PROTOTYPE OF ELECTRONIC NOSE BASED ON GAS SENSORS ARRAY AND BACK PROPAGATION NEURAL NETWORK FOR TEA CLASSIFICATION

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ABSTRACT

We have developed an electronic nose based on metal oxide gas sensor array and back-propagation neural network for tea classification. The sensor array consists of six Tagushi Gas Sensor (TGS) type devices. To recognize the pattern formed by the six sensors we used six neurons in the input layer. Since we only want to classify four tea samples, we used two neurons in the output layer. The four tea samples (different tea flavors) were purchased from local super store in Yogyakarta, namely, black tea, green tea, vanilla tea and jasmine tea. Under the relatively similar conditions, we measured each sample of tea as a function of time. Prior to the exposure of tea samples, the sensor array was tested with air ambient. Then the electronic nose was trained by using one set of four tea samples without pre-processing step. By using all data sets, the electronic nose is able to recognize the pattern for almost 80%. This result prove that our electronic nose is capable of discriminating between the flavors of tea samples. For further investigation, the performance of this system should be compared with the data sets with pre-processing.

Keywords : Odor, Tea flavor, Metal oxide gas sensor, Sensor array, Back Propagation Neural network.

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1. INTRODUCTION

Olfaction system (sense of smell by the nose) is one of three chemoreceptor systems of humans. Two others are gustation (sense of taste by the tongue) and trigeminal (sense of irritation) systems. The sense of smell is used to detect volatile compounds. Compared to the two others, the most contribution in the perception of flavor is the olfaction. Odorants are typically small hydrophobic, organic molecules containing one or two functional groups. The size, shape and polar properties of the molecules determine its odor properties. All naturally occurring odors are complex mixtures that are the mixture of many, different types of odorant molecules [Dutta, et.al., 2003a; Dutta, et.al., 2003b].

One of the interesting odors is the flavor of tea. In the conventional fabrication of tea, the process and the quality control are determined solely by using human olfactory of expert (Yu and Wang, 2007). However, the determination of quality of tea in a large industry may be performed by some expensive instruments like Gas Chromatography (GC) and Mass Spectrometry (MS). In the case of small and medium industries in Indonesia, these instruments are generally not available.

Since there is a large number of organic compounds present in tea, it is difficult to process tea to any accepted standard. The aroma and flavor are two quality factors of tea, which depends upon the number of volatile compounds present and their ratios. For example, main volatile compounds in black tea are t-2-Hexenal, cis-3-Hexena, t-2-Hexenyl formate, Linalool oxide (furanoid-cis), Linalool oxide (furanoid-trans), Linalool, Phenylacetal-dehyde, Linalool oxide, Pyranoid-cis, Methylsal-cylate, Geraniol, Benzylalcohol 2-phenylethanol, cis-Jasmone + ß-ionone (Yu and Wang, 2007).Therefore, in conventional tasting, it is very difficult to keep a consistency in the standard of tea quality from batch to batch during a production process. This is because the performance of the human taste panel is known to vary due to various factors Bhattacharyya, et.al., 2007,

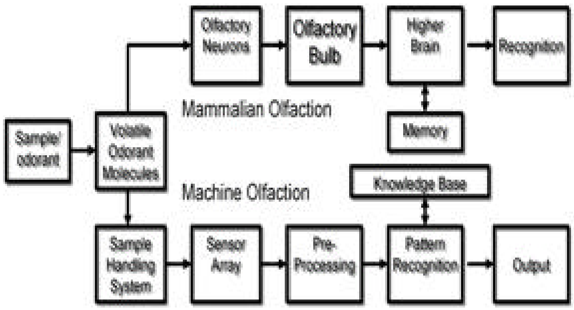

Figure 1. Basic elements that make up mammalian and machine olfaction Bartlett, et al, 1997

Human panel tasting is inaccurate, laborious and time consuming due to adaptation, fatigue, infection and adverse mental state at times. To imitate a specific part of the mammalian olfactory system, we develop a prototype electronic nose for tea classification. It consists of a gas sensor array and a back propagation neural network as a pattern recognition system. An electronic nose can be a better alternative to conventional methods for tea classification. This is because electronic nose is a fast, reliable and robust technology.

2. EXPERIMENTAL

Figure 1 shows the basic elements that make up mammalian and machine olfaction. In order to realize an electronic nose, we used sensor array consisting of six metal oxide gas sensors as listed in Table 1. In a lot of commercial electronic nose applications, tin oxide sensors like Tagushi Gas Sensor (TGS) type devices are used because of their low cost and their high sensitivity. Since this sensor type is relatively lack of selectivity, it can be advantage of the detection of odor (gas mixture) by arranging in array. Therefore, it is obvious that by combining a number of non-selective sensors, the combined sensor signals yield more information about a given aroma or flavor than that of an individual sensor signal. In this case, each gas sensor contributes to the formation of pattern of odor. The set-up for electronic nose system for tea classification is depicted in Fig. 2

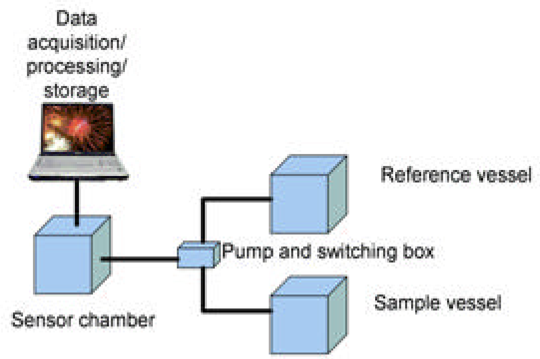

Figure 2. Set-up for electronic nose system for tea classification

The electronic nose is a system consisting of three functional components that operate serially on an odorant sample, a sample handler, an array of gas sensors, and a signal processing (pattern recognition) system. The output of electronic nose can be the identity of the odorant. Because odor is a mixture of volatile compounds (gases), each sensor in an e-nose is not high selective sensor. It has a different sensitivity from which the electronic nose can identify an odorant sample and estimates its concentration. Beforehand a database of known odorants must be created and presented to the sensor array. In term of intelligent system, the electronic nose should able to recognize the patterns of odor that have trained to it.

Table 1. Gas sensors used in the array Brezmes, et al, 2000

No	Sensor	Application	Vapor detected
1	TGS2620	Solvent vapor detection	Alcohol, organic solvent
2	TGS2611	Combustible gas detection	Methane, natural gas
3	TGS822	Solvent vapor detection	Alcohol vapor
4	TGS813	Combustible gas detection	General hydrocarbon
5	TGS826	Toxic gas detection	Ammonia
6	TGS825	Toxic gas detection	Hydrogen sulphide

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We have four tea samples (black tea, green tea, vanilla tea and jasmine tea) purchased from the local super store in Yogyakarta. Each sample, without any additional manipulation, was placed into glass vessels (Fig. 2). The vessels had two small holes in their covers, to allow the headspace to be analyzed with the electronic nose equipment. The ambient conditions (temperature and humidity) of the room in which the tea samples were kept and monitored for the duration of the experiments. The temperature and humidity variations in the laboratory were typically 28±2 °C and 80±1%, respectively, over the period of the experiments.

As shown in Fig. 3, we employed back propagation neural network that consisted of six neurons in input layer, three neurons in the hidden layer and two neurons in the output layer for pattern recognition system. The back-propagation trained multi-layer perceptron (MLP) paradigm is the most popular pattern-recognition method in aroma analysis today. We used six layers in the input layer because the number of gas sensors used in the array is six. Meanwhile, the output layer consisted of two neurons. This is because by using two neurons, we can combine to make four different samples of tea. Furthermore, once an electronic nose has been 'trained', it does not require a skilled operator and can potentially obtain the results in the order of few tens of seconds. In the electronic nose system, a pattern-recognition engine enables the system to perform complex aroma analysis of the sensor signals.

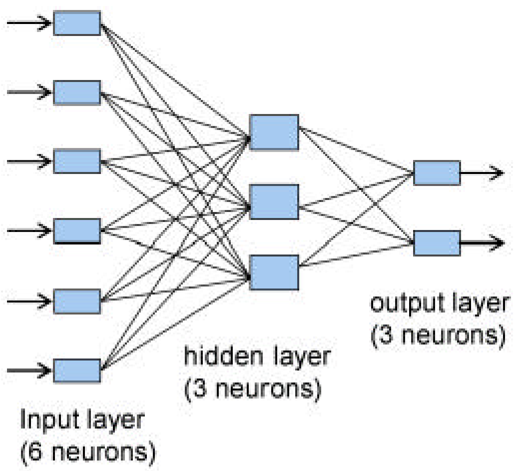

Figure 3. Back propagation artificial neural network for pattern recognition system of tea

The sensor system comprises six tin oxide gas sensors from the same housed in a sensor chamber. The sensors were chosen on the basis that the sensor responds well to different odors that are understood to be given off by tea, as can be seen in Table 1. The selected sensors are designed to respond to gases such as the cooking vapours, ammonia, hydrogen sulphide, alcohol, toluene, xylene, etc. which are also specified by the manufacturer.

Table 2. Classified tea (output target) based on the value of output layer

No.	Neuron 1	Neuron 2	Classified Tea
1	0	0	Black tea
2	0	1	Green tea
3	1	0	Jasmine tea
4	1	1	Vanilla tea

The electrical conductance of the sensors varies in the presence of reducing/oxidizing gases. A thin plastic tube was connected from the input to the sensor chamber to one of the two holes in the cover of both glass vessels. The headspace of the vessel containing the tea samples (four tea samples with four different types were used for experiment) and the reference vessel were sampled in sequence as follows.

A sample of measurement typically took 5 min to complete in sample vessel. The sampling time was chosen to optimize the stability of the sensor response to odor emitted by the tea samples. The air removed from the vessel by the pump was replaced by air from the room (see Fig. 1).

Room air from our laboratory was used as carrier gas as we aimed to make the experiment as simple as possible. Any variation of the 'base line' (which may be due to different volatiles present in room air) was monitored. There was no significant change in the base line during the time period of the experiments and consistent classification results from different data processing algorithms suggests that any variations of this type were not significant. One measurement comprises taking, alternatively, a headspace sample from the tea vessel followed by the reference vessel.

Reference vessel: Here, the tube from the input to the sensor chamber was connected to a glass vessel. The air ambient from the room was pumped into the sensor chamber through this vessel. In this way the sensors were allowed to return to their baseline level over a period of some 10 min after sampling the headspace of the tea vessel. We used the sensors' responses to the pure air ambient in the reference vessel as our baseline response for the experiments. This was to make sure that the electronic nose system was responding to the tea aromas rather than to any residual smell of the glass vessel or only to the different environmental conditions. During the process of the measurements, a sample of each sensor's resistance was taken every 10s and stored in a data file for subsequent processing.

3. RESULT AND DISCUSSION

Under applying the error tolerance of 0.01, the cycle of the iteration is depicted in Fig. 4. The number of cycle is relatively high may be because the input data is the raw data.

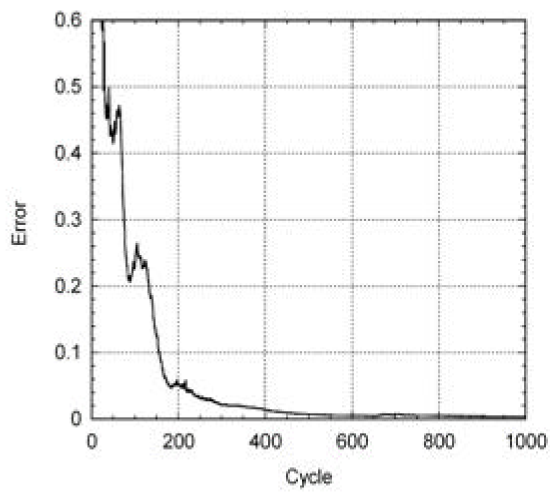

Figure 4. Cycle of iteration under training process toward error tolerance of 0.001

We used the data for training process of electronic nose shown in Fig. 5. Meanwhile, Figs 6-9 are the sensor voltage versus time under exposure of aroma of black tea, green tea, jasmine tea and vanilla tea, respectively for a period of time.

The tea samples used for each data-set were initially as fresh as possible. They would have experienced all sorts of variations prior to arrival in our laboratory. The number of days and samples were limited by practical circumstances though data collection continued 8 h per day, for each of the four tea dry periods.

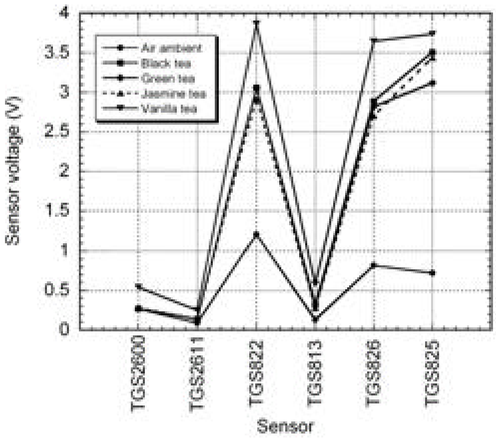

Figure 5. Patterns of sensor array under exposure of aroma of black tea, green tea, jasmine tea and vanilla tea, respectively for training process

At the testing stage, we used all data sets recorded under variation of time for each tea sample. By testing the electronic nose using ten data sets of black tea and jasmine tea, respectively, the electronic nose is only able to recognize 70%. It means that three data sets were not recognized as a black tea. However, the degree of recognition is higher to 80% when the electronic nose was tested by using ten data sets of green tea and vanilla tea, respectively.

Since this is a preliminary study of our system, the further investigation should consider the pre-processing data and other pattern recognition systems. Furthermore, under the pre-processing data prior to the main process, the effect of air ambient may be omitted.

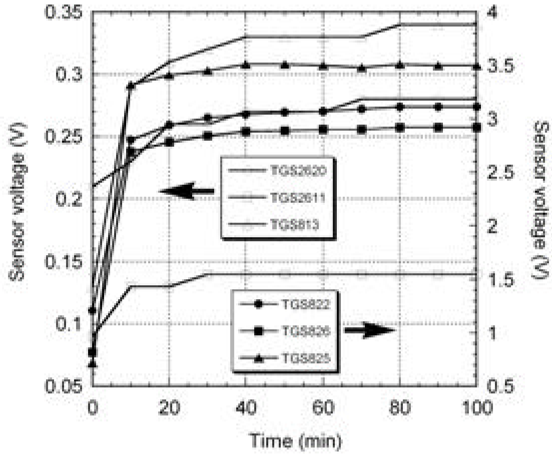

Figure 6. Sensor voltage vs time under exposure of black tea

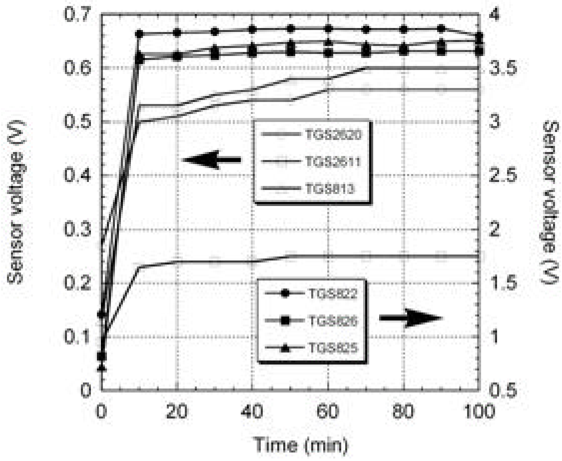

Figure 7. Sensor voltage vs time under exposure of green tea

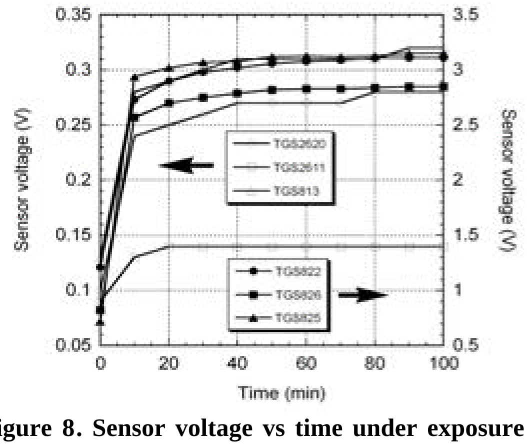

Figure 8. Sensor voltage vs time under exposure of jasmine tea

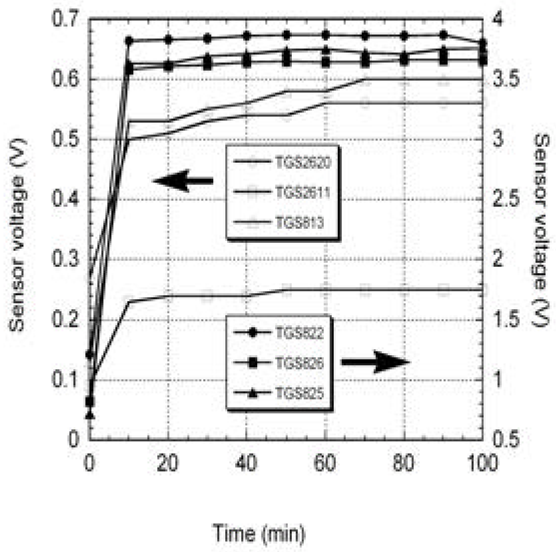

Figure 9. Sensor voltage vs time under exposure of vanilla tea

4. CONCLUSION

We have developed a prototype of electronic nose based on metal-oxide gas sensor array. By applying the data sets of measurement without any pre-processing data, the system is able to recognize all patterns for almost 80%. Some improvements should be carried out including the pattern recognition system and the sensor array.

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