Robotic Applications for Odor-Sensing Technology

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Abstract— **This paper presents a new application of the robotic s for odor-sensing technology. The amount of research in the field robotics application for odor-sensing technology has grown substantially. This work can be broadly categorized into two groups: artificial odor discrimination system and odor source localization by autonomous mobile sensing system. Artificial odor discrimination system can be used for automated detection and classification of aromas, vapors and gases. And odor source localization can be used for various attractive applications, including the search for toxic gas leak, the fire origin at its initial stage, and other potential applications. The robotic applications for odor-sensing technology discussed include those based on theory, implementation and experiment.**

Keywords - odor-sensing technology; artificial odor discrimination system; odor source localization

I. INTRODUCTION

The amount of research in the field robotics application for odor-sensing technology has grown substantially. This work can be broadly categorized into two groups: artificial odor discrimination system and odor source localization by autonomous mobile sensing system. Artificial odor discrimination system is being developed for automated detection and classification of aromas, vapors and gases. Conventionally, odors are discriminated by very trained persons based on their human sensory system. These human sensory tests have been used to evaluate odors in a variety of industrial fields, such as food and beverage industries, cosmetics industries and in the environment tests. However, the human sensory test is unavoidably affected by the state of the health and mood of the inspector, resulting in discrepancies among panelists. The artificial odor discrimination system is constructed to overcome the limitation of the already existing sensory test systems. This system is composed of an arrayed chemical sensing system and a pattern recognition system [1-3].

The second primary area of robotics application for odor-sensing technology is odor source localization by autonomous mobile sensing system. Odor source localization can be used for various attractive applications, including the search for toxic gas leak, the fire origin at its initial stage, and other potential applications [4-7].

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The primary difference between artificial odor discrimination system and the odor source localization is in implementation phase for laboratory condition and real world environment. The odor discrimination system have been widely used under laboratory condition, but so far there have been few applications on odor source localization by autonomous mobile sensing system in real world environment. The main problem to implement odor source localization with using gas sensor in real world environments is that the distribution of odorant molecules is dominated usually by turbulence rather than diffusion, which is known to be considerably slower transport mechanism for gases in general. The other problem is unstable wind in real world environment. When odor distribution was very complex and the wind direction was not stable, the robot will be haphazard and desultory [4-7].

Authors have been developing an artificial odor discrimination system [1-3] and odor source localization system [7] for several years. In this paper, we focus on the implementation in real robot, and describe our progress.

II. THE ARTIFICIAL ODOR DISCRIMINATION SYSTEM

A. The System Design Diagram

The artificial odor discrimination system consists of three parts namely: a sensory system, an electronic system and a neural network system. Sensory system and electronic system are used to measure the frequency declines of odor identification while neural network system is used to recognize and classify the odor that will be detected.

Figure 1 shows the detail parts of artificial odor discrimination system based on the function and the process. In this figure sensory sub-system and frequency counter sub-system components become the sensing system and neural network component become the automated pattern recognition system. This combination of broadly tuned sensors coupled with sophisticated information processing makes the artificial odor discrimination system powerful.

B. Sensory and Measurement System

The schematic diagram of the measurement system is depicted in Figure 2. The odor discrimination system consists of a quartz crystal microbalance as a sensor, and a frequency

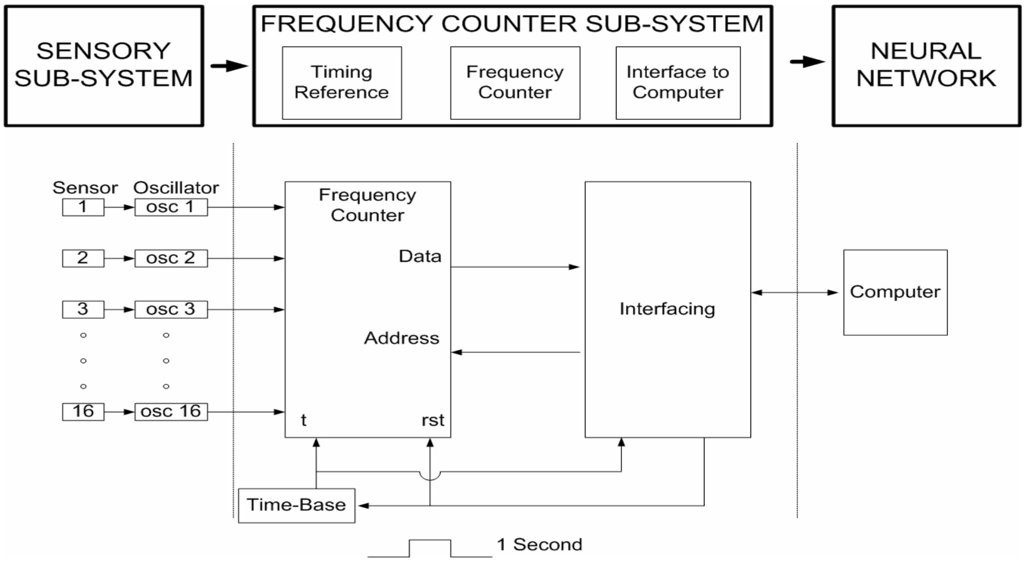

Fig. 1 The Artificial Odor Discrimination System Diagram

counter for measuring the shifted frequency of the sensor as it absorbed the odorant molecule, and a computer to perform neural network analysis of the data and determined the odorant category.

A chamber made of Corning Glass which has a volume of 1300 ml is placed in a temperature-controlled bath. Sixteen AT cut quartz crystal microbalance sensors and its oscillation circuits are attached on the inner and outer sides of the chamber lid, respectively. The water bath with the chamber and its oscillation circuits is placed in a heat-insulated box to keep the temperature at 27^0C. Each sensor is constructed by applying a sensitive membrane on the two surfaces of 20 MHz quartz resonator crystal. After a sample is injected and evaporated in the chamber, the frequency shift is measured at the equilibrium point. Then the next sample is repeatedly injected in the same manner. When the odorant molecules are adsorbed onto the membrane, the characteristic-frequency of the sensor will reduce to a certain degree, and will recover to its characteristics-frequency after the absorption procedure. This phenomenon is called the mass-loading effect [9].

Since the shifted frequency is proportional to the total mass of the adsorbed odorant molecules, it is possible to use this mechanism as the fingerprint of the odor concern. To increase the accuracy of the recognition system, various types of membrane-coated sensors are necessary, which is arranged as an arrayed sensor. The shift of the frequency is given by [9]:

$$\Delta F = -2{,}3 \text{ x } 10^{6} \text{ x } F^2 \text{ x } \frac{\Delta M}{A} \qquad (1)$$

where F denotes the characteristics frequency (MHz), ΔM the total mass of the absorbed molecule (g) and A the electrode area (cm^2).

The experimental set-up for determining the category of odor used two small pumps as can be seen in Figure 2, for delivering the fresh air and the aroma-contained air. Those pumps are controlled by microcomputer through magnetic relay. The process begin by flowing a fresh air to the glass chamber and after the frequency shift is recovered to its standard values, the aroma-contained air is delivered to the glass chamber. The frequency shift by this aroma is then be measured and transferred to the computer.

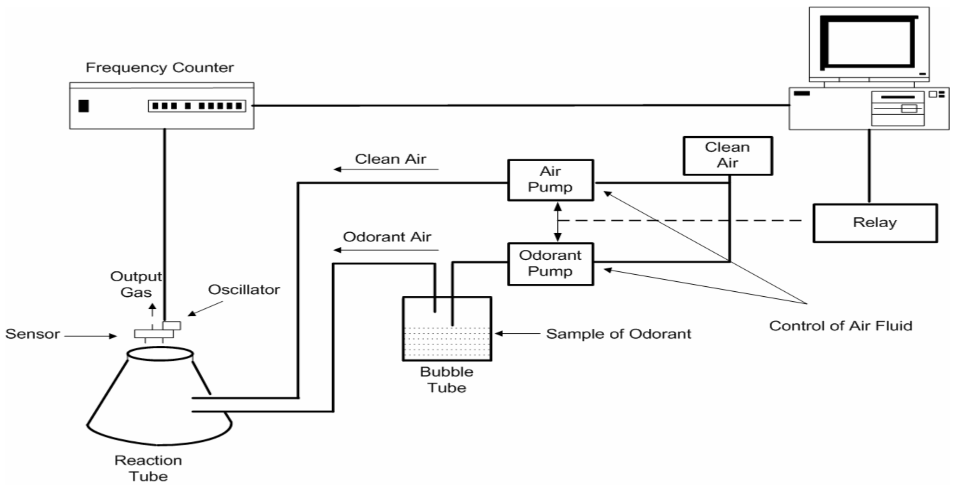

Figure 2. Schematic diagram of the measurement system

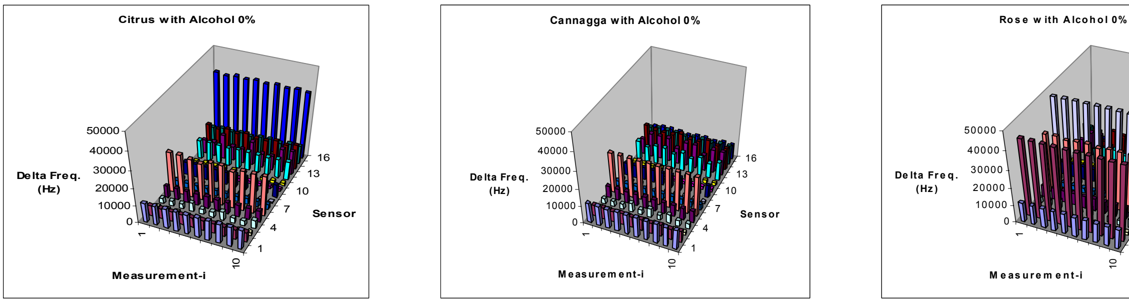

Figure 3. Signature or pattern characteristic from CiA0% (Citrus with Alcohol 0%), CnA0% (Cannagga with Alcohol 0%), and RoA0% (Rose with Alcohol 0 %)

Sixteen chemical vapors were being used as sensor in the experiment. Each chemical vapor presented to the sensor array produces a signature or pattern characteristic of the vapor. By presenting many different chemicals to the sensor array, a database of signatures can be built up. This database of labeled signatures is used to train the pattern recognition system. The purpose of the training process is to configure the recognition system in order to produce a unique classification of a chemical input, so that an automated identification can be implemented. Figure 3 is the database of signature from CiA0% (Citrus with Alcohol 0%), CnA0% (Cannagga with Alcohol 0%), and RoA0% (Rose with Alcohol 0 %). The patterns were shown overlapping one another for those odors; consequently, it was very difficult to discriminate between the odors in conventional way.

C. Experiment Design and Its Result

The output pattern recognition methods that are applied in the artificial odor discrimination are cluster analysis, discrimination of function analysis and neural network. The neural network method is generally used because it has easier recognizing process algorithm and better odor recognizing result than the other methods [8].

The experiments are designed to elaborate the capability of the developed odor discrimination system to recognize and determine mixture odors. Three types of neural classifiers, i.e. Back Propagation neural system, Probabilistic neural networks and Fuzzy-LVQ [10] are conducted and compared to recognize the odor mixture.

Two groups of odor mixture are prepared such as depicted in Table 1 and Table 2, respectively. In the two-mixture of odors, each odor-mixture is prepared by mixing a 50% of odor and 50% of alcohol with various gradient concentrations from 0% to 70%. While in three-mixture of odors, each odor-mixture is prepared by mixing a 33.3%of odor#1, 33.3% of odor#2 and 33.3% of alcohol with various gradient concentrations ranging from 0% to 70%

Results of experiment on recognizing various odor-mixture (Sample I and Sample II) are depicted in Table 3 and Table 4, respectively. Table 3 showed that the recognition rate of backpropagation to determine two-mixture of odors is about *89.97%* in average. This recognition rate is high enough, even though it is still lower than that of PNN and FLVQ which show recognition rate of about *97.90%* and *95.33%,* respectively. Experimental results also shown that the average recognition rates by all of the neural classifiers to each mixture odors are nearly the same. However, the recognition rate of Citrus+Alcohol (with various gradient concentrations) mixture is rather lower compare with that of two other mixtures of odors.

Table 4 showed the recognition rates of using various neural classifiers to determine and recognize three-mixture of odors. It is shown that the recognition rate of using backpropagation to this 3-mixture of odors *(57.33%)* is lower than when it is use to recognize two-mixture of odors *(90%),* showing the difficulties of recognizing three-mixture of odors. PNN and FLVQ however, showed higher recognition rate of about *71.73%* and *79.00%,* respectively. Even PNN has lost its recognition capability *(< 75%),* the recognition capability of the FLVQ can be considered to be enough to recognize three-mixture of odors properly, even though it still necessary to improve its performance.

Table 1. Sample of two mixture odor with various gradient alcohol concentrations

No	Sample I	
	Type of odor-mixture	***Odor-mixture with various gradient alcohol concentration***
1	**CiAlch** Citrus based Alcohol	CiA0%, CiA15%, CiA25%,
		CiA35%, CiA45%, CiA70%,
2	**CnAlch** Cannangga based Alcohol	CnA0%, CnA15%, CnA25%,
		CnA35%, CnA45%, CnA70%
3	**RoAlch** Rose based Alcohol	RoA0%, RoA15%, RoA25%
		RoA35%, RoA45%, RoA70%

Table 2. Sample of three mixture odor with various gradient alcohol concentrations

No	Sample II	
	Type of odor-mixture	***Odor-mixture with various gradient alcohol concentration***
1	**CiCnAlch** Citrus-Cannagga based Alcohol	CiCnA0%, CiCnA15%, CiCnA25%,
		CiCnA35%, CiCnA45%, CiCnA70%,
2	**CiRoAlch** Citrus-Rose based Alcohol	CiRoA0%, CiRo15%, CiRoA25%,
		CiRoA35%, CiRoA45%, CiRoA70%
3	**CnRoAlch** Cannagga based Alcohol	CnRoA0%, CnRoA15%, CnRoA25%
		CnRoA35%, CnRoA45%, CnRoA70%

Table 3. Recognition rate of the odor recognition system using various neural networks as the pattern calssifier for two-mixture of odors

Sample I	Neural Networks as the Classifier			
	BP	***PNN***	***FLVQ***	***Average***
CiAlch	76.80%	93.70%	94.00%	88.17%
CnAlch	99.00%	100.00%	96.00%	98.33%
RoAlch	94.10%	100.00%	97.00%	96.70%
Average	89.97%	97.90%	93.33%	

Table 4. Recognition rate of the odor recognition system using various neural networks as the pattern calssifier for three-mixture of odors

Sample II	Neural Networks as the Classifier			
	BP	*PNN*	*FLVQ*	*Average*
CiCnAlch	50.00%	70.20%	76.00%	65.40%
CiRoAlch	56.00%	72.00%	85.00%	74.15%
CnRoAlch	66.00%	73.00%	76.00%	71.67%
Average	57.33%	71.73%	79.00%	

To increase further the recognition rate of the developed recognition system to recognize three-mixture of odors, more rigorous study about the application of genetic algorithms on its optimization of fuzzy-neural network is under consideration.

III. THE ODOR SOURCE LOCALIZATION

A. Problem and Challenge

Although odor source localization can be used for various attractive and promising applications, so far there have been few applications on odor source localization by autonomous mobile sensing system in real world environment. The main problem to implement odor source localization with using gas sensor in real world environments is that the distribution of odorant molecules is dominated usually by turbulence rather than diffusion, which is known to be considerably slower transport mechanism for gases in general. The other problem is unstable wind in real world environment.

Researchers try to solve odor source localization problem in real environment. Ishida [6] have introduced multiphase algorithm concept to cope condition when robot find behavior in different situations. Hayes [5] has introduced multiple robot coordination concepts but still in stable odor distribution. In fact there are no real implementation on a mobile robot that works in true real environment to our knowledge.

B. Task Description

Before one begins the design process to implement odor source localization in real robot, the task to be accomplished must be specified exactly. Following a suggestion of Hayes et al. [5], the problem of gas source localization in an enclosed 2D area can be broken down into three subtasks: plume finding, plume traversal and source declaration. Figure 4 until figure 6 shows the detail explanation tasks of the odor source localization in stable wind direction environment.

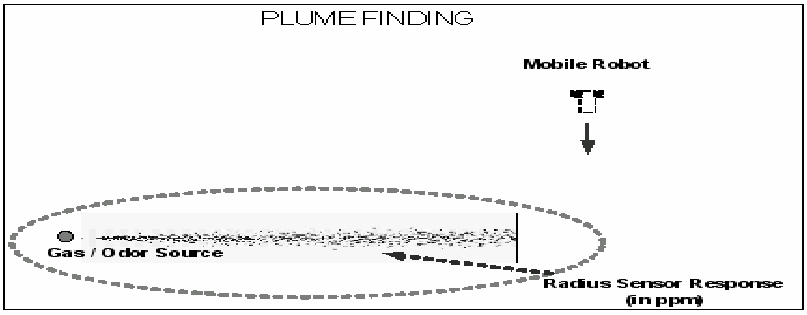

Figure 4. Plume Finding: getting into contact with the odor.

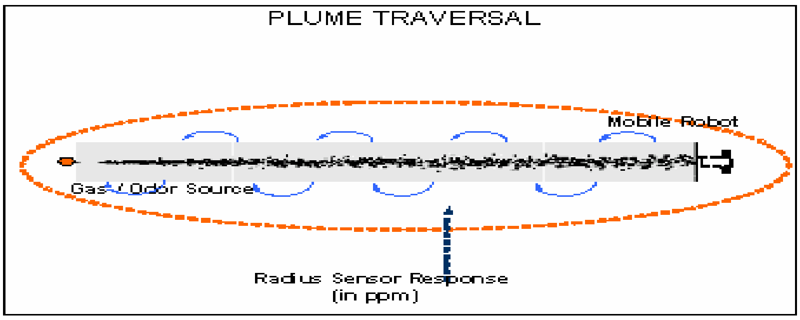

Figure 5. Plume Traversal: following the odor plume to its source

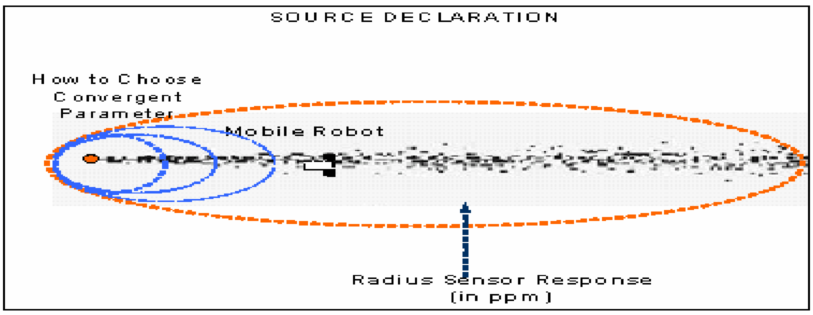

Figure 6. Source Declaration: determining the source is in the immediate vicinity or not.

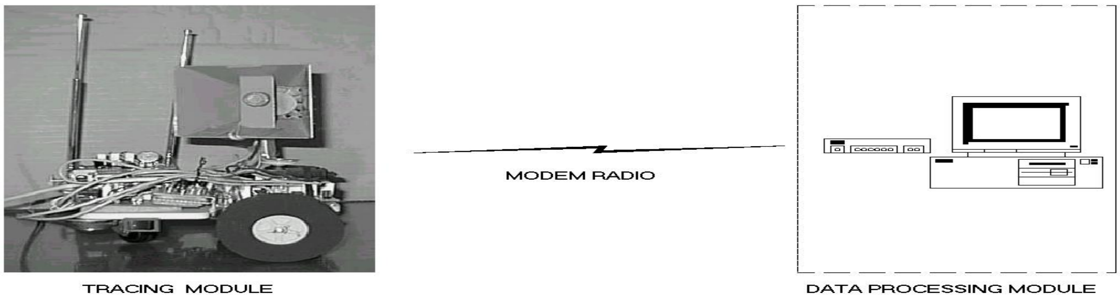

Figure 7. Real robot of odor source localization system.

In the plume finding, robot can use random search or wind navigation utilization search, until getting into contact with the odor. If environment had stable wind direction, robot can use wind direction information to minimize the searching time. Usually when the wind is stable, wind direction and odor distribution gradient vector have same direction as the result robot will move crossing the wind direction and find the gradient of odor distribution. The concept of plume finding task can be seen in Figure 4.

After getting contact with the odor, the second task is plume traversal, following the cues determined from the sensed gas distribution (and eventually using other sensor modalities) towards the source. This task requires more specialized behavior, both to progress in the direction of the source and to maintain consistent contact with the plume. The concept of plume traversal task can be seen in Figure 5.

The last task is source declaration, is determining with certainty that the gas source has been found. Source declaration does not necessarily have to be done using odor information, as typically odor sources can be sensed via other modalities from short range, the important factor is how choosing the convergent parameter. The concept of source declaration task can be seen in Figure 6.

C. Implementation and Experiment

The real robots implementation and experiment will focus on the plume traversal subtask with stable gradient concentration for experimental limitation and simplicity reason. The beginning of implementation, our robot consists of three parts, namely: tracking module system, data processing module system and modem radio system. Tracking module system can be used to collect data from environment and to move approaching the odor / gas source. Data processing module can be used for processing and storing the data. Tracking and data processing modules communicate using modem radio. Figure 7 shows the detail explanation of real robot.

Our robot used TGS-822 gas sensor for alcohol and volatile vapor detection from Figaro Inc. The sensing element of TGS-822 gas sensors is a tin dioxide (SnO2) semiconductor that has low conductivity in clean air. In the presence of a detectable gas, the sensor's conductivity increases depending on the gas concentration in the air. A simple electrical circuit can convert the change in conductivity to an output signal which corresponds to the gas concentration.

The TGS-822 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.

The processing algorithm of robot to collect the data can be seen in Figure 8. At the first step, the TGS-822 sensor will be rotated 180^o and divided in 28 points to gather the data. The raw data will be changed to the mathematic number between 0-255 by Analog-Digital Converter. The second step, data are collected and sent to data processing module after demodulation by modem radio and then enter through serial device in computer. After that computer will save the 28 points of data and compare the biggest value among alcohol concentrate. The Third step, from the 28 points of data experiment and for simplicity reason, the direction will be divided in 5 rotations area. After choosing among 5 directions PC will instruct motor to rotate the gases tracker module in desirable direction. The last step, robot will go to close odor source with iterative procedure.

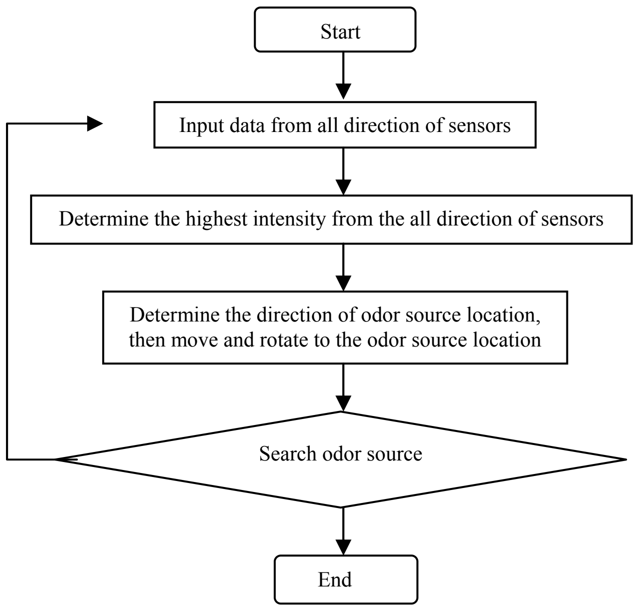

Figure 8. Flowchart odor source localization system to find the gas source.

The first experiment of artificial gas or odor localization system is to find the odor source location with fixed distance (40 cm). Before doing the system treatment, it is necessary to know the successful level of odor tracker to identify the validate direction of odor source. The training of each source point in this experiment is taken 20 times continually. The system will scan the odor source that is located in front of gas tracker module in five directions toward clockwise; -90^0(left side), -45^0(left side), 0^0(straight ahead), $+45^0$ (right side) and $+90^0$(right side). The result of this experiment can be seen in Figure 9.

The second experiment is to test the performance of the system with various distance. The purpose of the experiment are to know the number of step of the robot to complete plume traversal task and to know the maximum distance which robot still can reach the odor source. The result of this experiment can be seen in Figure 10.

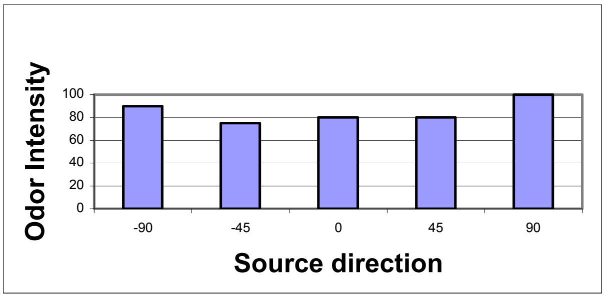

Figure 9. The percentage of successful level of the sensor to identify the validate direction in the distance 40 cm.

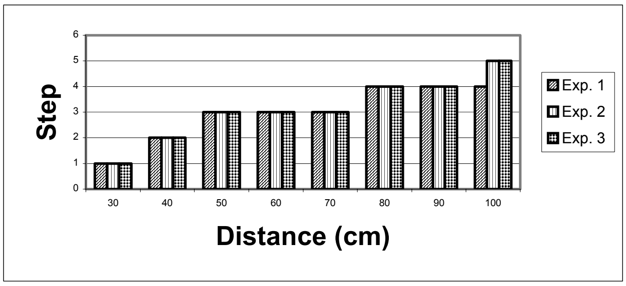

Figure 10. The step that is need by tracking module to search the odor source with the difference distance.

D. Discussion and Future Work

Our odor source localization system can work only in indoor environment and in stable odor concentration. There are relatively few system in which the relationship between fluid dynamic, odor plumes and robotic system in real natural environment. In real natural environment the robot will find variety of situation. Future work should use diverse algorithm to cover problem in variety of situation and also should study various aspect of the mechanisms underlying animal behavior have been transferred to robot through the interaction between biology and engineering [5] [11][12].

In our future work, we will use Micro Autonomous Robotic System (MARS) [13][14] combine with multiphase algorithm and multiple mobile robot concept. As the result Our odor source localization system by autonomous mobile sensing system can use for various attractive applications, including the search for toxic gas leak, the fire origin at its initial stage, and other potential applications in real natural environment [4-7][11][12].

IV. CONCLUSION

It is clearly apparent from this paper that robotic applications for odor-sensing, artificial odor discrimination system and odor source localization system still at an early stage of development. Especially in odor source localization system there are many important applications for this kind of capability, but current systems have not been developed to an application stage.

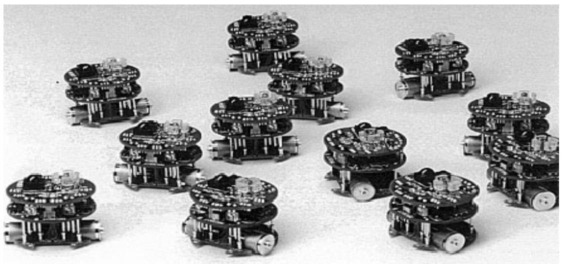

Figure 11. Micro Autonomous Robotic System (MARS)

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