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Metal Oxides Semiconductor Sensors for Odor Classification

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ABSTRACT

The performance of gas sensor will differ and vary due to the surrounding environment changing, the way of implementation, and the position of the sensors to the source. To reach a good result on gas sensors implementation, a performance test on sensors is needed. The results of the tests are useful for characterizing the properties of the particular material or device. This paper discusses the performances of metal oxides semiconductor (MOS) sensors. The sensors are tested to determine the sensors' time response, sensors' peak duration, sensors' sensitivity, and sensors' stability of the sensor when applied to the various sources at different range. Three sources were used in experimental test, namely: ethanol, methanol, and acetone. The gas sensors characteristics are analyzed in open sampling method in order to see the sensors' sensitivity to the uncertainty disturbances, such as wind. The result shows that metal oxides semiconductor sensor was responsive to the 3 sources not only in static but also dynamic conditions. The expected outcome of this study is to predict the MOS sensors' performance when they are applied in robotic implementation. This performance was considered as the training datasets of the sensor for odor classification in this research. From the experiments, It was got, in dynamic experiment, the senrors has average of precision of 93.8-97%, the accuracy 93.3-96.7%, and the recall 93.3-96.7%. This values indicates that the sensors were selective to the odor they sensed.

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1. INTRODUCTION

In recent years, sensors have received people's attention as one of the important devices in electronic systems and enormous capability for information processing has been developed within the electronics industry [1]-[4]. Of all sensors, gas sensors and light sensors have been most actively studied. Gas sensors are defined as a device that can substitute human olfaction. It is included as an e-nose.

Air quality monitoring [5]-[7], gas leakage localization [8], [9], forest monitoring [10], [11], military [12], [13], are some examples of gas sensor applications. In getting the information of the applications above, some sensors are needed in order to convert the environment physical phenomenon (in this case temperature, humidity, and pollutant concentration) into electrical signals. As such, sensors represent part of the interface between the physical world and the world of electrical devices, such as computers [6].

Gas sensor integrated to mobile robots can give some advantages, including safety, security, and environmental inspection [14]. The robots can be employed to the dangerous area with high concentration of odor contamination without being afraid of to be killed by the poisonous gas. They can also be used to monitor the environmental air quality continuously without being tired and giving inaccurate information. Moreover, train the robots are cheaper than human or animals [15].

The integration of the gas sensors is not only to the ground mobile robot but also to the under-water robot [16] and the flying robots, such as UAVs [17], [18]. Each of them has different purposes and gives different benefits. For the underwater robots' application, the goals are for searching the environmentally interesting phenomena, unexploded ordnance, undersea wreckage, and sources of hazardous chemicals or pollutants [16]. In similar way, the UAVs application's goals are for monitoring, searching, and localizing a hazardous chemical. Some researchers developed the research of e-nose in different manners. In order to increase the ability of the sensors, some of researchers conducted researches in the area of: sensor networks [19], sensor arrays [20], [21], and even sensor performance enhancements [22], [23].

Metal Oxide Semiconductor (MOS) sensors are one of the most investigated groups of gas sensors. There are a lot of researches used them as their sensors [20], [24]–[27]. The reasons of choosing this sensor are due to: low cost and flexibility associated to their production, simplicity of their use, large number of detectable gases/possible application [28], robust, light weight, fast response [29]. However, there was only little attention of researchers on MOS Performance.

The deployment of gas sensors in real environment (indoor or outdoor) faces some problems, such as the phenomenon of patches and eddies that occur due to the turbulent airflow of the wind [30], [31]. When molecules move away from the source, the concentration decreases, hence molecular diffusion and turbulent diffusion processes have the main role in determining the shape of plume. Molecular diffusion causes random motion of the molecules to move gradually apart, while turbulent diffusion tears apart the cloud of molecules physically by air turbulence [32].

Molecular diffusion effect on the plume shape can be neglected [31] due to its small effect on the plume shape. It is contradictive with turbulent diffusion that can change the shape of the plume. Therefore, the turbulent diffusion that dominates the dispersion of odor molecules becomes crucial parameter in odor localization. Some researchers have investigated the odor characteristics in airflow environment [33]-[35] and turbulence environment [36], [37]. However, the experiments were done in experimental simulation, not in real experimental environment. Although, there were also some real experiments in odor analyses, none of them analyzed the performance of the MOS sensor to the odor dispersion. Ali Marjovi in [31], [38] discussed about the coverage area of the sensors. However, this experiment was also done in simulation. In most other sensor performance tests, the data was taken using a chamber [39]-[41] where the sensors were placed in a chamber and the sources were injected to the chamber using a tube to pass through a tiny in the chamber.

As mention above, in odor classification, the first step that should be paid attention is the performance of gas sensors. Therefore, in this paper, the response of the MOS sensors was analyzed. From the previous researches it can be concluded that the data got from MOS sensor in conditioned environment (controlled temperature, humidity and sampling) will be different with the data in real environment. Marco Trincavelli in [42] stated that in a real-world and dynamic environment, the steady state of the sensors is almost never reached. The analysis of the system can only be done based on the transient phase of the signal. Thus, in this research, for having the result of quite the same with the real situation, gas sensors' performance in this research were tested in open environment.

The contribution of this paper is to provide performance of MOS sensors that can be used a database determination of the sensors for the odor classification application. This paper consists of 6 parts, i.e.: part 1 describes the background of the research, part 2 introduces component and parameters in odor localization tasks, part 3 explain the experimental setup, part 4 displays the result and the discussion of the experiment, part 5 indicates the future work, and part 6 is the conclusion of the research.

2. COMPONENTS AND PARAMETERS IN ODOR CLASSIFICATION TASKS

2.1. E-noses

E-noses are the sensors made by the researchers for imitating the human olfaction. They have been applied in wide variety of applications, such as: health, military, food, agriculture, air quality, etc. (see Table 1). They may consist of single sensor or of some sensors to build sensor arrays. The material used in making them come from many materials, such as polymers [43]-[45] and metal oxide [11], [46] (as presented in Table 1). These material w orks under the change of resistance or conductance. When there is a physical/chemical change in the property of the sensors' material, as the result of the emersion of detected odor, the resistance or the conductance of the sensor will change [47].

According to J. W. Gardner [48], some materials used in e-noses come from inorganic semiconducting materials, such as oxides and catalytic metals. In oxides, the version can be in the form of thick and thin film. The sensors made of this material type can work in the temperature of 100-600^{0}C under the sensitivity of 0.1-100 ppm [48]. Other materials that can also be used in making the e-nose are in the organic forms, such as polymers and biological lipid. The poly(pyrrole) and poly(aniline) are the samples of polymers materials. The sensors made from organic material can be operated at temperature 20-60^{0}C and

their sensitivity is 0.1-100 ppm [48]. As mentioned above, researchers chose MOS sensor due to their low cost and simplicity in use. Some more advantages and disadvantages of MOS materials and other e-noses' material are listed in Table 2.

Table 1. Applications of Sensor Arrays

Application		Array Type	References
Health	Cancer Detection	8 amperometric electro-chemical sensors, 2 non-dispersive infra-red optical devices and a 1photo-ionisation	WOLF [51]
	Respiratory	Inorganic conductor and insulating organic polymer	Cyranose 320® [44]
	Wound Inspection	15 Sensors arrays	TGS, MQ, WSP, QS, SP3S, AQ [52]
Food	Red wines	14 gas arrays of inorganic metal oxide (MOX)	[24]
	Mushroom	12 Metal Oxide Sensors	FOX 3000 [53]
	Olive Oils	Metal Oxide Sensors	AlphaMos [25]
	Coconut Oil	Polymers	[45]
	Onions	MOS chemical gas sensors	ISENose 2000 [26]
Air Quality	Indoor	Thin film of metal oxide semiconductor	[20]
	Outdoor	Two sensors arrays with 6 Figaro sensors each (MOX)	[27]
	Localization		
Agriculture	Post harvest	10 different metal oxide sensors	PEN 3 [11]
		Conducting polymer	[54]
	Compost	10 different metal oxide sensors (MOS)	PEN 3 [46]
Military	Warfare agent	Oxide thin film	[12]
		15 sensors, MOS	[13]

Table 2. Advantages and Disadvantages of E-Nose Materials

Materials	Advantages	Disadvantages
Inorganic	- Inexpensive [48]. - Usable life-span of 3 to 5 years [55]. - quite sensitive to the combustible material [48]. - Has high sensitivity [55]. - low susceptibility to changing environmental conditions [55].	- consume much more power [55]. - suffer from poor stability [48]. - insensitive to the sulphur and nitrogen [48]. - slow recovery after the target gas is removed (15-70 s) [55]. - poor selectivity [55].
Organic	- consume less power [55]. - Much wider choice of material [48]. - Can interact with different classes of odorant molecules [48]. - Easier to process [48], [55].	- effects of aging which manifests in sensor drift . - [55]. - a poor understanding of the mechanism behind the conducting polymers [55].
Quarts crystal (piezo-electronic substrate)	- offer rapid response (10 s) [55]. - Low power consumption [55]. - Long life time [55]. - possibility to control the selectivity over a wide range [55]	- low sensitivity to the target gas [55]. - Not robust in the variations of humidity [55]. - Complex fabrication processes [55]. - Poor signal to noise performance [55].

By depositing a metal oxide film onto a substrate, such as glass or ceramic, metal oxide gas sensors (MOS-type e-nose) can be made. The electrodes can be made by platinum, silver or aluminum that are also deposited onto the substrate. The heating element is printed on the back. MOS-type e-noses are widely used for detecting multiple odor sources mixtures. Its sensor arrays are capable of detecting multiple toxic compounds, particularly inorganic and organic types [49]. The operation of metal oxide sensors depends on the change of the oxide conductance when they interact with the odor. This change is usually proportional to the concentration of the odor [47]. The sensors come from this material (in this case the n-type material) will operate as follows: the oxygen comes from the air reacts with the surface of the sensor. The free electrons on the surface or at the grain boundaries of the oxide grains will be trapped. It produces large resistance in these areas due to the lack of carriers and the resulting potential barriers gas like produced between the grains inhibit the carrier mobility. When sensor is introduced to a reducing H2, CH4, CO, C2H5 or H2S [47] [50], the resistance of the sensor will become lower because the gas that reacts with the oxygen will release an electron. Due to this situation, the potential barrier becomes lower. That will allow the electrons to flow. Therefore, the conductivity increases [47].

Conducting polymers can be produced using chemical and electrochemical development. Their molecular sequence structure can be changed suitably by co-polymerization or structural derivations [3]. Two electrodes that are separated by a gap can be made using micro-fabrication techniques. Then, the conducting polymer is electro-polymerized between the electrodes by cycling the voltage between them [3]. Varying the voltage sweep rate and applying a series of polymer precursors has purpose to enlarge the variety of active materials. The electrical connections will be established between the two parallel electrodes. This connection permits the relative resistance change to be measured. The heater is required when metal oxides are used as the sensing material because very high temperatures are required for effective operation of metal oxide

sensors [47]. Response time is inversely proportional to the polymer's thickness. In order to increase the response times, micrometer-size conducting-polymer bridges are formed between the contact electrodes [3]. Arshak [47] shows the response time for conducting polymer composites in 4 categories, i.e: 1. <2-4 s; 2. 60 s; 3. 180-240 s; 4. 20-200 s. Thus, it can vary from second into minutes.

Besides conducting materials, there are some other materials usually used in making an e-noses' sensor. Lilienthal in [55] stated that the detection of an odor can also be done using optical sensors, surface acoustic wave sensors, gas sensitive field effect transistors and quartz microbalance (QMB) sensors. An acoustic wave sensor is usually made of piezo-electronic substrate, i.e. quart. An alternating electric field is applied to generate an elastic wave in the quartz crystal. Temporarily absorbed molecules perturb the propagation of the acoustic waves due to the effect of the added mass and by changing the viscoelastic properties of the coating layer. The resulting shift of the fundamental frequency of the quartz crystal is then measured as the output of the sensor [55].

The structure of e-nose consists of some parts, namely sensor array, signal transducer, and pattern recognition. This olfactory system can be seen in Figure 1. Sensor arrays are the first part of the olfactory system that has function to detect or sense the input of the system. The input of the system is usually in the form of odorant molecules. In the second part, there is signal transducer that has function to transduce the conductivity of material into electrical signal. That signal will be pre-processed and conditioned in the signal transducer. At the end part of the olfactory system, signal will be analyzed using pattern recognition in order to determine the concentration of the odor being measured.

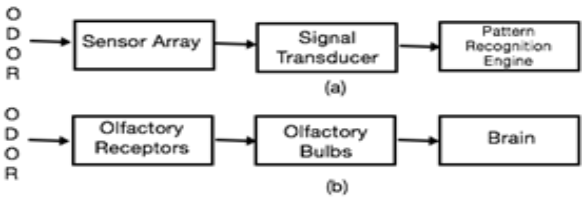


Figure 1. Olfactory system (a) E-nose, (b) Mammal

The MOS sensors are suitable for recognizing either reducing or oxidizing gases by or conductive measurements [56]. Sensor's performance is one of the important parts of the sensor application. By knowing the performance, it can be easily applied to an appropriate application with certain limitation and scope. According to V. E. Bochenkov [57], Some of parameters should be paid attention in order to characterize sensor performance, namely: sensitivity, selectivity, stability, detection limit, dynamic range, linearity, resolution, response time, recovery time, working temperature, hysteresis, and life-cycle. Part 2 of this paper gives a more explanation of these parameters.

2.2. Dispersion Model

The gas can move easily from one place to another place due to the wind or the difference of concentration in one place. The longer the distance of the gas from the source is, the smaller the concentration will be. In other word, the concentration near the source will be higher than the concentration of the gas far from the source. The turbulence and the diffusion that can cause the gas to move are influenced by the environmental condition, especially the wind characteristics. The movement of the gas from its source to the area around it will produce a concentration pattern or always called as the plume dispersion. The change of the concentration pattern will continuously happen in accordance with the occurrence of the wind that moves in the same direction or in the different direction.

The plume dispersion can be modeled using mathematic equation. In general, the models can be divided into two forms, i.e., 1. Basic Model; and 2. Diffusion Model. In basic model, the gas only moves due to the air flow speed. The concentration using this model is considered to be constant. Thus, the concentration in one place in one time is the same with the concentration in another place in different time. The basic model uses the equation as represented in Equation 1.

$$\frac{\partial \mathrm{C}}{\partial \mathrm{t}} + \mathrm{u}\frac{\partial \mathrm{C}}{\partial \mathrm{x}} = 0 \quad (1)$$

where: C = gas concentration (kg/m^3)
u = air flow speed (m/s)
t = time (s)
x = x coordiname (m)

For the diffusion models, there are a lot of researchers offered some solution. In paper [58], it discussed about Gaussian models and Farrel's filamentous model. These models assumed the meteorological condition and plume emission are stationary. For the 2 dimension room, the concentration of the gas would be the same with Equation 2, while for 3 dimension room the equation would be the same with Equation 3.

$$C(x,y,t) = \frac{M}{L_z 4\pi t\sqrt{D_x D_y}} exp\left(-\frac{(x-x_0-ut)^2}{4\,D_x t} - \frac{(y-y_0-vt)^2}{4\,D_y t}\right) \quad (2)$$

$$C(x,y,z,t) = \frac{M}{(4\pi t)^{3/2}\sqrt{D_x D_y D_z}} exp\left(-\frac{(x-x_0-ut)^2}{4\,D_x t} - \frac{(y-y_0-vt)^2}{4\,D_y t} - \frac{(z-z_0-wt)^2}{4\,D_z t}\right) \quad (3)$$

2.3. Sensor's Performance

Sensor performances are really needed for odor classification. By having sensor performance, the databases for classification can be got and the odor localization can be achieved. Some of the researchers discussed the training data of the sensors are described in the next paragraphs.

Marco Trincavelli in [42] investigated the odor classification in continuous monitoring. The electronic nose's responses were analyzed in five phases, i.e., baseline manipulation, segmentation, feature extraction, data normalization, and classification. The databases of the sensors were divided into four sampling phases, namely: base line, transient, steady state, and recovery. In controlled time and odor sources, the 4 phases can be got easily. It was contradictive, when the sensors were employed in uncontrolled one, the steady state could not be reached. It was due to the sensors were not continuously exposed for a long enough time to the odor sources. Marco Trincavelli used the transient response data to solve the dynamic odor problem. The classification was done by machine learning Relevance Vector Machine (RVM). He claimed that RVM was more powerful than SVM in estimating the posterior probabilities. He stated that the estimation of the posterior probabilities was important in considering a confidence measure of the decision made by the classifier [42].

Amy Loutfi [60] also tried to solve the problem of odor classification using the transient response of the sensors. In that research, the sensors were assumed to be in a state of transition due to when the robots' moving, the current concentration values were unknown. The input to the classification algorithm was taken from the comparison between a baseline and steady state. The steps of classification include: 1. collecting the training data, 2. doing the fractional baseline manipulation, 3. Decomposing the input signals to the training algorithm into the feature using Debauchies Wavelet Transforms. 4. Inputting the total wavelet coefficients of each odors into Principal Component Analysis (PCA), 5. Classifying the data using Support Vector Machine (SVM). The classification of the data was optimized by the Mitchell-Demyanov-Malozemov algorithm using a Gaussian Kernel Function.

Osuna [50] developed the research made by J W Gardner [61]. He used 4 databases of odors with different number of classes and various complexities. He stated that in the compression of the data, the sensor transient response did not improve the accuracy prediction but impair the accuracy. It could be concluded that the database was over fitting [50]. In that research, they concluded that the steady state data of the sensors could perform well in separating the classes. However, in that research, their goal was only to show the methodology that allowed the evaluation of the technique rather than determining the best techniques. Therefore, their conclusion about the best databases for the odor classification was still vague.

Another research by Osuna et al [62] reviewed 4 multi exponential models, namely: Gardner transform, multi exponential transient spectroscopy, Pade Laplace, and Pade Z transform. Their purpose was to model the transient response of conductivity-based gas sensors for odor recognition. They concluded that Gardner transform was extremely sensitive to the dispersion parameter, while the Pade Laplace and Pade Z methods were less sensitive to experimental noise than the spectral techniques and did not require low-pass filtering. Some parameters in sensor performances that can be analyzed (as mentioned in sub chapter 2.1.) [57] are described as follows:

2.3.1. Sensitivity

Sensitivity is a change of measured signal per analyte concentration unit [57]. Xin Zhou in [63] analyzed the sensitivity of the gas sensor based on ZnFe2O4 spheres and ZnFe2O4 nanoparticles. The gas sensor's response to the 30 ppm and 100 ppm acetone were recorded. The gas sensor's response to the acetone varied with the change of the temperature. Gas sensor gave low response to the acetone at low temperature (200^{o}C) due to acetone molecules cannot effectively react with the surface absorbed oxygen species. The responses of porous ZnFe2 O4 spheres were good at higher temperature at operating temperature 200^{o}C and 237.5^{o}C.

2.3.2. Selectivity

According to V. E. Bochenkov [57] selectivity is characteristics that determine whether a sensor can respond to a group of analytes selectively or even to a single analyte specifically. Selectivity is one of essential parameters in odor identification [64]. Selectivity will be easy if the odors to be identified are really different. It is contradictive when the odors are quiet similar as in paper [65]. The selectivity of the sensors will be better by additional methods or techniques, such as the integration of PCA, LDA, NN, SVM, etc.

2.3.3. Stability

Stability is the ability of a sensor to provide reproducible results for a certain period of time. This includes retaining the sensitivity, selectivity, response, and recovery time. One of the gas sensor's stability was conducted by Zhen Wen [66]. They tested several gas sensor's parameters in their research, such as: sensitivity, detection limit, working temperature, response/recovery kinetics, selectivity, and stability of the sensor. In that research, they got that Rhombic Co3O4 nanorod (NR) array-based gas sensor had a good stability over the 3 months test.

2.3.4. Detection Limit

Detection limit is the lowest concentration of the analyte that can be detected by the sensor under given conditions, particularly at a given temperature. One of the selective detection researches was offered by Qianqian in [67]. They observed ZnO gas sensor to the acetone sources. They got that detection limit for the acetone was 0.25 ppm.

2.3.5. Dynamic Range

Dynamic range refers to the analyte concentration range between the detection limit and the highest limiting concentration.

2.3.6. Linearity

Linearity refers to the relative deviation of an experimentally determined calibration graph from an ideal straight line.

2.3.7. Resolution

Resolution means the lowest concentration difference that can be distinguished by sensor.

2.3.8. Response Time

Response time is the time required for sensor to respond to a step concentration change from zero to a certain concentration value. Qianqian [67] as mentioned in sub chapter 2.3.4, also analyzed the response time of the ZnO sensor to the acetone. The response time of the sensor was as short as 3 s.

2.3.9. Recovery Time

Recovery time is the time it takes for the sensor signal to return to its initial value after a step concentration change from a certain value to zero.

2.3.10. Working Temperature

Working temperature is the temperature that corresponds to maximum sensitivity. As in the example mentioned in Sub Chapter 2.3.1, porous ZnFe2 O4 spheres were good at operating temperature 200^{o}C and 237.5^{o}C, it means that the working temperature range of that sensor was 200^{o}C until 237.5^{o}C. It is due to the sensitivity of the sensor become quite high in that range. Another example of working temperature can be seen from the research of Zhen Wen [66] (as stated in sub chapter 2.3.3) that analyzed some parameters in gas sensor's performances. Ethanol analyte was chosen as the gas source in their research. The optimal working temperature of Rhombic Co3O4 nanorod array based gas sensor for maximum sensitivity was at 160^{o}C. The response of the sensor increased with the operating temperature and then decreased with a further rise of the operating temperature. The phenomena were explained by Zhen Wen using the adsorption and desorption kinetics on the surface of the semiconducting metal oxides. When the working temperature was small (below 150^{o}C), the chemical activation was also small; therefore the response was also small (below 10). When the operating temperature was really high (above 200^{o}C), the adsorbed gas molecules escaped before their reaction; therefore, the response would also decrease (below 10). The working temperature was between 150^{o}C until 200^{o}C, with the highest sensitivity at 160^{o}C.

2.3.11. Hysteresis

Hysteresis means the maximum difference in output when the value is approached with an increasing and a decreasing analyte concentration range.

2.3.12. Life Cycle

Life cycle is the period of time over which the sensor will continuously operate.

3. EXPERIMENTAL SETUP

In this research, the response pattern of the sensors' array (TGS 2600, TGS 2602, and TGS 2600) was analyzed in the real environment in order to see the characteristics and performance of each sensor (The use of more than one sensor in odor classification is very important. It is due to the output of one sensor can refer to different concentration of various analytes [39]). The main goal of this research is to analyze the active coverage area of gas sensors in order to see the robustness of the sensors. By having the sensor's performance data, a planning of using an appropriate method for plume finding prediction in odor localization application can be built.

To the author's knowledge, there is no one discussed about the performance of gas sensors for the odor classification. In this research, the data of the sensor performance will be analyzed in four categories, namely: sensors' time response, sensors' peak duration, and sensors' sensitivity and sensors' stability. The temperature of the sensor will not be discussed in detail due to the data got from the first step in this research would be supplied as the data bases of odor classification which was done in the real environment. Therefore, in this research, the environmental temperature was taken around 28 0C until 31 0C as the real temperature measured in the experimental room.

3.1. The Experimental Environment

The experiment was done in a room 4 m x 10 m. The responses of the sensors were measured using 2 scenarios. At first scenario, the source was exposure to the environment for 20 s. The distance of the sensors to the sources was varied by 60 cm for each position. In the second scenario, the source was switched into on and off condition to see the sensitivity of the sensors.

3.2. Gas Sources

The gas sources were ethanol, methanol and butanol. The experimental source was set as shown in Figure 2. This source set-up imitated the odor sources introduced by Thomas Lochmatter [15]. The sources used in this experiments are ethanol (C2H6O), methanol (CH3OH), and acetone (C4H10O). Their molecular weights are heavier than air (28.97 g/mol), namely: 46.06844 g/mol for ethanol, 32.04 g/mol for methanol, and 58.08 g/mol for acetone. Therefore, They can evaporate quickly due to their low boiling point (780C, 640C, 560C respectively). Therefore, Their plume tends to be in the ground. In addition, their low boiling points enables to make gas sources in a spontaneous evaporation without heating. Liquid sources were transformed to be gas using the help of the wick and the fresh air supplied to the sources' chamber. The wick and a piece of tube (for the fresh air inlet) were used to increase the air-ethanol interface surface. Evaporated ethanol was mixed with the air on the top part of the chamber. This mixed gas was then pumped toward the gas outlet.

The air pump used as the experimental sources is capable to exhaust 14.0 Littre liquid source in a minute. It has six outputs that enable the deployments of the sources to any possible and desired points. The pressure of the pump is more than 0.016 MPa (≈ more than 2.32 psi) with 50-60 Hz frequencies. The type of the pump is a diaphragm pump that allows the output (in this case ethanol concentration) to be controlled. In addition, it is equipped with a knob that can be turned around from the lowest pressure to the highest one. This condition gave the easiness of controlling the concentration to be used.

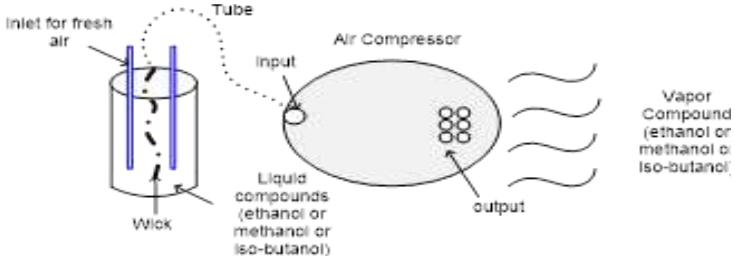


Figure 2. The gas sources setup

3.3. Gas Sensors

Three Metal Oxides gas sensors used in this experiment were TGS 2620, TGS 2602, and TGS 2600. These sensors are combined together in order to make an array sensor. The sensing element in TGS 2600, 2620, and TGS 2602 is made of a metal oxide semiconductor layer formed on the alumina substrate of a sensing chip together with an integrated heater. The conductivity of the sensor will change when there is a detected gas. Trough a simple electrical circuit, this change will be converted into an output signal correspond to the gas concentration.

The TGS 2600 has high sensitivity to low concentrations of gaseous air contaminants such as hydrogen and carbon monoxide which exist in cigarette smoke [68].

The TGS 2620 has high sensitivity to the vapors of organic solvents as well as other volatile vapors. It also has sensitivity to a variety of combustible gases such as carbon monoxide, making it a good general purpose sensor [69].

TGS 2602 has high sensitivity to low concentration of odorous gases, such as ammonia and H2S generated from waste material [70].

3.4. Block Diagram

The simple block diagram of the gas sensor development is shown in Figure 3. The chemical sources detected by sensors array were being converted into physical parameter. This parameter was processed in microcontroller and send to the output display. In this research, the output was also sent to the computer by means of wireless communication. The ADC data of the sensors were observed and processed to get the value of sensor's response.

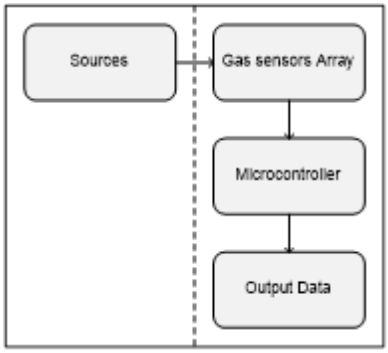


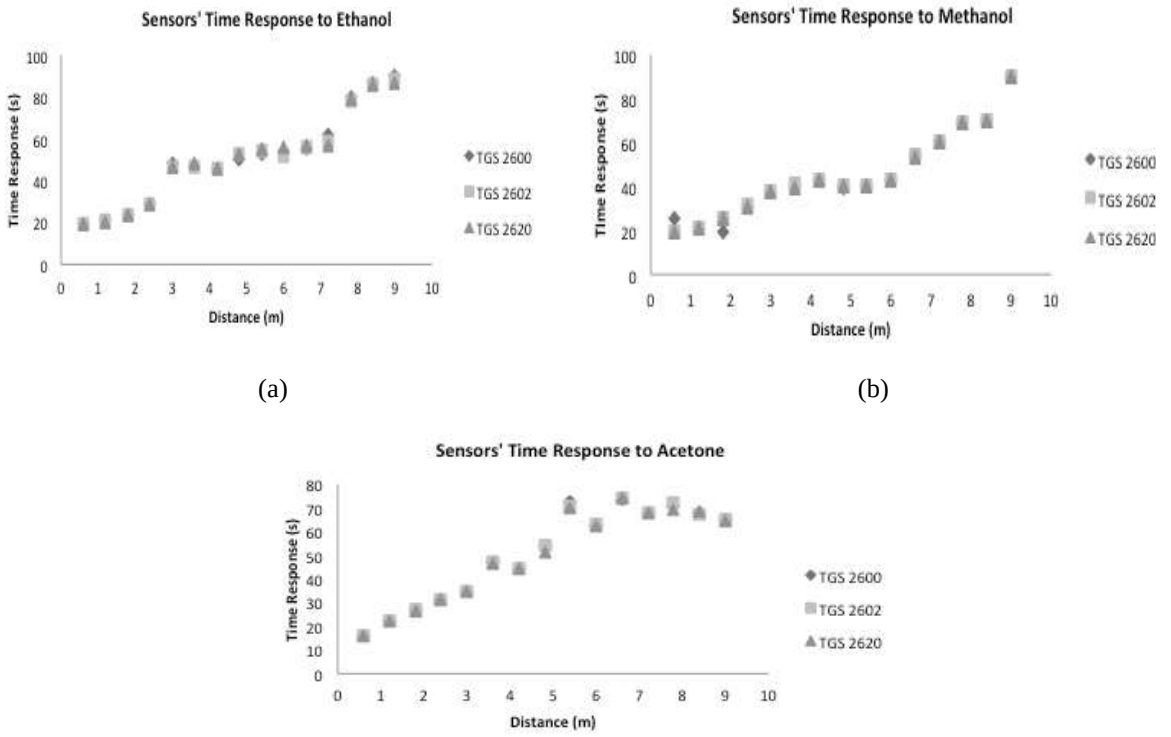
Figure 3. The block diagram of sensors array development

4. RESULTS AND DISCUSSION

4.1. Sensor Performance

In this sub chapter, the sensors' performances that were measured were focused on the sensors' time response, sensors' peak response duration, the sensitivity and the stability response of the sensor, while the selectivity performance of the gas sensors was determined in the sub chapter 4.3. The selectivity performance was indicated by the ability of the sensor in determining and classifying the odor that they sensed. In this research, SVM technique was used in order to enhance the ability of gas sensors in classifying the odor.

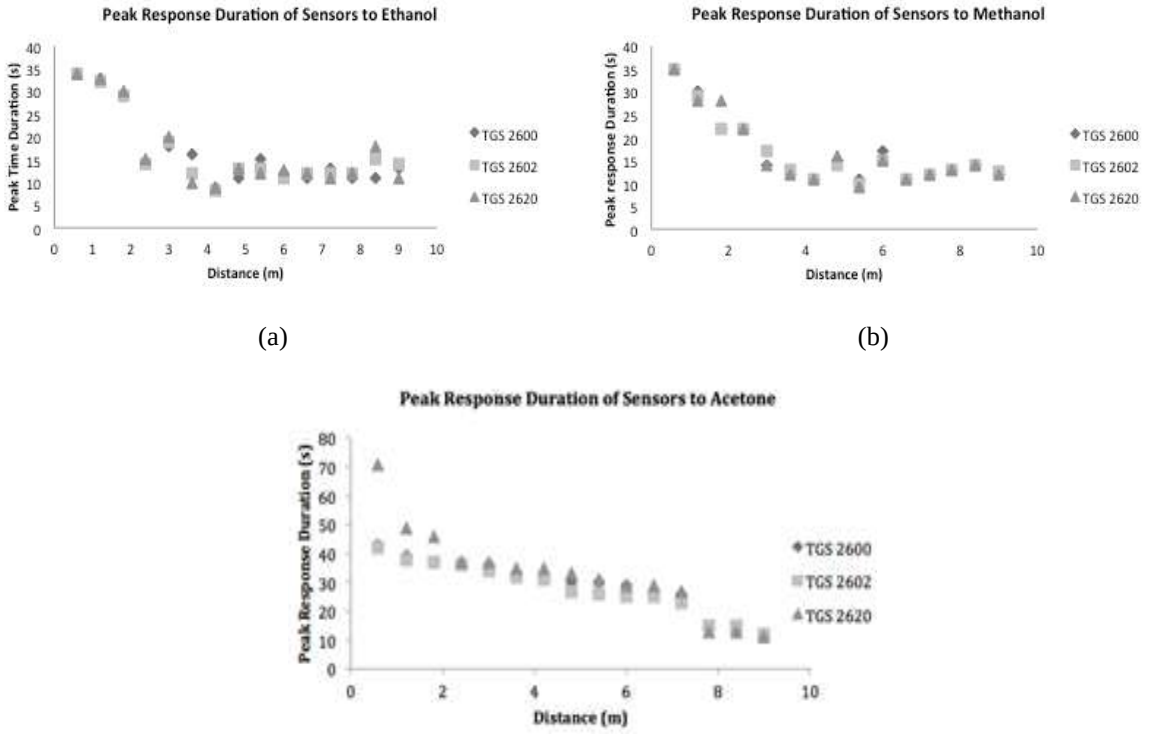
The speed of the sensor's response measured in different position was shown in Figure 4, the sensors' peak response duration was represented in figure 5, the sensitivity and stability response of the sensors was displayed in Figure 6 and Figure 7. Each of the sensors in response time testing showed that the response of them become slower due to the longer of the distance of the sources to reach the sensors. It is also the same with the sensors' peak response duration. The duration of the peak response would be shorter when the distance between the source and the gas sensors become longer.



(a) (b)

(c)

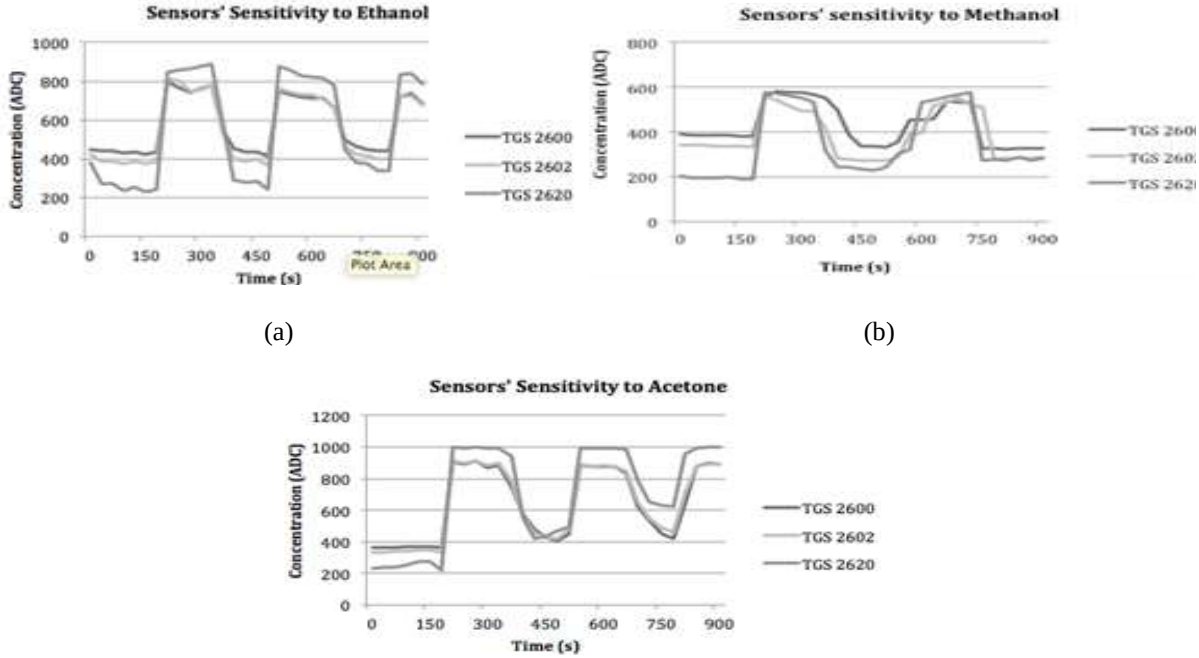
Figure 4. Sensor's time responses to some sources(a) to the ethanol, (b) to the methanol, and (c) to the acetone



(a) (b)

(c)

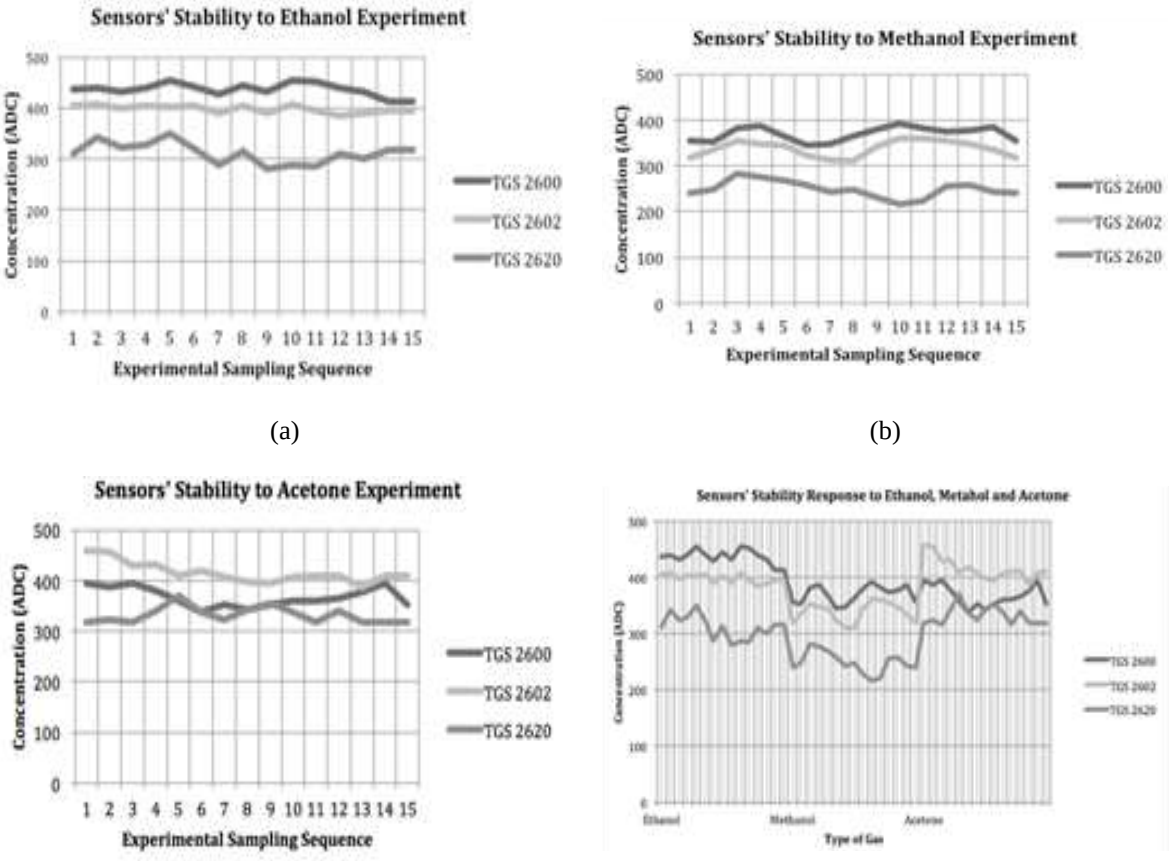
Figure 5. Sensor's peak duration responses for 3 different sources (a) ethanol, (b) methanol, (c) acetone



(a) (b)

(c)

Figure 6. Sensor's sensitivity for 3 different sources (a) ethanol, (b) methanol, (c) acetone



(a) (b)

(c) (d)

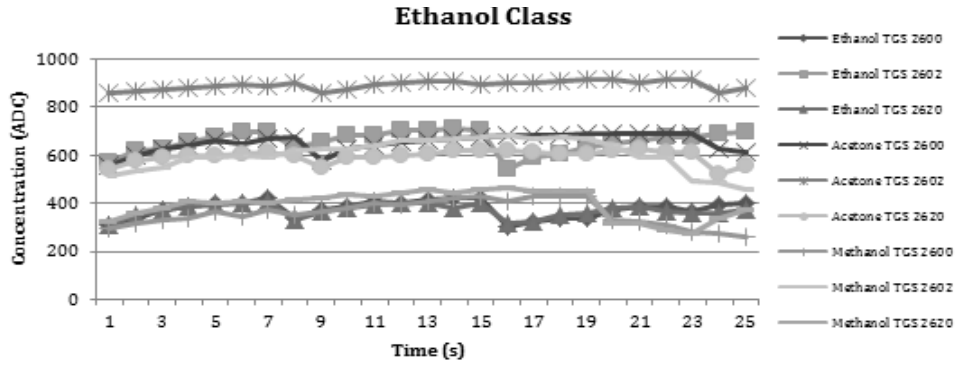
Figure 7. Sensor's stability for 3 different sources (a) ethanol, (b) methanol, (c) acetone

The sensitivity of the sensors shown in Figure 6 indicated that the TGS sensor was sensitive enough the change of the environment. In taking the data, the odor sources were exposed and unexposed to the robots interchangeably. The source was switched on for 120 s and was switched off 120 s. The data was got in the static position where the robots were placed in the 60 cm away from the source in the straight face to face position. The concentration of the acetone that the robots measured was the highest one (above 900 of ADC value), while the methanol was the smallest one (above 500 of ADC value). The detecting values of each gas sensors were not directly change when the processes of on and off happened. All of the sensors waited around 30-50 seconds until they changed their reading value based on the condition of the gas sources. It was due to the sensors needed more time to be back to its initial condition. When the source has been switched off, sensors still sensed the gas left in their surrounding, therefore, the sensors still read the gas concentration as high value for about 30-50 seconds after the gas source off. To overcome and minimize this transition condition, a fan could be used. It could help to clean the gas residue that stacked to the sensors' area.

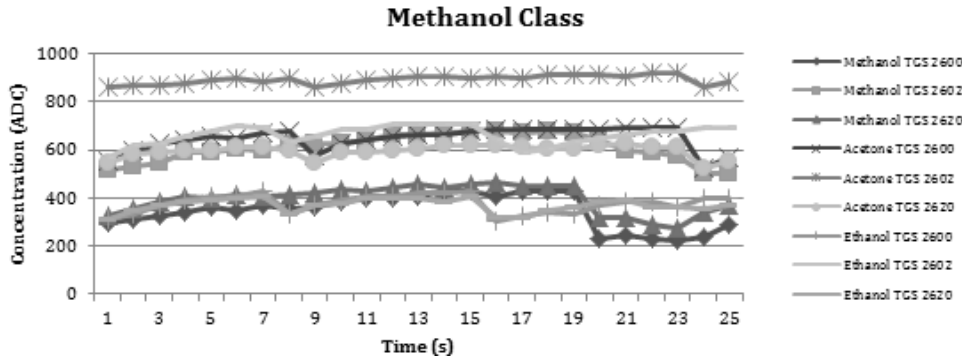
The stability response of the sensors was represented in Figure 7. This stability was needed in order to measure the time occupied by the sensors in detecting the source in a stable condition. By knowing the stability response, the mobile robots intelligences where the gas sensors were placed can be designed properly. In this research, the stability data got by collecting the sensors' response to the change of situation. The ability of the sensor to reach its initial condition was measured and recorded. From Figure 7, it can be stated that the gas sensors used in this experiments were stable enough. The concentration measured by the sensors was almost the same from the first sampling until the fifteenth sampling. Figure 7.a-7.c shows the stability of the sensors to the ethanol, methanol, and acetone. Figure 7.d represents the sensors' stability of the sensors to all of the sources used in the experiment. The gas sensors used in this experiment has the stability response to each sources around 34 second until 45 second for each sensors.

4.2. Collecting Data for the Training Datasets in Odor Classification

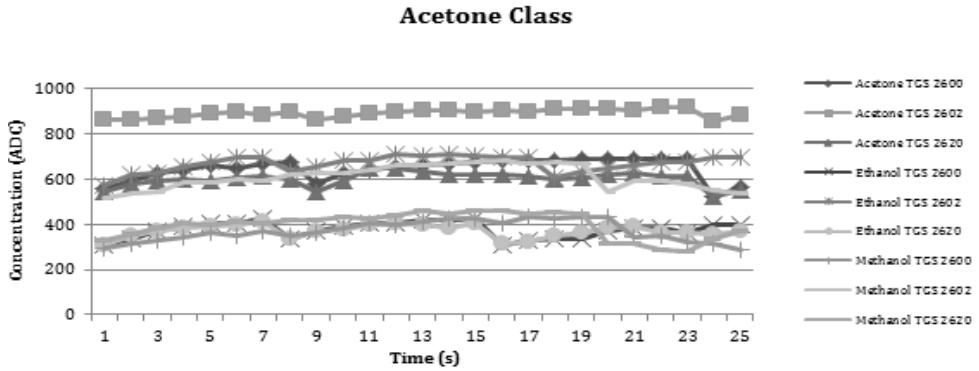
The training datasets were got from the gas sensors of the robots that were placed in a fix place approximate 60 cm from the source. The experimental environment was exposed to the gas source for 20 seconds. Then, the data came from 3 sensors of each robot were plotted in one graphics as shown in Figure 8. These data became the training datasets for the classification. The data was grouped into their classes. When exposed to the ethanol source, the data that was sensed by TGS 2600, TGS 2692, and TGS 2620 as ethanol classes were recorded, as well as the data of the other source, i.e. methanol and acetone (see Figure 8. a). Figure 8. b and 8. c show the response of the gas sensors for methanol class and the acetone class respectively.



(a)



(b)



(c)

Figure 8. Classes used as data training for gas classification

4.3. Odor Classification Using Support Vector Machine

4.3.1. Using Static sensor

The experimental results of odor classification were conducted using two conditions, i.e. using static sensors and mobile sensors. Static sensors data were taken by deploying the robots that were equipped with gas sensors TGS 2600, TGS 2602, and TGS 2620 to the experimental environment. The robots were placed in front of the gas source and moved them to a certain place manually. They were moved to get further from the source in scale of 0.5 m in each movement. The data were recorded in Table 3. From the data in Table 3, the accuracy, precision, and recall for each class can be calculated. The result of the calculation is presented in Table 4. The experiments were done in the experimental room for 10 times testing. The ability of the robots to guess what the sources they sensed was different. Most of them were successful in determining the source correctly. The stability of the robots was around 89.5-90.8 %, the accuracy was 89.2-90.8 %, and

recall around 89.2-90.8 %. This value indicated that the gas sensors in static experiment have good performance in selective parameter.

Table 3. Confusion Matrix of Gas Classification in Dynamic Experiment

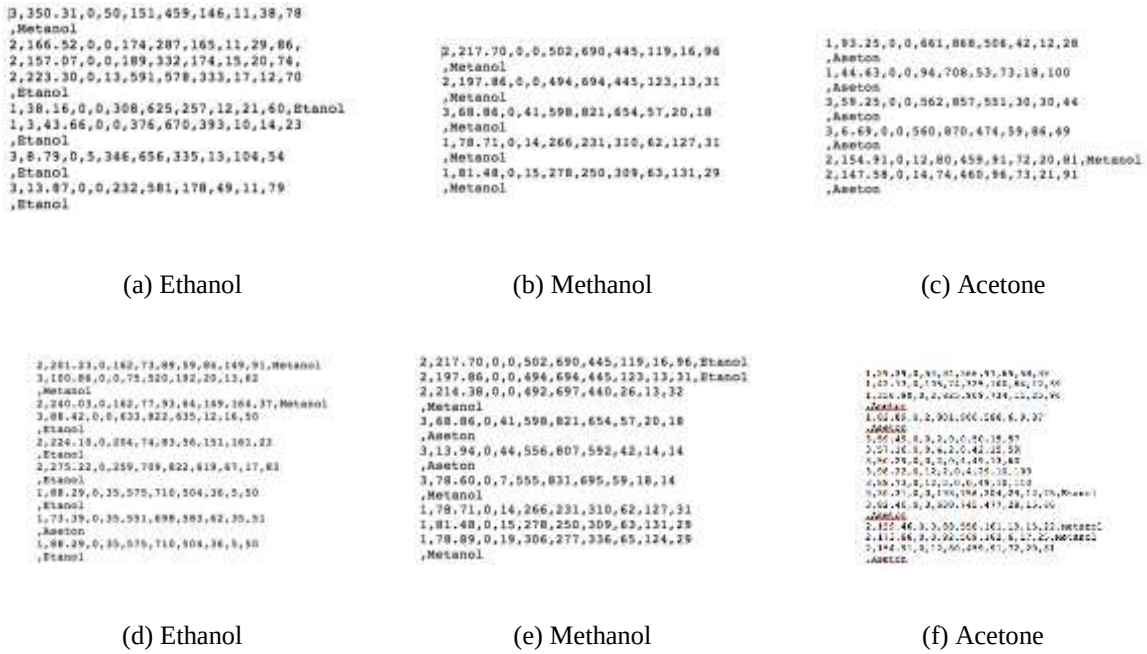
			Gas Classified by the Robots								
	Distance (m)	Gas Type	Ethanol			Methanol			Acetone		
			G1-1	G1-2	G1-3	G1-1	G1-2	G1-3	G1-1	G1-2	G1-3
Gas sprayed into the experimental environment	0.5	Ethanol	9	9	9	1	0	0	0	1	1
		Methanol	1	0	1	8	10	9	1	0	0
		Acetone	1	0	1	0	1	0	9	9	9
	1	Ethanol	9	9	9	1	0	1	0	1	0
		Methanol	1	0	0	9	9	9	0	1	1
		Acetone	1	1	0	0	0	1	9	9	9
	1.5	Ethanol	9	9	9	0	1	1	1	0	0
		Methanol	1	1	0	9	9	9	0	0	1
		Acetone	0	0	0	1	1	1	9	9	9
	2	Ethanol	9	9	9	0	0	0	1	1	1
		Methanol	0	1	1	9	9	9	1	0	
		Acetone	1	0	1	0	1	0	9	9	9

Table 4. Calculation of Precision, Accuracy and recall in Dynamic Experiment

Distance (m)	Gas Type	G1-1			G1-2			G1-3		
		Pre	Acc	Rec	Pre	Acc	Rec	Pre	Acc	Rec
0.5	Ethanol	81.8	86.7	90.0	100.0	93.3	90.0	81.8	90.0	90.0
	Methanol	88.9		80.0	90.9		100.0	100.0		90.0
	Acetone	90.0		90.0	90.0		90.0	90.0		90.0
1	Ethanol	81.8	90.0	90.0	90.0	90.0	90.0	100.0	90.0	90.0
	Methanol	90.0		90.0	100.0		90.0	81.8		90.0
	Acetone	100.0		90.0	81.8		90.0	90.0		90.0
1.5	Ethanol	90.0	90.0	90.0	90.0	90.0	90.0	100.0	90.0	90.0
	Methanol	90.0		90.0	81.8		90.0	81.8		90.0
	Acetone	90.0		90.0	100.0		90.0	90.0		90.0
2	Ethanol	90.0	90.0	90.0	90.0	90.0	90.0	81.8	90.0	90.0
	Methanol	100.0		90.0	90.0		90.0	100.0		90.0
	Acetone	81.8		90.0	90.0		90.0	90.0		90.0
Average		89.5	89.2	89.2	91.2	90.8	90.8	90.6	90.0	90.0

4.3.2. Using Mobile Sensors

For the dynamic sensors, the experimental data was got using the 3 mobile robots, i.e., G1-1, G1-2, and G1-3. The robots were placed near the sources with two starting points, 1 m and 2 m. Then, they were commanded to get closer to the sources and asked to decide what kind of sources they have detected. Each sources was dispersed to the environment alternately. The robots should able to recognize the smells of the gas sources using their intelligences that have been embedded to them. The robots were introduced to the sources (ethanol, methanol, and acetone) ten times in each distance. Then, the success and fail of the robot in detecting the sources were measured and recorded in Table 5. Figure 9 was the examples of the data sent by the robots to the server. The first number of each picture in the series data represented in each pictures indicate the type of robots. 1 indicates G1-1 robot, 2 means G1-2 robot, and 3 for G1-3 robot. The last parameters in each line of data series show the type of data sensed. Figure 9. a shows that at the first, G1-1 robot classified the odor its sensed as methanol, then after several times it decided that it was ethanol. All of the robots at last decided that the odor they sensed as ethanol. When the data sent to the server be the same with the odor source for several times, then, in this condition, it can be concluded that the robots have been able to recognize and classify the odor correctly. Figure 9(b) until Figure 9(f) show part of the data sent by the robot to the server, Figure 9(a) until 9(c) for 1 m distance and Figure 9(d) -Figure 9(f) for 2 m distance.



(a) Ethanol (b) Methanol (c) Acetone

(d) Ethanol (e) Methanol (f) Acetone

Figure 9. Classification result, a-c at 1 m distance, d-f at 2 m distance

Table 5 show the confusion matrix for the classification in dynamic experimental setup while the calculation of the precision, accuracy and recall is shown in Table 6. The dynamic experiment also show the succes in classifying the odor sources. The average of precision success was 93.8-97 %, the accuracy was 93.3-96.7 %, and the recall was 93.3-96.7 %. This values indicates that the sensors were selective to the odor they sensed.

Table 5. Confusion Matrix of gas classification in dynamic experiment

Gas sprayed into the experimental environment	Starting point (m)	Gas Type	Gas Classified by the Robots Rate								
			Ethanol			Methanol			Acetone		
			G1-1	G1-2	G1-3	G1-1	G1-2	G1-3	G1-1	G1-2	G1-3
	1	Ethanol	10	10	10	0	0	0	0	0	0
		Methanol	0	1	0	9	9	10	1	0	0
		Acetone	0	0	0	0	0	0	10	10	10
	2	Ethanol	10	9	10	0	0	0	0	1	0
		Methanol	1	1	1	8	9	9	1	0	0
		Acetone	0	1	9	0	0	0	10	9	9

Table 6. Calculation of precision, accuracy and recall in dynamic experiment

Starting point (m)	Gas Type	G1-1			G1-2			G1-3		
		Pre	Acc	Rec	Pre	Acc	Rec	Pre	Acc	Rec
1	Ethanol	100.0	96.7	100.0	90.9	96.7	100.0	100.0	100.0	100.0
	Methanol	100.0	96.7	90.0	100.0	96.7	90.0	100.0	100.0	100.0
	Acetone	90.9	96.7	100.0	100.0	96.7	100.0	100.0	100.0	100.0
2	Ethanol	90.9	93.3	100.0	81.8	90.0	90.0	83.3	93.3	100.0
	Methanol	100.0	93.3	80.0	100.0	90.0	90.0	100.0	93.3	90.0
	Acetone	90.9	93.3	100.0	90.0	90.0	90.0	100.0	93.3	90.0
Average		95.5	95.0	95.0	93.8	93.3	93.3	97.2	96.7	96.7

5. CONCLUSION

Metal Oxide Semiconductors sensors are good to be used as classifiers. They are stable, sensitive to the changes, and really selective. However, some treatments should be done before employing these sensors in odor classification or localization. These sensor would not show their stability when they are not being heated for several hours of their usage. They would measure wrong concentration and the value of measurement would swing with a wide range. Therefore, heating before usage become one of the key in odor

classification task. The other problems often occured are unlinear data. Sometimes, the data of the sensors has a wide range of variation. If it happened, a preprocessing data is needed. The prepocessing data could help to ommit the error data occur in the experiment.

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REFERENCES

[1] J. Lobo, L. Marques, J. Dias, U. Nunes, and A. T. De Aimeida, "Sensors for Mobile Robot Navigation."
[2] L. Seminara, L. Pinna, M. Valle, L. Basirico, A. Loi, P. Cosseddu, A. Bonfiglio, A. Ascia, M. Biso, A. Ansaldo, D. Ricci, and G. Metta, "Piezoelectric polymer transducer arrays for flexible tactile sensors," *IEEE Sens. J.*, vol. 13, no. 10, pp. 4022–4029, 2013.
[3] S. E. Zohora and N. Hundewale, "Chemical Sensors Employed In Electronic Noses : A Review," *Soft Comput. Eng.*, vol. 3, no. 2, pp. 405–408, 2013.
[4] L. Zhang, F. Tian, and G. Pei, "A novel sensor selection using pattern recognition in electronic nose," *Measurement*, vol. 54, pp. 31–39, 2014.
[5] B. Ji, W. Zheng, R. S. Gates, and A. R. Green, "Design and performance evaluation of the upgraded portable monitoring unit for air quality in animal housing," vol. 124, pp. 132–140, 2016.
[6] N. L. Husni, A. Silvia, and S. Nurmaini, "New Challenges in Air Quality Sensing using Robotic Sensor Network," 2013.
[7] S. Nurmaini, "Low-cost robotic sensor networks platform for air quality monitoring," vol. 145.
[8] N. L. Husni, A. Silvia, S. Nurmaini, and I. Yani, "Odor Localization Sub Tasks : A Survey 2 Localization Sub Tasks."
[9] D. Chengjun, L. Ximao, and D. Ping, "Development on Gas Leak Detection and Location System Based on Wireless Sensor Networks," *2011 Third Int. Conf. Meas. Technol. Mechatronics Autom.*, vol. 1, no. 6, pp. 1067–1070, 2011.
[10] J. Banick, K. Lenz, J. Sanders, and J. Zolkowski, "Monitoring Carbon Dioxide and Methane Levels above Retired Landfill and Forest Control Sites with a Tethered Aerostat to Determine Remediation Effectiveness Jesse Banick, Kathryn Lenz, Jonathan Sanders, Jeshanah Zolkowski 1 University of Wisconsin-Fox Val."
[11] A. D. Wilson, "Diverse applications of electronic-nose technologies in agriculture and forestry," *Sensors (Switzerland)*, vol. 13, no. 2, pp. 2295–2348, 2013.
[12] V. B. Raj, H. Singh, A. T. Nimal, M. U. Sharma, and V. Gupta, "Sensors and Actuators B : Chemical Oxide thin films (ZnO , TeO 2 , SnO 2 , and TiO 2) based surface acoustic wave (SAW) E-nose for the detection of chemical warfare agents," vol. 178, pp. 636–647, 2013.
[13] C. Olgu??n, N. Laguarda-Mir??, L. Pascual, E. Garc??a-Breijo, R. Mart??nez-Ma??ez, and J. Soto, "An electronic nose for the detection of Sarin, Soman and Tabun mimics and interfering agents," *Sensors Actuators, B Chem.*, vol. 202, no. April 1972, pp. 31–37, 2014.
[14] M. Turduev, G. Cabrita, and M. Kırtay, "Experimental studies on chemical concentration map building by a multi-robot system using bio-inspired algorithms," 2012.
[15] T. Lochmatter, "Bio-Inspired and Probabilistic Algorithms for Distributed Odor Source Localization using Mobile Robots," vol. 4628, 2010.
[16] W. Li, J. A. Farrell, S. Member, S. Pang, and R. M. Arrieta, "Moth-Inspired Chemical Plume Tracing on an Autonomous Underwater Vehicle," vol. 22, no. 2, pp. 292–307, 2006.
[17] P. P. Neumann, V. Hernandez Bennetts, A. J. Lilienthal, M. Bartholmai, and J. H. Schiller, "Gas source localization with a micro-drone using bio-inspired and particle filter-based algorithms," *Adv. Robot.*, vol. 27, no. 9, pp. 725–738, 2013.
[18] G. Chmaj and H. Selvaraj, "Distributed processing applications for UAV / drones : a survey Distributed processing applications for UAVs," 2015.
[19] B. Tutuko, S. Nurmaini, and A. Triadi, "Gas Leak Localization Using Mobile Sensor Networks," no. August, pp. 19–20, 2015.
[20] S. Zampolli, I. Elmi, F. Ahmed, M. Passini, G. C. Cardinali, S. Nicoletti, and L. Dori, "An electronic nose based on solid state sensor arrays for low-cost indoor air quality monitoring applications," *Sensors Actuators, B Chem.*, vol. 101, no. 1–2, pp. 39–46, 2004.
[21] G. Hierro, "Gas sensor array for VOC ' s monitoring in soils contamination," vol. 1, pp. 45–54, 2010.
[22] B. Kay, H. An, S. Y. Jeong, H. R. Hwang, and Y. H. Lee, "Enhanced Sensitivity of a Gas Sensor Incorporating Single-Walled Carbon Nanotube ± Polypyrrole Nanocomposites **," no. 12, pp. 1005–1009, 2004.

[23] J. Zhang, X. Liu, S. Wu, B. Cao, and S. Zheng, "Sensors and Actuators B : Chemical One-pot synthesis of Au-supported ZnO nanoplates with enhanced gas sensor performance," *Sensors Actuators B. Chem.*, vol. 169, pp. 61–66, 2012.
[24] M. L. Rodriguez-Mendez, C. Apetrei, M. Gay, C. Medina-Plaza, J. A. De Saja, S. Vidal, O. Aagaard, M. Ugliano, J. Wirth, and V. Cheynier, "Evaluation of oxygen exposure levels and polyphenolic content of red wines using an electronic panel formed by an electronic nose and an electronic tongue," *Food Chem.*, vol. 155, pp. 91–97, 2014.
[25] D. Melucci, A. Bendini, F. Tesini, S. Barbieri, A. Zappi, S. Vichi, L. Conte, and T. Gallina Toschi, "Rapid direct analysis to discriminate geographic origin of extra virgin olive oils by flash gas chromatography electronic nose and chemometrics," *Food Chem.*, vol. 204, pp. 263–273, 2016.
[26] M. Russo, R. Di Sanzo, V. Cefaly, S. Carabetta, D. Serra, and S. Fuda, "Non-destructive flavour evaluation of red onion (Allium cepa L.) Ecotypes: An electronic-nose-based approach," *Food Chem.*, vol. 141, no. 2, pp. 896–899, 2013.
[27] A. C. Romain and J. Nicolas, "Long term stability of metal oxide-based gas sensors for e-nose environmental applications: An overview," *Sensors and Actuators, B: Chemical*, vol. 146, no. 2. pp. 502–506, 2010.
[28] N. Barsan, D. Koziej, and U. Weimar, "Metal oxide-based gas sensor research : How to ?," vol. 121, pp. 18–35, 2007.
[29] G. F. Fine, L. M. Cavanagh, A. Afonja, and R. Binions, "Metal oxide semi-conductor gas sensors in environmental monitoring," *Sensors*, vol. 10, no. 6, pp. 5469–5502, 2010.
[30] M. Trincavelli and A. Loutfi, "Feature selection for gas identification with a mobile robot," *Proc.-IEEE Int. Conf. Robot. Autom.*, pp. 2852–2857, 2010.
[31] A. Marjovi and L. Marques, "Optimal spatial formation of swarm robotic gas sensors in odor plume finding," *Auton. Robots*, vol. 35, no. 2–3, pp. 93–109, 2013.
[32] J. Murlis, "Odor Plumes And How Insects Use Them," *Annu. Rev. Entomol.*, vol. 37, no. 1, pp. 505–532, 1992.
[33] L. I. Ji-gong, Y. Jing, L. I. U. Jia, L. U. Guang-da, and Y. Li, "Odor-source Searching using a Mobile Robot in Time-variant Airflow Environments with Obstacles," pp. 8559–8564, 2014.
[34] J. G. Li, Y. Jing, S. G. Cui, and L. H. Geng, "Speed limitation of a mobile robot and methodology of tracing odor plume in airflow environments," *Procedia Eng.*, vol. 15, pp. 1041–1045, 2011.
[35] J. Zhou, J. Li, and S. Cui, "A bionic plume tracing method with a mobile robot in outdoor time-varying airflow environment," *2015 IEEE Int. Conf. Inf. Autom.*, no. 61304153, pp. 2351–2355, 2015.
[36] S. Zhang, R. Cui, and D. Xu, "Swarm olfactory search in turbulence environment," *Process. 2014 Int. Conf. Multisens. Fusion Inf. Integr. Intell. Syst. MFI 2014*, vol. 2, 2014.
[37] D. Chang, W. Wu, D. R. Webster, M. J. Weissburg, and F. Zhang, "A Bio-inspired Plume Tracking Algorithm for Mobile Sensing Swarms in Turbulent Flow."
[38] A. Marjovi and L. Marques, "Optimal Swarm Formation for Odor Plume Finding," *IEEE Trans. Cybern.*, 2014.
[39] W. Khalaf, C. Pace, and M. Gaudioso, "Least Square Regression Method for Estimating Gas Concentration in an Electronic Nose System," pp. 1678–1691, 2009.
[40] L. Gugel, Y. Shkolnisky, and S. Dekel, "MACHINE OLFACTION USING TIME SCATTERING OF SENSOR," pp. 1–19, 2016.
[41] H. J. Kwon, D. G. Kim, and K. S. Hong, "Multiple odor recognition and source direction estimation with an electronic nose system," *Int. J. Distrib. Sens. Networks*, vol. 2013, 2013.
[42] M. Trincavelli, S. Coradeschi, and A. Loutfi, "Odour classification system for continuous monitoring applications," *Sensors Actuators, B Chem.*, vol. 139, no. 2, pp. 265–273, 2009.
[43] S. J. Patil, N. Duragkar, and V. R. Rao, "An ultra-sensitive piezoresistive polymer nano-composite microcantilever sensor electronic nose platform for explosive vapor detection," *Sensors Actuators, B Chem.*, vol. 192, pp. 444–451, 2014.
[44] M. Bofan, N. Mores, M. Baron, M. Dabrowska, S. Valente, M. Schmid, A. Trové, S. Conforto, G. Zini, P. Cattani, L. Fuso, A. Mautone, C. Mondino, G. Pagliari, T. D'Alessio, and P. Montuschi, "Within-day and between-day repeatability of measurements with an electronic nose in patients with COPD.," *J. Breath Res.*, vol. 7, no. 1, p. 17103, 2013.
[45] R. A. G. Rañola, K. S. Santiago, and F. B. Sevilla, "Use of array of conducting polymers for differentiation of coconut oil products," *Talanta*, vol. 146, pp. 75–82, 2016.
[46] R. López, I. Giráldez, A. Palma, and M. Jesús Díaz, "Assessment of compost maturity by using an electronic nose," *Waste Manag.*, vol. 48, pp. 174–180, 2016.
[47] K. Arshak, E. Moore, G. M. Lyons, J. Harris, and S. Clifford, "A review of gas sensors employed in electronic nose applications," *Sens. Rev.*, vol. 24, no. 2, pp. 181–198, 2004.
[48] J. W. Gardner and P. N. Bartlett, "A brief history of electronic noses *," vol. 19, pp. 211–220, 1994.
[49] A. D. Wilson, "Review of Electronic-nose Technologies and Algorithms to Detect Hazardous Chemicals in the Environment," *Procedia Technol.*, vol. 1, pp. 453–463, 2012.
[50] R. Gutierrez-osuna and H. T. Nagle, "A Method for Evaluating Data-Preprocessing Techniques for Odor Classification with an Array of Gas Sensors," vol. 29, no. 5, pp. 626–632, 1999.
[51] E. Westenbrink, R. P. Arasaradnam, N. O'Connell, C. Bailey, C. Nwokolo, K. D. Bardhan, and J. A. Covington, "Development and application of a new electronic nose instrument for the detection of colorectal cancer," *Biosens. Bioelectron.*, vol. 67, pp. 733–738, 2015.
[52] P. Jia, F. Tian, Q. He, S. Fan, J. Liu, and S. X. Yang, "Feature extraction of wound infection data for electronic nose based on a novel weighted KPCA," *Sensors Actuators, B Chem.*, vol. 201, pp. 555–556, 2014.

[53] L. Henrich, J. McClure, and M. Crozier, "Effect of hot air drying on volatile compounds of Flammulina velutipes detected by HS-SPME–GC–MS and electronic nose e," *Int. J. Disaster Risk Reduct.*, 2015.
[54] J. Gruber, H. M. Nascimento, E. Y. Yamauchi, R. W. C. Li, C. H. A. Esteves, G. P. Rehder, C. C. Gaylarde, and M. A. Shirakawa, "A conductive polymer based electronic nose for early detection of Penicillium digitatum in post-harvest oranges," *Mater. Sci. Eng. C*, vol. 33, no. 5, pp. 2766–2769, 2013.
[55] A. J. Lilienthal, A. Loutfi, and T. Duckett, "Airborne Chemical Sensing with Mobile Robots," *Sensors*, vol. 6, no. 11, pp. 1616–1678, 2006.
[56] A. Einollahi, "Selectivity Enhancement for a Temperature Modulated Electronic Nose using Phase Space and Dynamic Moments," 2012.
[57] V. E. Bochenkov and G. B. Sergeev, "Sensitivity, Selectivity, and Stability of Gas-Sensitive Metal-Oxide Nanostructures," vol. 3, pp. 31–52, 2010.
[58] N. L. Husni, A. Silvia, S. Nurmaini, and I. Yani, "Odor Localization Sub Tasks : A Survey," *J. Telecommun. Electron. Comput. Eng.*, vol. 8, no. 3, 2016.
[59] W. Jatmiko, *Swarm Robot dalam Pencarian Sumber Asap*. Fakultas Ilmu Komputer Universitas Indonesia, 2010.
[60] A. Loutfi, S. Coradeschi, A. Lilienthal, and J. Gonzalez, "Gas Distribution Mapping of Multiple Odour Sources using a Mobile Robot," pp. 1–15.
[61] J. W. Gardner, M. Craven, C. Dow, and E. L. Hines, "The prediction of bacteria type and culture growth phase by an electronic nose with a multi-layer perceptron network," vol. 9, pp. 120–127, 1998.
[62] R. Gutierrez-osuna, H. T. Nagle, and S. S. Schiffman, "Transient response analysis of an electronic nose using multi-exponential models," pp. 170–182, 1999.
[63] X. Zhou, J. Liu, C. Wang, P. Sun, X. Hu, X. Li, K. Shimanoe, N. Yamazoe, and G. Lu, "Highly sensitive acetone gas sensor based on porous ZnFe 2 O 4 nanospheres," *Sensors Actuators B. Chem.*, vol. 206, pp. 577–583, 2015.
[64] T. Maekawa, K. Suzuki, and T. Takada, "Odor identification using a SnO 2 -based sensor array," vol. 80, pp. 3–6, 2001.
[65] S. Güney and A. Atasoy, "Sensors and Actuators B : Chemical Multiclass classification of n -butanol concentrations with k -nearest neighbor algorithm and support vector machine in an electronic nose," *Sensors Actuators B. Chem.*, vol. 166–167, pp. 721–725, 2012.
[66] Z. Wen, L. Zhu, W. Mei, L. Hu, Y. Li, and L. Sun, "Rhombus-shaped Co3 O4 nanorod arrays for high-performance gas sensor," *Sensors Actuators B. Chem.*, vol. 186, pp. 172–179, 2013.
[67] Q. Jia, H. Ji, Y. Zhang, Y. Chen, X. Sun, and Z. Jin, "Rapid and selective detection of acetone using hierarchical ZnO gas sensor for hazardous odor markers application," *J. Hazard. Mater.*, vol. 276, pp. 262–270, 2014.
[68] Http://www.figarosensor.com/products/2600pdf.pdf, "PRODUCT INFORMATION TGS 2600."
[69] http://www.figarosensor.com/products/2620pdf.pdf, "PRODUCT INFORMATION TGS."
[70] Http://www.figarosensor.com/products/2602pdf., "tgs 2602.pdf." .