Intelligent Electronic Nose Systems with Metal Oxide Gas Sensors for Fire Detection

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***Abstract*— In this paper, a reliable electronic nose system designed from the combination of various semi-conductor metal oxide gas sensors (MOGS) is applied to the detection of fire resulting from various sources in a kitchen. The time series signals obtained from the same source of fire are highly correlated, and different sources of fire exhibit unique patterns in the time series data. Therefore, the error back-propagation (BP) method can be effectively used for the classification of the tested smell. The accuracy of 99.6% is achieved by using only a single training data set from each source of fire. The accuracy achieved with the *k*-means algorithm is 98.3%, which also shows the high ability of the EN in detecting the early stage of fire from various sources.**

***Index Terms*— electronic nose, neural networks, learning vector quantization, metal oxide gas sensor, smell classification**

I. Introduction

Over the last decade, odor-sensing systems (so-called electronic nose systems) have undergone important developments from technical and commercial viewpoints. The electronic nose (EN) refers to a device of reproducing human sense of smell based on sensor arrays of smell and pattern recognition methods. Recently, there are several commercial EN instruments currently in use in the world such as quality control of food industry [1], environmental protection [2], public safety [3] and space applications [4].

Every year the damage from the household fire disaster brings about not only severe loss to property assets, but also physical and psychological injuries of the people.

In this paper, we will explain the human olfactory process and the EN system. After surveying various types of the odor sensors, we explain the and then the reliability of a new EN system developed from various semi-conductor metal oxide gas sensors (MOGSs) is presented to specify the smell from various sources of fire.

James A. Milke [5] has proved that two kinds of MOGS have the ability to classify several sources of fire more precisely compared with conventional smoke detector. However, his results achieve only 85% of correct classification.

In this paper, a new EN [6] is applied to measure smells from various sources of fire such as household burning materials, cooking smells, the leakage from the liquid petroleum gas (LPG). The new EN has been successfully applied to the classification of not only similar smells from different kinds, but also the same kind of smell at different concentration levels. The time series signals of the MOGS from the beginning to the time until the MOGS fully adsorbs the smell from each source of fire are recorded and analyzed by the error back-propagation (BP) neural network and the *k*-means algorithm. The average classification rate of 99.6% can be achieved by the BP method with only a single training data set from each source of fire. The accuracy with *k*-means algorithm is 98.3%, which is much better than the results in [5]– [9]. These results confirm the reliability of this new device in detecting various sources of fire in the early stage.

II. Human Olfactory Processes

Although the human olfactory system is not fully understood by physician, 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.

The first process of human olfactory system is to breathe or to sniff the smell into the nose. 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 is flown directly to the upper part of the nose and interacts with the olfactory receptors. The odorous molecules are dissolved at the mucous layer before interacting with olfactory receptors in the olfactory epithelium. 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. The input data from olfactory receptors are transformed to be the olfactory information to the olfactory cortex. Then the olfactory cortex distributes the information to other parts to the brain and human can recognize odors precisely. 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. The next process is to clean the nose by breathing fresh air to dilute the odorous molecules until those concentrations are lower than the detecting threshold. The time to dilute the smell depends on the persistence qualification of the tested smell.

The processes to analyze smell by a human nose can be summarized by a diagram shown in Fig. 1.

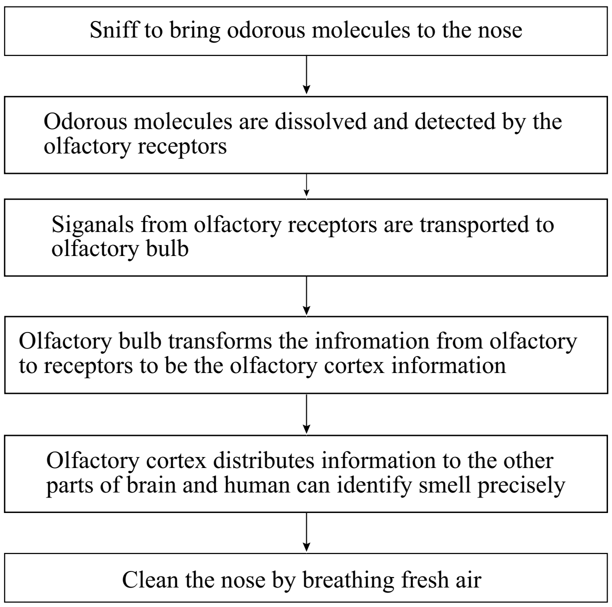

Fig. 1. Olfactory system

III. EN System

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

A. EN concept

The mechanism of EN systems can be divided into main four parts as shown in Fig. 2.

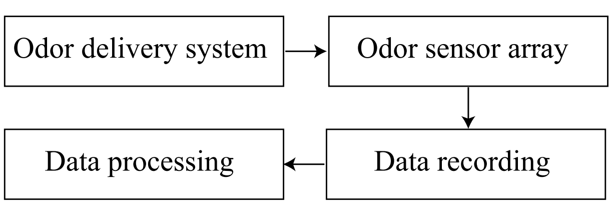

Fig. 2. Main parts of EN systems.

1) Odor delivery system: The first process of human olfactory system is to sniff the odorous molecule into the nose. Thus, the first part of the EN system is the mechanism to bring the odorous molecules into the EN system. There are three main methods to deliver the odor to the EN unit, sample flow, static system, and preconcentration system.

The sample flow system is the most popular method to deliver odorous molecule to the EN 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 EN unit via the outlet port. The mechanism to control the air flow of an EN 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 ENs contain complicated odor delivering systems and this makes the price of the ENs become expensive.

The static system is the easiest way to deliver odorous molecules to the EN unit. The EN 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 accuracy results. Normally, this method is applied for the calibration process of the EN. 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 preconcentration 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 EN unit. The preconcentrator must contain some adsorbent material such as silica and tested odor is continuously accumulated into the preconcentrator for specific time units. Then the preconcentrator is heated to desorb the odorous molecule from the adsorbed material. The carrier gas is flown through the preconcentrator to bring the desorbed odorous molecules to the EN unit. By using this method, some weak smells can be detected by the sensor array in the EN unit.

2) EN unit: All ENs must contain an array of odor sensors which act like the human olfactory receptors. Various kinds of odor sensors can be used to detect odors. The details of odor sensors will be explained in the following section. The number of sensors in the ENs unit is around 4 to 50 sensors depending on the design of each EN. The electrical circuit to control the input and the output of the sensor array are varied on the types of sensors. It is also possible to use several sensors from the same model for analyzing the odor just like the human olfactory receptors that may contain the same kind of receptors from different ages (human olfactory replacement time is around 30 days as an average). Inside of the EN units may contain some mechanism to clean the sensor after finishing the testing process in order to speed up the EN to analyze new smell.

3) Data recording: It is necessary to record the output of the sensor array in the EN unit while absorbing the tested odor continuously. Generally, the output from the sensor array is analog signal and it is necessary to convert the analog signal to digital signal before being recorded in the computer memory starage and A/D converters are used which include the software to control the sampling time with the user interface. This part of the EN system is like the function of olfactory bulb to collect the signal from the olfactory receptors before passing to the olfactory cortex.

4) Data processing: Once the data from the tested odor are completely available for analyzing, it may be able to apply various methods to analyze these data such as artificial neural networks(NNs)or statistical analysis. It may be necessary to modify the]raw data from the sensor array to increase the speed of data processing, that is, training time for the supervised NNs, or to correct some variation of data due to the effect of measuring environment. The way to modify the data is just like the internal function of olfactory bulb before passing the input to the olfactory cortex. The NNs or the statistical analysis with the software to interface with the user will act like the olfactory cortex and cerebral cortex in the human olfactory system.

The data processing part is one of the most important step to make the EN system become reliable. Most commercial ENs have a complicated mechanism for the odor delivery system and the EN unit, but if the data processing part of those ENs are not well designed, the high reliability of the ENs system may not be achieved. This paper will focus on the data processing to classify the several smells precisely.

IV. Odor Sensors

Actually there are many kinds of sensors that can be used to detect odorous molecules. However, only a few kinds of them have been successfully applied as artificial olfactory receptors in commercial ENs. Those sensors are a conducting polymer (CP)[1], a quartz crystal microbalance (QCM)[6], a surface acoustic wave (SAW)[1], and MOGSs[6].

A. Conducting polymer (CP) sensor

The CP sensor is widely applied as the array of artificial olfactory receptor in the commercial EN. These sensors are made by a thin film electro-polymerization of the conducting polymer across the gap between two inert electrodes. Variety of different monomers can be polymerized to give conducting polymer film.

CPs show reversible changes in conductivity when chemical substances such as methanol, ethanol, and ethyl acetate adsorb and desorb from the polymer. However, the mechanism that the conductivity is changed by this adsorption is not clearly understood like the case of MOGSs. Anyway, variety of polymers film responds to different kinds of odor. The choices of CPs sensors are wider than those of MOGSs. CP sensor is operated at the nearly room temperature and it consumes low power consumption. However, the response to odorous molecule is slower than those of MOGSs and it is really sensitive to humidity. The CP sensors are used in some commercial ENs, but only the sensor itself is not sold separately.

B. Quartz crystal microbalance (QCM) sensor

The QCM sensor is a kind of acoustic wave gas sensors. The main element of a QCM sensor is made from a slice of single crystal quartz typically around 1 cm in diameter. The electrodes, usually gold, are coated on both surfaces of the crystal quartz. The suitable alternative voltage is applied across the two electrodes. The electromechanical effect can make the crystal oscillate at its resonant frequency.

The oscillation wavelength and resonant frequency are altered depending on the thickness (weight) of the crystal quartz. The acoustic waves are oscillated at ultrasonic frequency typically around 1 to 500 MHz. The sensitivity of the QCM sensor to the odorous molecules depends on the gas sensitive coating material on the surface of the crystal quartz. The adsorbent coating materials are generally electro-polymers since the wide ranges of materials must be synthesized. When the adsorbent coating material adsorbs odorous molecules, the wave velocity, frequency, and the amplitude of oscillation of the sensor are changed. Therefore, the QCM with various kinds of coating materials can be used as an array of artificial olfactory receptors in the EN.

C. Surface acoustic wave (SAW) sensor

A surface acoustic wave (SAW) sensor is another kind of acoustic wave sensor that is similar to the QCM sensor. The SAW sensor comprises with a thick plate of crystal quartz. A surface of the SAW is coated with the gold electrodes to excite the oscillation of the surface of sensor. The wave is generated by applying an alternative voltage to the gold electrodes on the surface of the sensors. There are two electrode pairs, one is for transmitting the wave and the other pair is for receiving the acoustic wave.

The adsorbent coating material is coated on the surface between the transmitter and receiver electrode pairs. The changes in frequency of acoustic wave on the surface of the SAW sensors can be detected while the adsorbent material adsorbing odorous molecules. The properties of acoustic are affected by the changes in the properties of the crystal surface. The operating frequency of an SAW is between 30 to 300 MHz. The sensor also requires an integrated circuit to generate and receive acoustic wave like the QCM sensor. SAW sensor is sensitive to humidity and the response time that is not as fast as the MOGS and the CP sensor.

D. Semi-conductor metal oxide gas sensors (MFGOGSs)

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

Therefore, we will use MOGSs as the smell classification in what follows. The picture of some commercial MOGSs are shown in Fig. 3.

Various kinds of metal oxide, such as SnO_2, ZnO_2, WO_2,TiO_2 are coated on the surface of semi-conductor, 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 MOGS when adsorbing with the CO gas is shown as follows:

$$\frac{1}{2}O_2 + (SnO_{2-x}) \rightarrow O^{-}ad(SnO_{2-x}) \tag{1}$$

$$CO + O^{-}ad(SnO_{2-x}) \rightarrow CO_2 + (SnO_{2-x}) \tag{2}$$

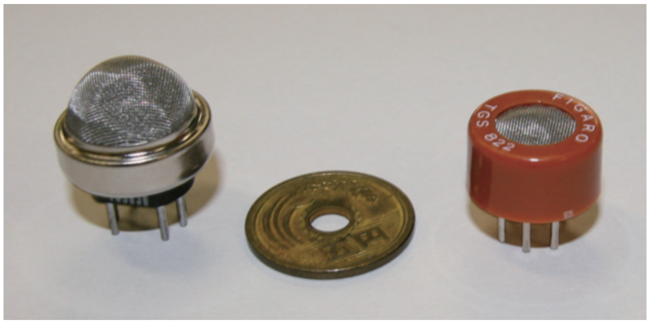

Fig. 3. MOGS

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. 3. 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. 3. 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 charge of oxygen at the surface of the metal oxide element and the deoxidizing gas as shown in (2). The chemical reaction between adsorbing gas and the negative charge of the oxygen on the surface of MOGS reduces the grain boundary barrier of the metal oxide element as shown in the right hand side of 4. Thus, the electron can flow from one cell to another cell easier. This makes the resistance of MOGS lower by the change of oxygen pressure according to the rule of (3).

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

$$R_s = A[C]^{-\alpha} \tag{3}$$

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

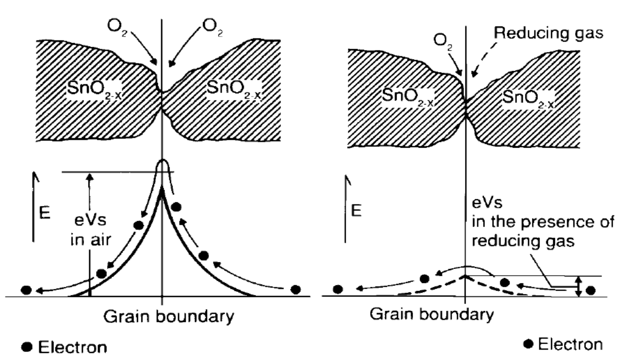

Fig. 4. Principle of MOGS[7]

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

MOGSs 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 MOGSs are proved to be good to detect volatile organic compounds (VOCs), combustible gas, and so on [7]. However, the choices of MOGSs are still not cover all odorous compounds and it is difficult to create an MOGS that responds to one odor precisely. Generally, the commercial MOGS responds to various odors in different ways. Therefore, we can expect if we use many MOGSs to measure a smell, the vector data reflect the specific properties for the smell.

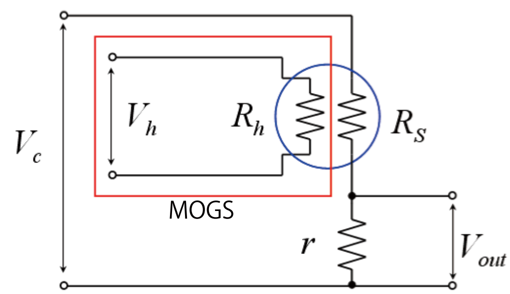

Fig. 5. Principle of MOGS[7]

Generally, it is designed to detect some specific smell in electrical appliances such as an air purifier, a breath alcohol checker, and so on. Each type of MOGS has its own characteristics in the response to different gases. When combining many MOGS together, the ability to detect the smell is increased. An EN system shown in Fig. 6 has been developed, based on the concept of human olfactory system stated above. The combination of MOGS, listed in Table I, are used as the olfactory receptors in the human nose. The MOGS unit is combined with the air flow system to lead the air and the tested smell into the MOGS unit. The A/D converter transforms the analog signals to digital signals and stores them in the data recording system before being analyzed by multivariate analysis methods, such as the BP method and the *k*-means algorithm.

TABLE I
LIST OF MOGS FROM THE FIS INC. USED IN THE 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 main part of the MOGS is the metal oxide element on the surface of the sensor. When this element is heated at a certain high temperature, the oxygen is adsorbed on the crystal surface with the negative charge. The reaction between the

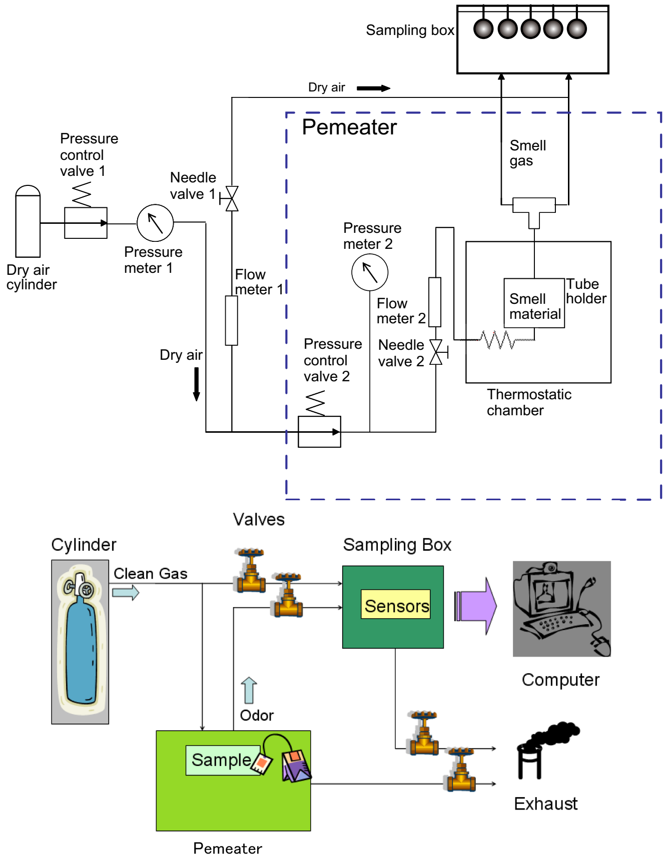

Fig. 6. Structure of the electronic nose system

negative charge of the metal oxide surface and deoxidizing gas makes the resistance of the sensor vary as the partial pressure of oxygen changes[7]. Based on this characteristic, we can measure the net voltage changes while the sensors adsorb the tested odor.

V. Experimental Data Collection

The investigation of the EN under temperature and humidity controlled environments is performed and the experiment is done in winter season.

1) Experimental conditions : Each data is repeatedly tested consecutively forty times under similar weather conditions to keep the temperature and the humidity constant. The concentration of all tested smells is controlled as constant as possible in order to observe the repeatability qualification of the MOGSs in this EN.

The temperature and humidity of normal air during the test period are controlled by adjusting the valves shown in Fig. 6. The carrier gas in this experiment is the dry air. Since the measuring environment is controlled by using the permeator, which can control the temperature, flow rate of the air, and humidity, we assume that the measurement data do not depend on the environment in this experiment.

2) Measuring method : There are two methods to measure the smell. The first method called “ transient method (TM)” is done by injecting the tested smell into the EN for a short period of time, for example, 120s, while measuring the smell. The other method called “saturation method (SM)” is done by continuously providing the tested smell to the EN until the smell data approach the saturation stage.

3) Measuring data : The smell from twelve sources of fire listed in Table II are measured by the EN system explained in the previous section. Each source of fire has been tested with forty repetition of data measured on different days, in order to check the repeatability in the response of the MOGS to the same smell.

TABLE II
List of Burning Materials in the Experiment

Sources of fire	**Abbreviation**
Steam from boiling water	Steam
Burning joss stick	Joss
Burning mosquito coil	Mos
Aroma oil	Aroma
Aroma candle	Candle
Flame from liquid petroleum gas(LPG)	Flame
Leakage of LPG	LPG
Steam from Japanese soup “oden”	Oden
Boiling vegetable oil	Oil
Toasted bread	Toast
Burning paper	Paper
Burning wood	Wood

For each data set, the voltage signal in the dry air is measured every two seconds for a sensor s during one minute, and its average value $\bar{V}_s(air)$ is used as the reference point. After that, a testing smell is adsorbed, and the voltage $V(s,t)$ is measured every two seconds for a period of two minutes on each smell sample. Finally, the net change of the voltage signal in each period, $V_{smell,t}$, is calculated by

$$V_s(t) = V(s,t) - \bar{V}_s(air), s = 1, 2, ..., 8 \qquad (4)$$

where t is the time from 0 to 120s and s denotes a kind of sensor.

After testing one smell the MOGS need to be cleaned by removing the tested smell and supplying only the fresh air until the output of the MOGS return to a stable point and a new sample can be tested. This process is just like the human nose which needs to breath the fresh dry air before being able to recognize a new smell accurately. Some time series data are shown in Fig. 7. From these data, we can see that many time series data of smells approach the saturation stages within the measuring periods. But Some smells can not approach the saturation stages within the measuring period, such as OIL, PAPER, WOOD, because of two reasons. First reason is that the distance from the tested smell to the EN unit is increased and it takes longer time for smell to flow to the EN unit. The second reason is the changes of smell of the burning material. For example, the smell of OIL is stronger and stronger if heating is provided to the container of the vegetable oil. The vegetable oil is able to turn to be the flame of fire if the heating is continuously provided to the container of the tested oil. Thus, we decided to measure the smell only two minutes even though the data signals of some smells can not reach the saturation stage.

The smells from AROMA, CANDLE, and the FLAME are not as strong as the other tested smell. Thus, the responses of the data signals from these data are lower than the other smells. The signals from the same smell in every repetition are similar and each smell has a unique pattern. However, some smells like PAPER, OIL, and WOOD have some repetition data of different patterns from their main repitition data due to the inconsistent burning rate of these smells. Since all tested smells in every repetition data are measured under similar environment, it is not necessary to apply the normalization method to modify the data. In this case, the raw data obtained from Eq.(4) can be used as the input data for the NNs or the statistical analysis, directly.

The method to measure the correlation of the data will be performed in order to choose the proper training data for the NN with the BP algorithm. Furthermore, the signals from the same source of fire in every repetition data are similar in most data sources. The results using the BP method and the *k*-means algorithm to analyze the time series data from each source of fire every two seconds and the average signals during the saturation stages (time 100–120s) are discussed.

VI. Correlation of the Experimental Data

Before classifying each source of data, the correlation of each data source is investigated by using the similarity index (SI) and the principal components analysis (PCA).

A. Similarity Index

In the statistical application, the correlation value developed mainly by Karl Pearson is widely used to find the relationship between two random variables. In this paper, we call the correlation value as a similarity index (SI). The SI value varies from -1 to $+1$. Two random variables with an SI of either -1 or $+1$ are highly correlated, because the knowledge of one provides precise knowledge of the other. However, the SI provides information only for linear relationships between random variables. Random variables could have a nonlinear relationship but still have a SI close to zero [4]. Therefore, we make an assumption on this application that each data pattern has nearly linear relationship to the other data patterns. The SI value between two data is calculated by

$$r_{xy} = \frac{\sum_{i=1}^{n}(x_i-\bar{x})(y_i-\bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i-\bar{x})^2\sum_{i=1}^{n}(y_i-\bar{y})^2}} \tag{5}$$

where r_{xy} is the the SI value, x and y are the comparing data, $\bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i$, $\bar{y} = \frac{1}{n}\sum_{i=1}^{n} y_i$, and n is the the size of each data set.

In this experiment, sensor SP-MW1 has some responses with the smell that has high humidity such as the STEAM, ODEN, and LPG. Thus, the signal from this sensor is included as the analytical data. Therefore, the dimension of data vector, n, in this experiment is equal to 480 (8 sensors$\times$60 samples).

The SI values of the data that have consistent burning rates such as the JOSS and the MC are higher than 0.995 in every compared data. The data with inconsistent burning rates like the PAPER and the WOOD have lower SI values in some pairs of data. This means that the repetitions of these data types are less correlated than the data with high SI values. Later we will show that the classification rate of the data with high SI values is higher than those of the data with low SI values.

Since a pair of data with high SI values has linear relationship to each other, the signals from the same smell in every repetition data have high SI values. It means that the EN has reproducibility qualification under similar measuring environment. Thus, it may be able to use only a single data from each smell to be training data of the NN by the BP method or the initial data vector for the statistical analysis like the *k*-means algorithm. Only a single data from each smell with the highest average SI value to the other repetition data of its own smell is selected as the training data.

B. Principal Components Analysis (PCA)

The PCA is applied to transform the time series data by using the input data obtained from Eq.(4). The dimension of the input data is equal to four hundred and eighty. The plot of two main components from the PCA is shown in Fig. 8 where two cases of the experimental data are shown. The loading factors of principal components 1, 2 are about 64%,16% and about 71%, 19%, for full time series stage and saturation stage, respectively. The full time series stage data use the data signals every two seconds, and the saturation stage data case uses only the average data from time 100s to 120s for the analysis. The distributions of the data with inconsistent burning rate such as the PAPER and the WOOD are more scattered than the other data with consistent burning rates such as the JOSS, especially in the saturation stage data. Most of the tested data are separated into their own clusters with some overlap zones among different data sources.

C. k-*means Algorithm*

The *k*-means algorithm is a kind of statistical method. It is an unsupervised learning method that assign an input vector to the nearest cluster center based on the Euclidean distance. The *k*-means algorithm is performed as follows:

Step 1. Select an initial set of cluster centers, $C_i = (c_{i1}, c_{i2}, \cdots, c_{ij})$ where i and j are an index of cluster and a dimension of the input vector. The number of clusters in the input vector space is assumed to be known such as k. The cluster center $C_i, i = 1, 2, ..., k$ are selected from a sample of the input vector that should belong to that cluster.

Step 2. Assign an input vector l of $X_l = (x_{l1}, x_{l2}, \cdots, x_{lj})$ to its closest cluster index by calculating the Euclidean distance between the input vector X_l and each cluster center, $C_i, i = 1, \cdots, k$. Here, x_{lm} denotes an input data from cluster index l and *m*-th component of the input vector.

Step 3. Repeat *Step 2* until all n input vectors are assigned to any cluster.

Step 4. Compute the new cluster centers by calculating the mean value of all input vectors that belong to that cluster.

Step 5. If the position of any cluster center changes, return to *Step 2*. Otherwise stop.

The processing time of the k-means algorithm is much faster than the training time of the NN by the BP method. Thus, it is a useful method to analyze the data that have high dimension size like this experiment.

VII. Classification Results Using Full Time Series Data

Full time series data is obtained from Eq.(4) with the dimension of four hundred and eighty that is equal to the number of sensors times the measurement data (8×60). They are used as the input data for the NN by the BP method as well as the data of k-means algorithm.

A. Experimental Results Using the NN

The structure of the NN by the BP method as shown in Fig. 9 has three layers. The input layer contains four hundred and eighty input neurons that are equal to the number of sensors (8) tomes the sampling number (60) where the sampling time is 2[s] and the measurement interval is 2[min]. The hidden layer has been tried with several values and finally forty hidden nodes give the best result. The output layer contains twelve nodes where each node represents the smell from each source of fire as listed in Table II. The learning rate, α, and the momentum rate, μ, during the training period are set by trail and error to o.1 and 0.001, respectively.

After checking the correlation of the data by applying the SI value and the PCA, it is found that most data are highly correlated to its own repetition data and most data are distributed densely in its own area with some overlap zone as shown in Fig. 8. The smells that have consistent burning rate like JOSS, MC, LPG have the average SI value between their repetition data higher than 0.995. This means that these data have highly linear relationship with their own repetition data.

In the other way, some smells that have inconsistent burning rate like PAPER or WOOD have some scattered repetition data and these data have the average SI value to their repetition data only around 0.980 which is not as high as the average SI value of JOSS or MC. However, this experiment decides to choose only a single data from each smell in Table II to use as the training data for the NN by the BP method. This data is selected by choosing the data that has the highest average SI value to its own repetition data. The training process is started by the randomized initial weight, and the process to update the weights continues until the minimum mean squared error is less than or equal to 0.0003.

In this experiment, it is assumed that a smell is classified correctly if the highest value of output node is greater than or equal to 0.6 while the corresponding reference value is equal to 1, and those of other output nodes are equal to 0. The results obtained by NN with the BP algorithm are shown in Table IV.

TABLE III
RESULTS USING NN

Sources of fire	Correct rate	Correct%	Output value
STEAM	39/39	100	0.988
JOSS	39/39	100	0.997
MOS	39/39	100	0.995
AROMA	39/39	100	0.995
CANDLE	39/39	100	0.963
FLAME	38/39	100	0.978
LPG	39/39	100	0.998
ODEN	39/39	100	0.992
OIL	34/39	100	0.987
TOAST	39/39	100	0.982
PAPER	37/39	94.9	0.935
WOOD	39/39	100	0.964
Average		**99.6**	**0.982**

B. Experimental Results Using the k-Means Method

The k-means method is applied to analyze the same data as in the case of NN with the BP algorithm. At first, the number of cluster is set to be twelve. Each cluster represents a tested smell shown in Table II. The initial set of cluster center uses a data vector from each smell by choosing the data that has the highest SI value to its own repetition data. All input data have been assigned to each cluster and the processes to determine the new cluster center are performed by the k-means algorithm stated above. The final classification results using the k-means method are shown in Table IV

TABLE IV
RESULTS USING THE k-MEANS METHOD

Sources of fire	Correct rate	Correct%
STEAM	40/40	100
JOSS	40/40	100
MOS	40/40	100
AROMA	40/40	100
CANDLE	40/40	100
FLAME	40/40	100
LPG	40/40	100
ODEN	40/40	100
OIL	40/40	100
TOAST	40/40	100
PAPER	35/40	87.5
WOOD	37/40	92.5
Average		**98.3**

C. Discussions of both results by NN and the k-means methods

The results from the NN method have only two incorrectly classified data from paper burning smell (PAPER). These data are not misclassified as the other smells, but only the value of their output nodes are not high enough to classify them as the paper burning smell.

VIII. Another Experiments

The input data are changed in the two cases:1) number of sensors are 4 and 4 to check the effect of classification according to the number of input data(Experiment 1), 2) number of sensors are eight and the input data has been characterized by the regression coefficients (Experiment 2).

A. Result in case of four and six sensors

We have used four and six sensors for this experiment. The former is SP-MW1, SP-31, SP-32, and SP-42A in Table 1 and the latter is SP-MW1, SP-19, SP-31, SP-32, SP-53, and SP-42A in Table 1. In the former case total number of the input data is 240 samples for 4 sensors since the sampling time is 2 [s] and the measurement time is 2 [min]. In the latter case it has 360 samples for 6 sensors. For the hidden layer, we have tried several values, and the number of nodes which gives good accuracy and reasonable training time for both data turned out to be forty. The output layer contains twelve nodes, each node representing one data source. The learning rate, the momentum rate, and the minimum mean square error (MSE) during the training period are set by trial and error method to 0.1, 0.001, and 0.0003, respectively.

Two case of data are analyzed by the BP method and *k*-means algorithm.

The results in Table III show that the variation of sensor to the quality of the classification performance. Compared with the classification rate of four sensors, those of six sensors are little bit improved as we expected although the difference is a little. It can be noted that the classification rate of the smell that can be controlled the quality of smell like JOSS and MOS can be perfectly classified in all cases. In the opposite way, the smell that has some fluctuation in the quality of smell tend to have low classification when the information of the input data is decreased. Therefore, to achieve the high classification results, it is important to note the quality of the tested smell.

B. Result for SMM

It seems that the results will be improved if we use many measurement data as much as possible. But there will be some measurement noises in the data, which make the results worse compared with the case that typical measurement data were used. Therefore, we try to reduce the noisy effect in the measurement data by using the regression model.

First, we divide the measurement data into n intervals. The measurement data in each segment are replaced by the linear regression model. We take $n = 3$ and the number of the data in each division becomes 20. Then we get the following linear regression model.

$$y_i = \beta_0 + \beta_1 x_i, i = 1, 2, ..., 20 \tag{6}$$

where y_i is the estimated voltage, $\beta_0$is the intercept and β_1 is the slope of the regression line, and x_i is the time. Then the slopes become

$$\beta_1 = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sum_{i=1}^{n}(x_i - \bar{x})^2} \tag{7}$$

where $\bar{x}$ and $\bar{y}$ are mean values of x_i and y_i, respectively.

The slope maximum mean(SMM) is to adopt the features of the data as five dimension(three slopes in each segment plus the maximum value and the mean value among the total data)as shown in Fig. 10. We use eight sensors as shown in Table I and the total number of input becomes forty(5 data times 8 sensors). For the hidden layer, we have tried several values, and the number of nodes which gives good accuracy and reasonable training time for both data turned out to be forty. The output layer contains twelve nodes, each node representing one data source. The learning rate, the momentum rate, and the minimum mean square error (MSE) during the training period are set by trial and error method to 0.1, 0.001, and 0.0003, respectively.

As the comparison of the features by SMM, we adopt the average of the TSD in the steady state, which means the maximum values among the total data.

Based on the information during the investigation of the correlation among data sets, most data sources are highly correlated to their repetition data with high SI values. Therefore, only one data set which has the highest average SI value to other repetition data sets from each source of fire are used as the training data for the BP, and the rest of the data are used as the test data. We assume that a pattern is classified correctly if either the output is not less than 0.7 and the target is 1, or the output is not greater than 0.3 and the target is 0.

For the *k*-means algorithm, the training data of the BP method are used as the initial data, and then the data patterns are assigned to the nearest cluster center according to the Euclidean distance. After that, the new cluster center is recalculated. The process continues until the position of the cluster center is not changed. The final results of this experiment are shown in Table III.

The results using the TSD from both the BP method and the *k*-means algorithm are better than those of the SSD case. The data signals from the MOGS are affected by many factors, such as the sampling condition, the inconsistency in burning rate, the fluctuation from the standard air, and so on. Therefore, the saturation stages of the data vary by those factors. By including the signal before approaching the saturation stage, the accuracy of classifying all the smells is increased.

C. Discussion

Although the distribution of PCA shown in Fig.6 cannot clearly separate similar sources of smell such as the aroma oil and the aroma candle, the BP method and the *k*-means algorithm are capable of classifying them perfectly as shown in Table III. The results of TSD using the BP method have only two incorrectly classified data. These two data are not misclassified as the other smells. Only the output value of their paper node are not high enough to classify them as the paper. The output values of these two data on the paper node are only 0.4951 and 0.4799 respectively, and the output of the other output nodes are nearly zero. The results are much better than those in [1], where two kinds of MOGS are used for classifying several sources of fire into three fire condition levels of flaming, smoldering, and nuisance, and its accuracy is only 85%. The smoke density of the tested data are not high enough to trigger the alarm of the smoke detector. In case of unusual burning smells in the residences such as the wood burning, flaming from the LPG, or the leakage of LPG, it is necessary to have a proper device to detect these sources before becoming unable to extinguish the fire. We can conclude that the new EN system shown in this paper is

TABLE V
RESULTS OF EXPERIMENT 1 TO SHOW THE EFFECT OF NUMBER OF SENSORS

Sources of fire	Four sensors data				Six sensor data			
	BPNN		*k*-means		BPNN		*k*-means	
	Correct	%	Correct	%	Correct	%	Correct	%
Steam	37/39	94.9	40/40	100	38/39	97.4	4040	100
Joss	39/39	100	40/40	100	39/39	100	40/40	100
Mos	39/39	100	40/40	100	39/39	100	40/40	100
Aroma	39/39	100	40/40	100	39/39	100	40/40	100
Candle	39/39	100	40/40	100	39/39	100	40/40	100
Flame	38/39	97.4	40/40	100	39/39	100	40/40	100
LPG	39/39	100	40/40	100	39/39	100	40/40	100
Oden	39/39	100	40/40	100	39/39	100	40/40	100
Oil	34/39	87.2	37/40	92.5	39/39	100	37/39	92.5
Toast	39/39	100	40/40	100	39/39	100	40/40	100
Paper	34/39	87.2	35/40	87.5	31/39	94.9	35/40	87.5
Wood	39/39	100	39/40	97.5	39/39	100	38/40	95
Average		97.2		98.1		99.4		98.5

TABLE VI
RESULTS OF EXPERIMENT II

Sources of fire	Full Time Series Data (TSD)				Saturation Stage Data(SSD)			
	BP		*k*-means		BP		*k*-means	
	Correct	%	Correct	%	Correct	%	Correct	%
Steam	39/39	100	40/40	100	38/39	97.4	39/40	97.5
Joss	39/39	100	40/40	100	39/39	100	40/40	100
Mos	39/39	100	40/40	100	39/39	100	40/40	100
Aroma	39/39	100	40/40	100	39/39	100	40/40	100
Candle	39/39	100	40/40	100	39/39	100	40/40	100
Flame	39/39	100	40/40	100	39/39	100	40/40	100
LPG	39/39	100	40/40	100	39/39	100	40/40	100
Oden	39/39	100	40/40	100	39/39	100	40/40	100
Oil	39/39	100	40/40	100	38/39	97.4	37/39	92.5
Toast	39/39	100	40/40	100	38/39	97.4	40/40	100
Paper	37/39	94.9	35/40	87.5	31/39	79.5	28/40	70
Wood	39/39	100	37/40	92.5	32/39	82.1	28/40	70
Average		99.6		98.3		96.2		94.2

a proper device for this application.

IX. CONCLUSION

We have presented the reliability of a new EN system designed from various kinds of MOGS. The EN has the ability to identify various sources of fire in the early stage with more than 99% of accuracy by using only a single training data set in the BP case. The results from the *k*-means algorithm also shows the ability to predict the sources of fire with more than 98% of accuracy. It can be concluded that the EN is suitable for detecting the early stage of fire.

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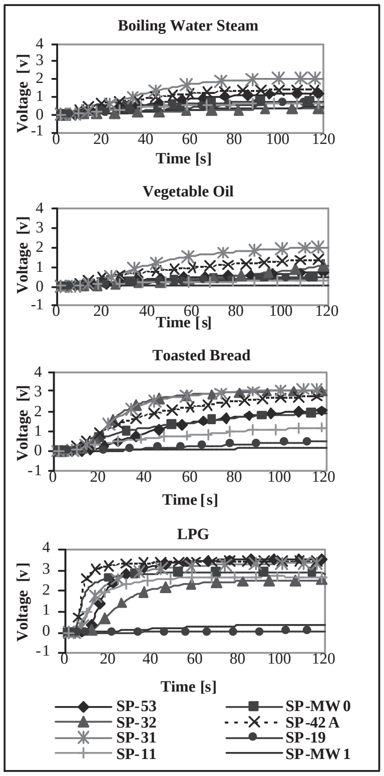

Fig. 7. Time series data from some sources of fire in the experiment

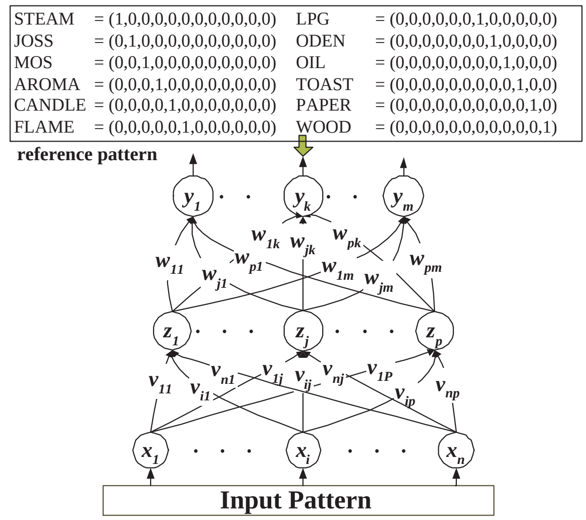

Fig. 9. Neural network for classification

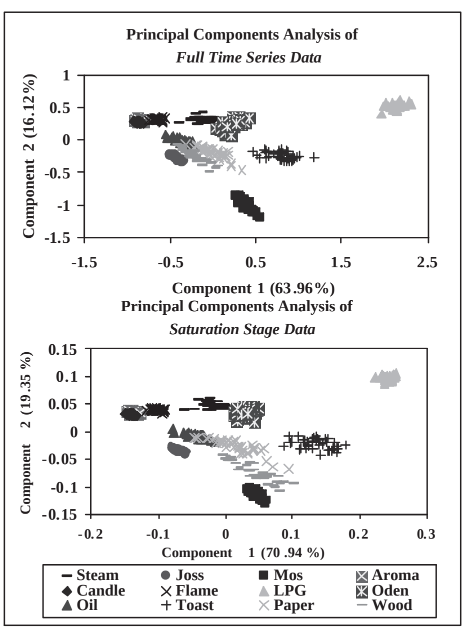

Fig. 8. Two main components of the experimental data using the PCA

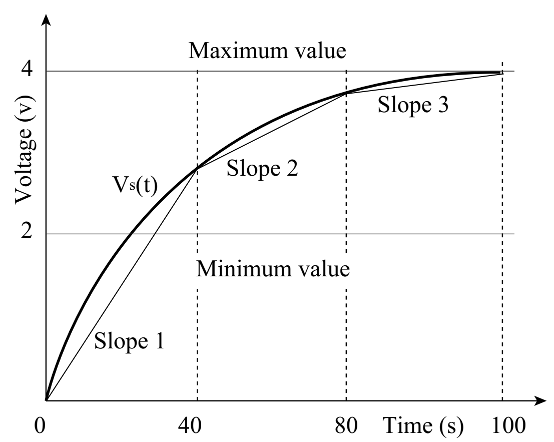

Fig. 10. Neural network for classification