Odor Classification Using Support Vector Machine

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***Abstract*—This paper discusses about the process of classifying odor using Support Vector Machine. The training data was taken using a robot that ran in indoor room. The odor was sensed by 3 gas sensors, namely: TGS 2600, TGS 2602, and TGS 2620. The experimental environment was controlled and conditioned. The temperature was kept between 27.5 ^{0}C to 30.5 ^{0}C and humidity was in the range of 65% -75 %. After simulation testing in Matlab, the classification was then done in real experiment using one versus others technique. The result shows that the classification can be achieved using simulation and real experiment.**

***Keywords*—odor; SVM; classification; TGS**

I. Introduction

The mechanisms of human olfactory system inspired the researchers to develop imitating noses (called as electronic noses). The inventory of these noses gives a lot of changes in life. The human works can be easier and more quickly due to the amazing help of these e-noses. They are applied in many areas for variety of applications, i.e., military as warfare agents [1]-[2]; agriculture for post harvest management [3]-[4]; food sectors for determining the red wines [5] or olive oil [6]; health in detecting the cancer [7] or wound inspection [8], and air quality monitoring either in indoor [9] or outdoor [10].

As human beings fresh air is a main need. Human can live without food and water for some hours but they will die quickly without the supply of air. Poisonous air suddenly occurs in the surrounding of human accidentally. Some of them have no smell, no color and no sound. Thus, unconsciously, the human inhale them. Air quality monitoring gives some benefits for human being [11]–[13]. It can prevent dangers and decrease the victims due to poisonous air.

Some of dangerous pollutants exposure, such as CO, NO_2, SO_2, O_3 can impair cognitive function, degrade function in producing the heredity, influence social behavior [14]. Some negative syndromes also appear due to those pollutants, such as sick building syndrome (SBS), toxic mold syndrome, and multiple chemical sensitivity [15]. Therefore, it is better to protect our body from them. The National Ambient Air Quality Standard (http:www.epa.gov/air/criteria.html) established the limit exposure of some dangerous gases.

Some researchers nowadays tried to minimize the dangers of the dangerous pollutant. They made researches on localizing the odor [16], fire fighter assistance [17], gas leak detection [18], and classify the odor [19]. Odor classifying was widely investigated for many purposes with different point of view [20]. The classification of odor using simple equipment is really useful for industry and also domestic application [21]. It can be easily substitute the role of human, for instance in classifying odor in perfumes and in food industries [22], [23]. Using electronic nose that can classify the type of odor precisely can increase the performance of industrial production. For environment monitoring, classifying odor can also give advantage human. Using a system that is able to classify the odor can give advantage to the human, such as giving the information and a warning to the human when the odor that the human inhales is danger and poisonous.

In classifying and identifying the odor, previous researchers used ANN [24] and SVM algorithm [25], [26], [27], [28], [29]. The classification of odor substances can be achieved using NN, however, it needs more time in order to get convergence condition. It is contrary to SVM. In SVM, the convergences can be got more quickly than NN. It's due to the data that should be generated will be divided into some parts by the SVM. It can separate the datasets by searching for an optimal separating hyper-plane between them [30].

SVM can work using a restricted amount of training data. By exploiting optimal hyper-plane, the largest distance or margin from the separating hyper-plane to the closest training vector can be provided. The maximizing of that linear discriminant margin can minimize the generalization errors. Thus, better generalization with high probability can be got [31]. These facts are contradictive with NN that cannot run well using a limited training data. Therefore, SVM are widely used in overcoming pattern recognizing problems [25], [26], [27], [28], [29]. The success of SVM application has been proved by Marcela [32] who compared 3 classification techniques, i.e. 1. Statistical Classifier (LDA); 2. Multi Layer Perceptron (MLP) using NN; and 3. Support Vector Machine (SVM). Marcela stated that SVM was better than two other classification techniques. Weizhen Lu also stated that SVM was better than NN [33]. There were three reasons introduced by Weizhen in order to state SVM power, such as: 1. It contains less number of free parameters than the conventional NN models; 2. SVM method provides better predicting results than neural network does; 3. The typical drawbacks of neural network models, e.g., "over-fitting" training and local minima, can be eliminated in SVM method. These 3 reasons were proved using research in [33]. In this research, 3 gas sources were investigated, namely: ethanol, methanol, and acetone. These 3 gases were introduced to electronic nose in order to analyze the robustness of the robots in determining what type of gas that it has sensed.

II. Odor classification

In determining the success of odor classification, some aspects should be paid attentions, such as, the sensors and machine learning. A brief explanation of them is given as follows:

A. Electronic Nose

Electronic nose consists of 3 major parts, i.e., 1. Sensor Arrays, 2. Signal Transducer, and 3. Pattern Recognition. 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 [34]. The similarity of human olfactory system and electronic nose is described in Fig. 1. Support Vector Machine

Support Vector Machine (SVM) is one of learning machines. It was first introduced by Vapnik in 1979 [35] The method in this techique uses a hyper-plane that separates the dataset. Zhu and Blumberg, 2002 in [36] classified the terms used in SVM hyper-plane into 2 categories, i.e. optimal and learning. Optimal means that the separation hyper-plane obtained can minimize the misclassifications of training data, while learning means the iterative process of finding the classifier.

For getting optimal hyper-plane, assume that a training data $(x_1, y_1), \dots, (x_l, y_l), x \in R^n, y \in \{+1, -1\}$ can be separated by a hyper-plane as in equation (1):

$$(w.x) - b = 0 \qquad (1)$$

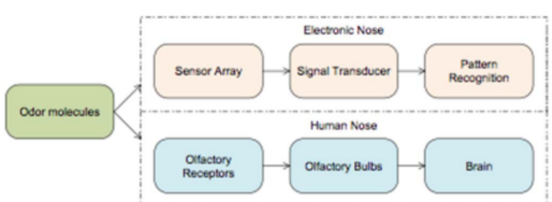


Fig. 1. Human olfactory system versus electronic nose

See Fig. 2 for the hyper-plane position. In this case, the set of vectors is separated by optimal hyper-plane (or maximal margin of hyper-plane) if it is separated without error and the distance between the closest vector to the hyper-plane is maximal [35].

Use these 2 conditions in order to describe the separating hyper-plane:

$$(w - x_i) - b \geq 1 \quad \text{if } y_i = 1$$

and

$$(w - x_i) - b \leq -1 \quad \text{if } \; y_i = -1.$$

The compact notation for those inequalities is:

$$y_i[(w - x_i) - b \geq 1], \quad i = 1, \dots, l \qquad (2)$$

For optimal solution, some non linear problems in SVM can be solved using α value of Lagrange multiplier as stated by S. Lee [37], as follow:

$$Q(\alpha) = \sum_{i=1}^{N} \alpha_k - \frac{1}{2} \sum_{i=1}^{N} \sum_{j=1}^{N} \alpha_i \alpha_j y_i y_j K\langle x_i, x_j \rangle \qquad (3)$$

If it subjects to the constraints, the equation will be:

$$\sum_{i=1}^{N} \alpha_i y_i = 0$$

$$\text{where: } \; 0 \leq \alpha_i \leq C, i = 1, \dots, l$$

In non linear case, the function of $K\langle x_i, x_j \rangle$ can be solved by using kernels, such as polynomial, gaussian, radial basis function, and multi layer perceptron [37]. The solution of equation (3), will be :

$$\alpha^* = (\alpha_1, \dots, \alpha_i)^T \qquad (4)$$

The decision function can be counted using equation [38]:

$$f(x) = sign(\textstyle\sum_{i \in SV} \alpha_i \, y_i K(x_i, x) + \alpha_i y_i \lambda^2) \qquad (5)$$

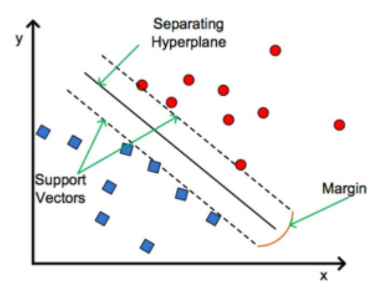


Fig. 2. Hyperplane

where α_i is the support vector value, x_i for the data that has correlation to support vector, x as testing sample data, y as target class and λ as constant.

Most of odor classification that used static sensors extracted the information of the sensor's steady state response. Thus, the input of the SVM algorithm is the comparison between the baseline and the steady state [39]. Amy Loutfi in [39] tried another method in classifying the odor. The training data of the SVM was got from the transient response of the sensors, not from the steady state response. Discrete Wave Transform (DWT) was used to improve the classification of the odor. DWT has function to decompose input signals of the training algorithm. The wavelett coefficients of the DWT were then inputted to the Principle Component analysis (PCA) to be extracted and finally classified by the SVM.

Marco Trincavelli in [40] tried to make a classification of odor in continuous monitoring application. The transient responses of the signals were used. The signals were collected using three-phase sampling technique, namely rise, steady state, and decay. The sensors mounted on the robot got samples continuously altough the robot was not in the stopping condition. However, the steaady state phase could not be reached although the speed of the robot in moving from one place to another place was constant. That is all was due to sensors was not exposed to the sources for long enough time. Therefore, Marco proposed a segmentation method to identify each phases of the output of the sensors. This method became one of important researches in reaching reliable e-nose application.

Alexander Vergara in [41] introduced Inhibitory Support Vector Machine (ISVM) to train a sensor array and evaluate its ability in detecting and indentifying odor in complex environment. Vergara's proposed method was a valuable tool in guiding to a decision which training condition should be chosen. It also became an important basic in understanding the degradation of the sensor to the change of the environmental condition.

Frank Michael Schleif in [42] proposed Generative Topographic Mapping Through Time (GTM-TT) to overcome some limitation occur in classical classification methods such as high dimensionality characterization. To evaluate the robustness and sustainability of proposed technique, it was compared to 3 other different classical algorithms, i.e. SVM, NN (Nearest Neighbor), and RTK (Reservoir ComputingTime- series Kernel). However, The GTM-TT is still under evaluation and reserach. It still needed to be developed and analyzed.

In paper [43], the SVM was used to recognize the source in a complex environment. The odor localization in that research was done using visual aid. The SVM was used to make segmentation of color image. Then, the feature candidates got from SVM (color, shape, and orientation) were extracted so that the robot can move to search the target by analyzing the characteristic of the areas. Besides to be used in odor classification for plume tracking/tracing or plume finding, SVM was also used in plume declaration [43].

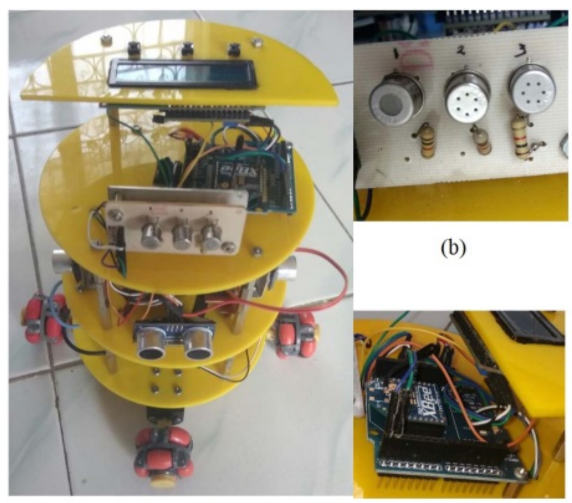
The sensor output will be different when it is applied in mobile robot. The movement of the robot will produce inconsistency of the collected data. Therefore, it needed a special method to manage instability of odor concentration. In this paper, a basic experiment to the classification of odor is introduced. Due to its complexity, in this paper, it only shows the simulation and the classification of gas using a static robot. For the next research, a mobile one will be considered.

III. Experimental Setup

A. Preparation

The first step in odor classification is to prepare the training data for the machine learning. A robot equipped with 3 odor sensors was set up (Fig. 3). The 3 sensors used were TGS 2600, TGS 2602, and TGS 2620. The block diagram process of the robot can be seen in Fig. 4 and Fig. 5.

The sources used were Ethanol, methanol, and acetone. These three sources are safer to be used in the real experiment. The array of sensors (TGS 2600, TGS 2602, and TGS 2620) sensed and detected the source and produced a signal response that formed a pattern. This pattern was used in the array sensors data processing. In this research, 2 controllers were used, namely: Arduino Mega and Raspberry. The use of raspberry was intended to process the classification in the robot itself, not using external processor, such as computer or other processors.



(b)

(a) (c)

Fig. 3. Odor classification robot (a) Physical robots (b) three TGS sensors arranged from left to right: TGS 2620, TGS 2600, and TGS 2602. (c) X-bee transmitter module.

From Fig. 4, it can be seen that the signal sensed by the sensor array was first sent to the Arduino Mega. The signal was then converted to digital signal in the arduino. The next, the digital signal was then sent to Raspberry. In this controller, the SVM process was conducted. The training data and testing were processed in this raspberry. An algorithm using one versus others technique was used (See Fig. 6) to identify and classify the gas. The process of the classification can be summarized in some steps, as follows:

1. **Training Data**
   a. Determine the number of classes in SVM process
   b. Map the data from input space to feature space using Kernel Radial Basis Function using the equation (6).

$$K(\vec{x},\vec{y}) = exp(-\gamma\gamma\|\vec{x}-\vec{y}\|^2) \quad (6)$$

   c. Determine support vector value $\alpha \neq 0$ by counting the value of α_1, α_2,... α_n (where n is the amount of training data) from quadrating programming in equation (3). The correlation data x_i that correlates to $\alpha \neq 0$ as support vector can be achieved by using this programming.

2. **Testing process**
   a. Determine the number of classes in SVM process
   b. Map the data from input space to feature space using Kernel Radial Basis Function using the equation (6)
   c. Count decision function using equation (5).

The data base (training data) used in this experiment was taken in indoor environment of 4 m x 9 m. The robot was run under controlled and conditioned environment. The temperature was kept between 27.5 ^{0}C - 30.5 ^{0}C and humidity 65 % - 75 %.

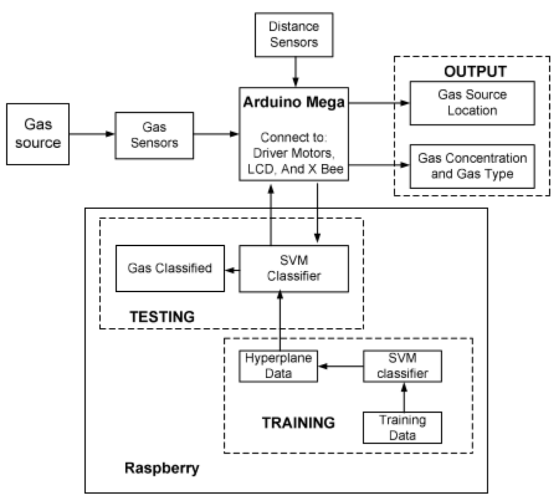


Fig. 4. Block Diagram Process

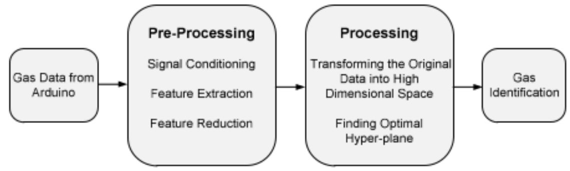


Fig. 5. Block diagram process in SVM

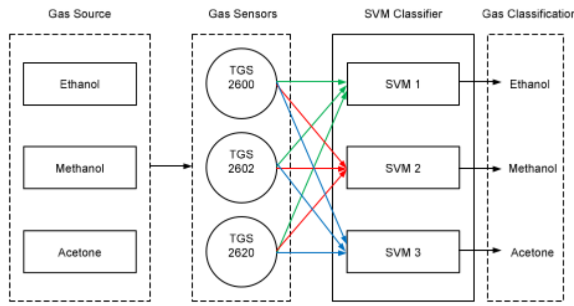


Fig. 6. One versus Other Technique

For the simulation and real experiment importance, at the beginning, the data training was got using these steps: The robot used as validation of the experiments was accomplished with wireless communication modules (X-bee communication). The transmitter was attached in the robot while the receiver was connected to the server. The data from the sensors can be easily monitored in the server. The choice of using X-bee communication was based on its superiorities (low cost, low power consumption, simple protocol, greater useful range and global implementation). It is suitable for this experiment due to the research used low data rate applications with limited battery power

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B. Data Prepocessing

The continuous data sent to the server was then sampled, mined and processed. The final output data was then supplied as the training data of the SVM. For the simulation process, the pattern recognition or the classification simulation was then processed using Matlab. For real experiment, the training data was supplied to raspberry. In this part, the SVM process followed the block diagram process in Fig. 5.

IV. Result and Discussion

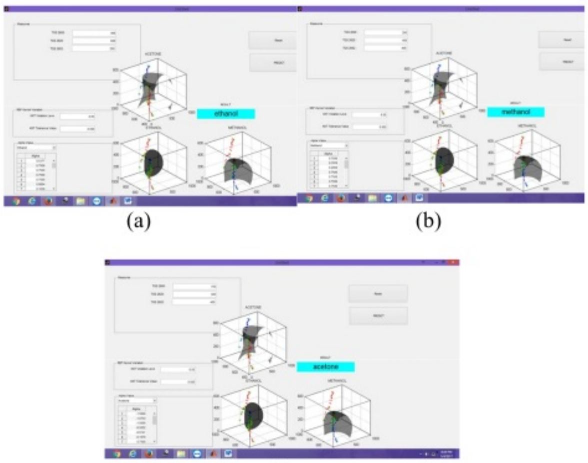
A. Training data

The data got from the real experiment in preparation process that was sampled, mined and processed as mentioned above was then supplied to the matlab to be simulated and raspberry for the real eksperiment. The data has been divided into two classes -1 and +1. See Sub Chapter III. A. point 1 for the detail.

B. *Classification in Simulation*

After the training data got, the next step was to construct the simulation. The simulation was done using GUI in matlab program. The experimental result was shown in Fig. 5. of some dangerous gases.

The simulation has a high percentage of success. From the experiment, it had more than 90% success (see Table II). Its success depends on the situation and condition of the environment to be tested. It is a must for the user to pay attention on the surrounding condition. It should be in the same condition with the training data prepared at the beginning.

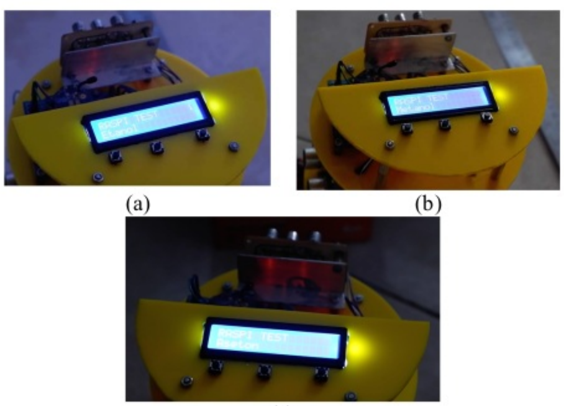


(a) (b) (c)

Fig. 7. Simulation of SVM when detected different sources (a) Ethanol (b) Methanol (c) Acetone

C. *Classification in Real Experiment*

For the real experiment, the data got can be seen in Fig. 8 and Table 2.



(a) (b) (c)

Fig. 8. Real experiment of SVM when detected different sources (a) Ethanol (b) Methanol (c) Acetone

TABLE I. SUCCESS RATE OF REAL EXPERIMENT

No.	Gas Source	Tested Output	Success Rate (%)
1.	Ethanol	Ethanol	95
2.	Methanol	Methanol	95
3.	Acetone	Acetone	90

V. CONCLUSION

The experiments on gas are really difficult. It is due to the gases are really sensitive. They can spread and dilute easily in the air. Therefore, the concentrate of the gas in one position will be different with other position although they are in the same room or area. The robustness of the gas sensor also affected the success of the experiment. It is better to be conditioned as already recommended by the data sheet of the sensors. For TGS series, especially TGS 26xx series, they should be conditioned for 7 days before they are used. When it was not conditioned in correct rules, the sensor will not work efficiently, some times the reading become false. Thus, the experiments will come to fail. The experiments done here was already successful. However, it is still far from the real one. Therefore, for the next experiments, we will try to conduct a real experiment using mobile robot, not static one..

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