligned} e_k &= d_k - O_k, \delta_k = e_k O_k (1 - O_k) \\ \delta_j &= \sum_{k=1}^{K} \delta_k w_{kj} O_j (1 - O_j). \end{aligned}$$

Step 5. If e_k is sufficiently small for all k, END and otherwise

$$\begin{aligned} \Delta w_{kj} &= \eta O_j \delta_k, \quad w_{kj} \Leftarrow w_{kj} + \Delta w_{kj} \\ \Delta w_{ji} &= \eta O_i \delta_j, \quad w_{ji} \Leftarrow w_{ji} + \Delta w_{ji}. \end{aligned}$$

Step 6. Go to *Step* 3. Using the above recursive procedure, we can train the odor data. The measurement data is an eight-dimensional vector which are obtained with eight sensors stated in Table II.

VII. Classification Results Using MOG Sensors

We have measured four types of tea using MOG sensors shown in Table I. The odors used here are shown in Table III. Note that the chemical properties of these odors are very

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similar and it has been difficult to separate them based on the measurement data by using MOG sensors. We have examined

TABLE III
TEAS USED IN EXPERIMENT I.

Label	Materials	Samples
A	English tea	20
B	Green tea	20
C	Barley tea	20
D	Oolong tea	20

two examples, Experiments I and II. For Experiment I, we classify kinds of teas. The numbers of neurons for this experiment are eight in the input layer, four in the hidden layer, and four in the output layer, that is, 8-4-4 structure.

The number of training samples is fifteen and the number of test samples is five. We change the training data set for 100 times and check the classification accuracy for the test data samples. Thus, we have obtained 500 test samples as the total number of classification. The classification results are summarized in Table IV. Average of the classification is 96.2 %. For Experiment II, we consider to classify the five

TABLE IV
CLASSIFICATION RESULTS FOR EXPERIMENT I.

Odor data	Classification results(96.2%)					
	A	B	C	D	Total	Correct
A	500	0	0	0	500	100.0%
B	0	494	6	0	500	98.8%
C	0	71	429	0	500	85.8%
D	0	0	0	500	500	100.0%

kinds of coffees as shown in Table V where the smell data A, B, and C are the coffees of Mocha made from different companies. The numbers of neurons are eight in the input layer, five in the hidden layer, and five in the output layer, that is, 8-5-5 structure.

The numbers of training samples are twenty and he number of test samples is fifteen. We change the training data set for hundred times and check the classification accuracy for the test data samples. Thus, we have obtained 1,500 test samples as the total number of classification. The classification results are shown in Table VI. From Table VI we can see that the

TABLE V
SMELL DATA OF TEAS USED IN EXPERIMENT II.

Label	Materials	No. of samples
A	Mocha coffee1	35
B	Mocha coffee2	35
C	Mocha coffee3	35
D	Kilimanjaro coffee	35
E	Char-grilled coffee	35

total classification is 88.8%. Compared with Table IV, this case is worse by about 7%. In the latter case, the classification of Mocha coffees 1, 2, and 3 is not so good. The difference of the company may affect the classification results in a bad way although the smells are similar.

TABLE VI
CLASSIFICATION RESULTS FOR EXPERIMENT II.

Odor data	Classification results(88.8%)						
	A	B	C	D	E	Total	Correct
A	1190	253	29	27	1	1500	79.3%
B	225	1237	9	10	19	1500	82.5%
C	142	7	1325	26	0	1500	88.3%
D	9	14	3	1437	37	1500	95.8%
E	0	18	0	11	1471	1500	98.1%

TABLE VII
KINDS OF ODORS MEASURED OF EXPERIMENT III.

Symbols	Kind of odors
A	Ethanol
B	Water
C	Methyl-salicylate
D	Triethyl-amine

VIII. CLASSIFICATION RESULTS USING QCM SENSORS FOR MIXED ODOR DATA

We have measured four types of odors, as shown in Table VII. The sampling frequency is 1 [Hz], the temperatures of odor gases are 24∼26 [°C], and the humidity of gas is 6∼8 [%]. To control the density of gases, we use diffusion tubes. Odor data are measured for 600 [s]. They may include impulsive noises due to the typical phenomena of QCM sensors. We call this experiment as Experiment III.

To remove these impulsive noises we adopt a median filter which replaces a value at a specific time by a median value among neighboring data around the specific time. In Fig. 9, we show the measurement data for the symbol A (ethanol) where the horizontal axis is the measurement time and the vertical axis is the frequency deviation from the standard value (9M [Hz]) after passing through a five-point median filter.

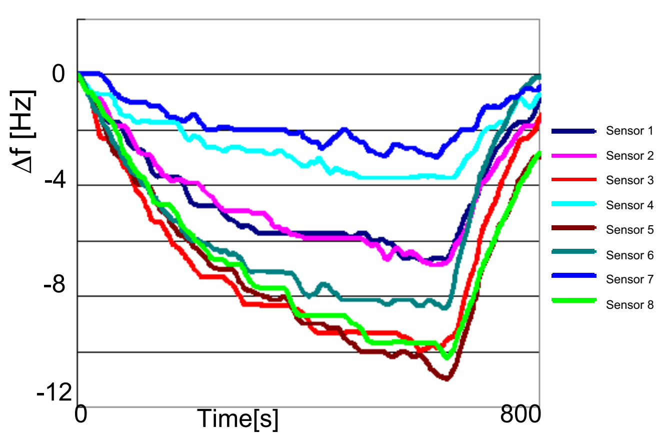

Fig. 9. Measurement data of Experiment III. Here, eight sensors are used and for 800 [s] the data were measured. The maximum value for each sensor among eight sensors is selected as a feature value for the sensor. Therefore, we have eight dimensional data for an odor and they will be used for classification.

TABLE VIII
TRAINING DATA SET FOR ETHANOL (A), WATER (B), METHYL-SALICYLATE (C), AND TRI-ETHYLAMINE (D) FOR EXPERIMENT III.

Symbols	Output A	Output B	Output C	Output D
A	1	0	0	0
B	0	1	0	0
C	0	0	1	0
D	0	0	0	1

TABLE IX
TESTING THE MIXED ODORS FOR EXPERIMET III. HERE, BOLD FACE DENOTES THE LARGEST VALUE.

Symbols	Output A	Output B	Output C	Output D
A and B	**.673**	.322	.002	.001
B and C	.083	**.696**	.174	.001
C and D	.001	.004	.016	**.992**
D and A	.003	.003	.002	**.995**
A and C	**.992**	.006	.002	.000
B and D	.003	.003	.003	**.995**

A. Training for Classification of Odors

In order to classify the feature vector, we allocate the desired output for the input feature vector where it is nine-dimensional vector, as shown in Table VIII since we have added the coefficient of variation to the usual feature vector to reduce the variations for odors. The training has been performed until the total error becomes less than or equal to 0.5 $\times 10^{-2}$ where η=0.3.

B. Classification Results and Discussion for Mixed Odor Data

After training such that all the smells, A, B, C, and D, have been classified correctly, we have tested the mixed data sets such that two kinds of odors are mixed with the same rate where the data set of mixed smells are $\{$A&B, B&C, C&D, D&A, A&C, B&D$\}$. Then, the classification results are shown in Table IX where the values in boldface denote the top case where the maximum output values are achieved. The maximum values show one of the mixed odors. But, some of them do not show the correct classification for the remaining odor. Thus, we have modified the input features such that

$$z = x - 0.9y,$$

where x is the feature, y denotes the top value of each row in Table IX, and z is a new feature. Using the new feature vector, we have obtained the classification results as shown in Table X. By changing the features according to the above relation, better classification results have been obtained. But, the coefficient 0.9 used in the above equation is not necessarily appropriate. The value might be replaced by the partial correlation coefficient in multivariate analysis.

TABLE X
TESTING THE MIXED ODORS WHERE EXCEPT FOR THE LARGEST VALUE THE TOP IS SELECTED AS THE SECOND ODOR AMONG THE MIXED ODORS FOR EXPERIMENT III. HERE, ASTERISK * DENOTES THE TOP EXCEPT FOR THE LARGEST VALUE.

Symbols	Output A	Output B	Output C	Output D
A and B	.263	**.290***	.166	.066
B and C	.358	.029	**.631***	.008
C and D	.002	.071	**.644***	.163
D and A	**.214***	.004	.037	.230
A and C	.031	.020	**.527***	.026
B and D	.108	.010	**.039***	.325

IX. CONCLUSIONS

In this paper, a new approach to odor classification has been presented and discussed by using MOG sensors and QCM sensors. After surveying the smell sensing and classification methods, we have examined two examples, Experiment 1 and Experiment II. Then, mixed effects of two different odors have been considered in Experiment III. From these results, we could know that the electronic nose systems might be applied to many applications in real world such that small detection of bad gas or uncomfortable smell, Odor classification of perfume of joss tics kinds, food freshness, etc.

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