A Particle Swarm-based Mobile Sensor Network for Odor Source Localization in a Dynamic Environment

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Abstract. This paper addresses the problem of odor source localization in a dynamic environment, which means the odor distribution is changing over time. Modification Particle Swarm Optimization is a well-known algorithm, which can continuously track a changing optimum over time. PSO can be improved or adapted by incorporating the change detection and responding mechanisms for solving dynamic problems. Charge PSO, which is another extension of the PSO has also been applied to solve dynamic problem. Odor source localization is an interesting application in dynamic problem. We will adopt two types of PSO modification concepts to develop a new algorithm in order to control autonomous vehicles. Before applying the algorithm in a real implementation, some important hardware parameters must be considered. Firstly, to reduce the possibility of robots leaving the search space it is needed to limit the value of vector velocity. The value of vector velocity can be clamped to the range [$-V_{max}$, V_{max}]; in our case for the MK-01 Robot, the maximum velocity is 0.05 m/s. Secondly, in PSO algorithm standard there is no collision avoidance mechanism. To avoid the collision among robot we add some collision avoidance functions. Finally, we also add some sensor noise, delay and threshold value to model the sensor response. Then we develop odor localization algorithm, and simulations to show that the new approach can solve such a kind of dynamic environment problem.

Keywords. Particle Swarm Optimization, Odor Source Localization, Dynamic Environment

1. Introduction

The amount of research in the field of robotics application for odor-sensing technology has grown substantially. This work can be broadly categorized into two groups namely artificial odor discrimination system [1,2], and odor source localization by autonomous mobile sensing systems [3]. The artificial odor discrimination system has been developed for automated detection and classification of aromas, vapors and gases. The second prime area of robotics applications for odor-sensing technology is odor source localization. Odor source localization can be used for various attractive applications, including the search for detection of toxic gas leak and the fire origin at its initial stage, etc. This paper will address the second area of applications.

There have been several reported implementations of odor source localization by autonomous mobile sensing system. Most work on chemical sensing with mobile robots assume an experimental setup that minimizes the influence of turbulent transport by either minimizing the source-to-sensor distance in trail following [4,5] or by assuming a strong unidirectional air stream in the environment [6-9], including our previous work [10]. However, not much attention has been paid to the natural environment problem.

There has been no real implementation on a mobile robot that works in the natural environment to the best of our knowledge. The main problem in implementing odor source localization using a gas sensor in real world environments is that the distribution of the odorant molecules is usually dominated by turbulence rather than diffusion, the latter of which is known to be a considerably slower transport mechanism for gases in general. The other problem is the influence of unstable wind. When odor distribution is very complex and the wind direction is not stable, the robot will be haphazard and desultory [3].

This paper focuses on our new approach that exploits particle swarm optimization with multiple robots to solve odor source localization in natural environment where the odor distribution will change over time. Particle Swarm Optimization (PSO) simulates behaviors of bird flocking. Suppose the following scenario: a group of birds is randomly searching food in an area. There is only one piece of food in the area being searched. Not all of the birds know where the food is. However, they know how far the food in each iteration. So what is the best strategy to find the food? The effective approach is to follow the bird, which is nearest to the food. PSO learned from the scenario and applied it to solve the optimization problems [9]. However, the main problem with standard PSO used for dynamic optimization problems appears to be that PSO eventually will converge to an optimum and thereby looses the diversity necessary for efficiently exploring the search space and consequently the ability to adapt to a change in the environment when such a change occurs.

Two ways of improving PSO to solve this problem will be developed. Firstly, PSO is run in standard fashion, but when change in the environment has been detected, explicit actions are taken to increase diversity and thus to facilitate the shift to the new optimum. Therefore, PSO can be improved or adapted by incorporating change detecting and responding mechanisms for solving dynamic problems [12,13]. Secondly, multiple populations are used, some to track known local optima, some to search for a new optima. Two types of robot swarms, neutral and charged robots, will be used for solving the dynamic problem [14]. Odor source localization is an interesting dynamic problem application. We will adopt these two types of PSO modification concepts as described above to develop a new algorithm to control autonomous vehicles. These two types of PSO then will be compared for solving odor source localization in a dynamic environment.

2. Motivation

From early 1990 we developed real single mobile robot for solving odor source localization in natural environment. And also we developed simulation tool to implement several of sophisticated algorithm which we adopt from biological inspiration. In fact our system only can solve odor source localization with many simplicity parameters, like, stable wind and indoor environment [3, 10].

In the case of using mobile robots and multiple sensory modalities (e.g., odometry, anemometry, olfaction), we should carefully consider the feasibility of the hardware [15]. PSO, which incorporates change detecting and responding mechanisms, can be implemented with a simple algorithm in actual hardware.

Charged PSO, which employs two types of robots, neutral and charged robots, can also be implemented with a simple algorithm. With multiple populations, we can maintain the diversity of swarm particles. Applying a notion of electric potential field, charged swarm particle is introduced to make a balance of diversity. The potential field method is widely used in autonomous mobile robot path planning due to its elegant mathematical analysis and simplicity. The goal of this model is to have a number of sub-populations explore the best local optima. For this purpose, a part of the population is split off when a local optimum is discovered, and remains close to the optimum for further exploration. The remainder of the population continues to search for new local optima, and the process is repeated until better solutions are found. While the neutral swarm particles continue to optimize, the surrounding charged swarm particles maintain enough diversity to cope with dynamic changes in location of the covered peaks.

Evaluation on solving odor source localization problem in dynamic environment requires hardware and software platforms [16]. During the initial design stages, software evaluation is preferred, since such tools allow competing strategies to be evaluated under identical conditions for various environmental scenario. This paper presents a simulation implementation that addresses the tradeoffs between computational efficiency and inclusion of realistic hardware parameters.

3. Particle Swarm Optimization Frame Work

Recently, evolutionary techniques such as PSO have been applied to dynamic problem [11-14]. PSO can be improved or adapted by incorporating change detecting and responding mechanisms [12,13] for solving dynamic problem. CPSO, which is another extension of PSO, has also been applied to solve dynamic problem [14]. We will adopt concepts from modification two type of PSO as described above to develop a new algorithm to control autonomous vehicles.

3.1 Particle Swarm and Robot Interactions

A more detailed interaction of robot with Particle Swarm Optimization algorithm will be described as follows. A population of robots is initialized with certain positions and velocities and a function (plume distribution) is evaluated, using the robot's positional coordinates as input values. Positions and velocities are adjusted and the function evaluated with the new coordinates at each time step. When a robot discovers a pattern that is better than any it has found previously, it stores the coordinates in a vector P_i. The difference between P_i (the best point found by i so far) and the individual's current position is stochastically added to the current velocity, causing the trajectory to oscillate around that point. The stochastically weighted differences among the population's best position P_g and the individual's current position are also added to its velocity, adjusting it for the next time step. These adjustments to the robot's movement through the space cause it to search around the two best positions.

The values of element in P_g (concentration gas and position of robot) are determined by comparing the best performances of all the members of population, defined by indexes of other population members and assigning the best performer's index to the variable g. Thus, P_g represents the best position found by all member of population. Ad-hoc wireless network and Global Position System are assumed to be equipped among all robots. Via the ad-hoc network, each robot can collect the gas concentration data and choose the best one. Then the position of the robot can be determined by GPS system.

The PSO model is described as following:

$$V_i^{n+1} = \chi\left\lfloor V_i^n + c_1.rand().(p_i^n - x_i^n) + c_2.Rand().(p_g^n - x_i^n)\right\rfloor \quad (1)$$

$$x_i^{n+1} = x_i^n + V_i^{n+1} \quad (2)$$

After finding the two best values, the particle updates its velocity and positions with eq. (1) and (2). Let X_i and V_i denote position and velocity vector of the i-th particle at the iteration time n (n=1,2...). Also p_i and p_g are defined as the local best and the global best respectively as stated above. Rand () and rand () are the random functions returning a value between (0,1). Coefficient χ is constriction factor, which is supposed to take less than 1. Also coefficient c_1 and c_2 are learning parameters, which are supposed to be $c_1 = c_2 = 2$. All of the parameters are referred to [11, 12, 13], which was the best of PSO parameters in common optimization problem.

In the dynamic environment the standard PSO cannot solve the problem [11]. In order to solve the dynamic problem, PSO has to be improved or adapted by incorporating change detecting and responding mechanisms [12, 13]. Detection function is used for monitoring the global best information. If it has not changed for certain number of iterations, there supposed to be a possible optimum change. After the detection of environment changes, there must be an effective strategy to respond to a wide variety of changes. However, if the whole population of robot has already converged to a small area, it might not be easy to jump out to follow the changes. Therefore, we investigate the spreading response when a change is detected. All robots will spread at a certain step to jump out to follow the changes, for simplicity reason [12, 13].

3.2 Multi Swarm Robot Interaction

With the charged swarm robots we add repulsion function to make balancing diversity (like potential field idea). This keeps robots from gathering at a small area. The charged swarm robot will enable to explore different regions of the search space by different swarm. Charged swarm robots are adopted from the concept of Coulomb's law.

Figure 1 shows the repulsion function for charged swarm robots. Additional avoidance is only between pairs of robots that have non-zero charge Q (charged robot), and the radius of the avoidance was adopted from Coulomb's law, like in the shell $r_{core} \le r \le r_{perc.}$ At separations less than the core radius r_{core}, the repulsion is fixed at the value at the core radius, and there is no avoidance for separations beyond the perception limit of each robot r_{perc}.

$$\vec{a}_i = \Sigma a_{i,p} \quad \rightarrow \text{Summation of repulsive force}$$

$$a_{i,p} = \begin{cases} \dfrac{Q_i . Q_p}{\left|x_i - x_p\right|^3}(x_i - x_p) \ldots r_{core} < \left|x_i - x_p\right| < r_{perc} & \text{"Region} - 2\text{"} \\ \dfrac{Q_i . Q_p (x_i - x_p)}{r_{core}{}^2 \left|x_i - x_p\right|} \ldots\ldots\ldots\ldots\ldots\ldots \left|x_i - x_p\right| < r_{core} & \text{"Region} - 1\text{"} \\ 0 \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \left|x_i - x_p\right| > r_{perc} & \text{"Region} - 3\text{"} \end{cases} \tag{3}$$

Two types of robot swarm can be defined as neutral and charged robots. The neutral swarm robots have no charged function and identical with the standard PSO, as described in eq. (1) and (2). However, in charged swarm robot, there is an additional term to facilitate collision avoidance.

The charge swarm robot is described in eq. (4) and (5).

$$V_i^{n+1} = \chi \left\lfloor V_i^n + c_1 .rand().(p_i^n - x_i^n) + c_2 .Rand().(p_g^n - x_i^n) \right\rfloor + \vec{a}_i \tag{4}$$

$$x_i^{n+1} = x_i^n + V_i^{n+1} \tag{5}$$

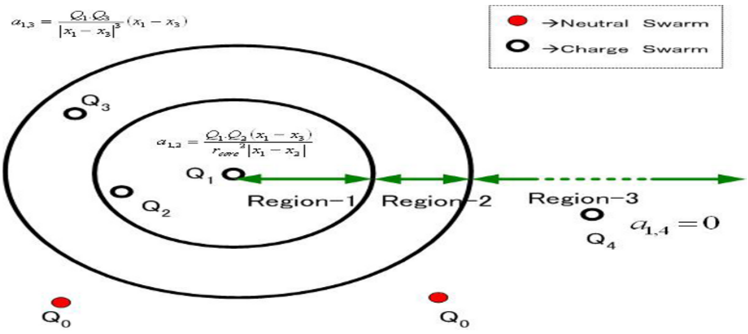


Figure 1 Charged Swarm Robot Interaction

3.3 Algorithm Implementation

The problem of gas source localization in an enclosed 2D area can be decomposed into three subtasks: plume finding (coming into contact with the plume), plume traversal (following the plume to its source) and source declaration (determining the source is in the immediate vicinity).

We used a random search until one robot getting into contact with the plume. After getting into contact with the plume, the second task is plume traversal. Particle Swarm concept will be applied for following the cues determined from the sensed gas distribution toward to the source. The last task is source declaration, determining certainty that the gas source has been found. We also used Particle Swarm Optimization convergence parameter, which is to find global maximum, which value is known.

4. Simulation Experiment

4.1 Environment

The Gaussian plume model was adopted from J. O. Hinze [17] and Ishida [18]. The Gaussian gas distribution is expressed by:

$$C(x,y) = \frac{q}{2\pi.K.d_s}\exp\left[-\frac{U}{2K}(d_s - \Delta x)\right] \tag{6}$$

where,

$$d_s = \sqrt{(x_s - x)^2 + (y_s - y)^2} \tag{7}$$

$$\Delta x = (x_s - x)\cos\theta + (y_s - y)\sin\theta \tag{8}$$

C is concentration of plume (ppm), q is emitted rate of the gas (mL/s), U is wind speed (m/s), K is turbulent diffusion coefficient in m^2/s, θ is the angle from the x-axis to the upwind direction.

4.2 Robot Behavior

When applying the algorithm in a real implementation, some important parameters should be considered. Firstly, in order to reduce the possibility of robots leaving the search space it is needed to limit the value of velocity vector. The value of velocity vector can be restricted to the range [$-V_{max}$, V_{max}]; in our case for the MK-01 Robot, the maximum velocity is 0.05 m/s. Secondly, in PSO algorithm standard there is no collision avoidance mechanism. To avoid the collision among robots we add some collision avoidance functions. Finally, we also add some sensor noise and threshold value to model the sensor response.

$$S(x, y) = C(x, y) + e(x, y) \tag{9}$$

$$S(x, y) = \begin{cases} S(x, y) & \textit{if} \ldots C(x, y) > \tau \\ 0 & \textit{otherwise} \end{cases}$$

Where S(x,y) is the sensor's response, C(x,y) is gas concentration, e(x,y) is the sensor noise with e(x,y) << C(x,y) and τ is 1 ppm.

4.3 Typical Approach

Firstly we apply the PSO approach in static environment (the plume is very stable), to show the robot interaction. The parameter settings for PSO algorithm were fixed at standard value [12,13] and we will use ten robots for all the experiments. As shown in Fig. 2, three sub-tasks of algorithm will be applied to solve the static environment and we can see the approach can easily find the odor source.

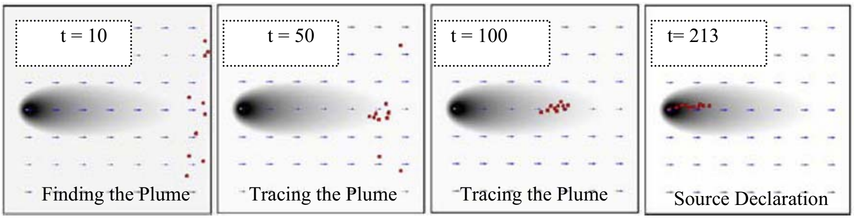


Figure 2 Visualization of proposed approach with three sub-tasks: Plume Finding, Plume Traversal and Source Declaration

4.4 Experiment Result in Dynamic Environment

In reality many real-world problems are dynamic, like odor localization in natural situation is also dynamic. The next experiment we apply the PSO approach in dynamic environment (the plume is not stable). The plume changes randomly according to the wind speed and wind direction.

In our simulation the wind speed changed randomly from 0.5 m/s to 1 m/s and the wind direction changed randomly from 160^0 to 200^0. The timer for make random changing is from 20 s until 50 s. Two types of modified PSO are used to solve the problem. Firstly, PSO incorporating change detecting and responding mechanisms and secondly Charge PSO.

In dynamic environment the standard PSO can not solve the problem. As we can show in figure 3, the robot was trapped in local maximum area. Experimental result of detect and respond PSO is shown in Fig. 4. Detection function use for monitoring the global best information, if it has not changed for 20 iterations, there is a possible optimum change and the value of global best will be restarted at the initial value (global best=0). After the detection of environment changes, we investigated the spreading response when a change is detected. All robots will spread at 5 steps to jump out to follow the changes.

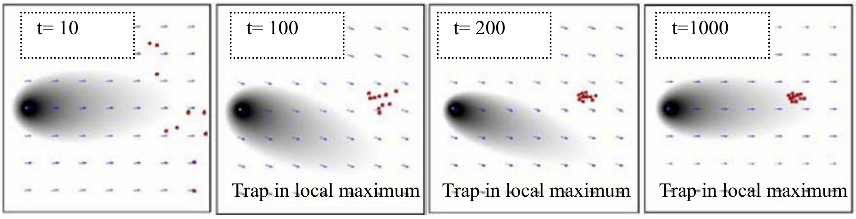


Figure 3 The propose approach with standard PSO can not follow the changing of environment, trap in local maximum.

The effect of restarting the global best and spreading implies loss of information gathered during the search so far. As an alternative adaptation, Charge PSO approach is investigated. Experiment result of Charge PSO is shown in Fig. 5. The parameters for charge robot used in the experiment are charge value Q=1, r_{core} =1 meter and r_{perc}=2 meter.

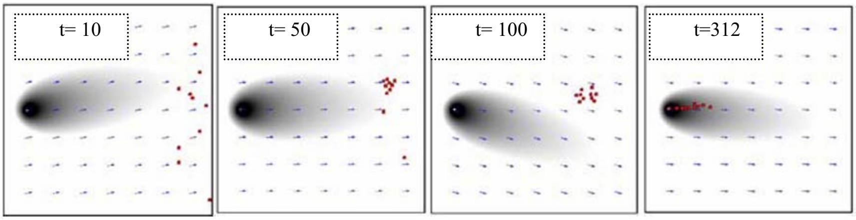


Figure 4 The proposed approach with Detect and respond PSO can follow the changing of environment.

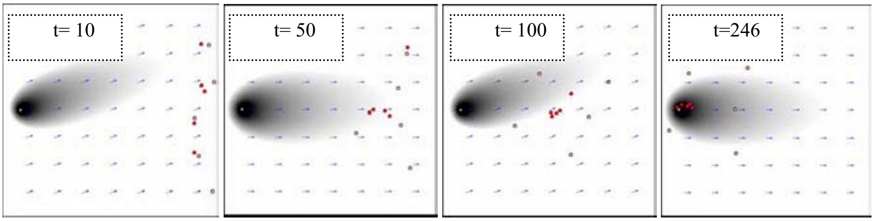


Figure.5 The proposed approach with Charged PSO can follow the changing of environment.

4.5 Analysis

It is important to analyze the results from several repeated runs by statistical methods, in order to obtain empirical evidence of the capabilities of proposed method. We analyze the efficiency of the proposed method which expressed as the number of iterations to find the solution. Then with MEAN statistical analysis, we measure the performance.

Figure 6 shows the compared results among PSO algorithms modification for solving odor source localization in dynamic environments. The PSO standard can not solve the problem until the last iterations. The Detect and Respond PSO can solve the odor source lo-

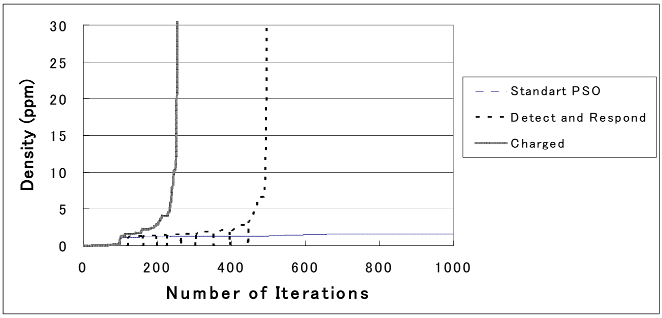
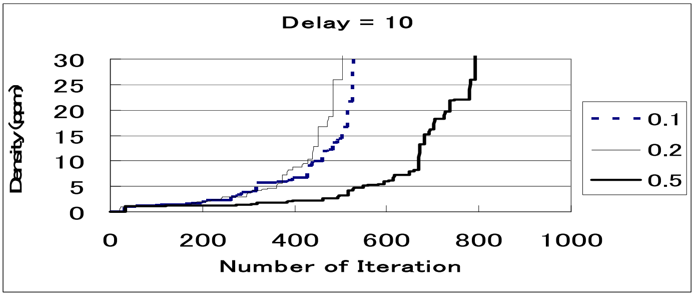
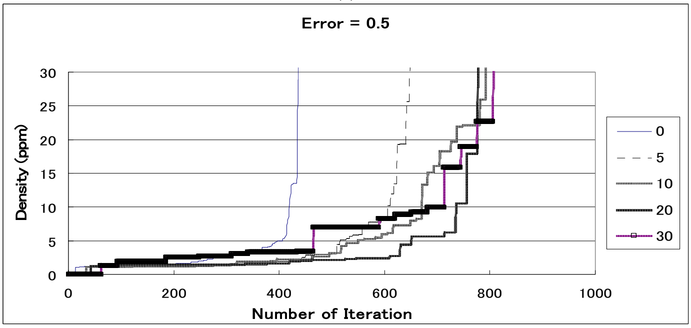


Figure 6 Time development of global best coping with dynamical change of environment with various PSO algorithms. (Taking by 25 times)

calization problems however the drawback is with the arbitrary nature of the detection and response algorithms. Particle Swarm with charge need no further adaptation to cope with dynamic scenario due to the extended swarm shape. The next experiment we just concern with the Charged PSO algorithm. Figure 7 shows the results the time development of global best coping with dynamical change of environment when delay and noise sensor was employed.



(a)



(b)

Figure 7 Time development of global best coping with dynamical change of environment used Charged PSO algorithm with employed uncertain sensor parameters (a). with delay 10 s and various error, i.e., 0.1, 0.2 and 0.5 (b). with error 0.5 and various time delay, i.e., 0 s, 5 s, 10 s, 20 s and 30 s. (Taking by 25 Times)

We also used another advanced turbulence model by Farrell et al [16], chosen because of its efficiency, realism (i.e., its instantaneous and time-averaged results much measurement of actual plume), and multi-scale properties – including chemical diffusion and advective transportation. Figure 8 shows our approach can solve the advanced turbulence model.

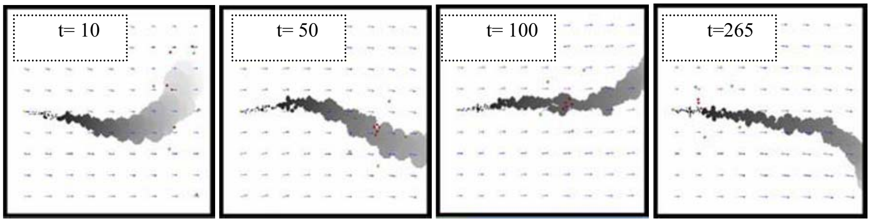


Figure 8 The proposed approach with Charged PSO can follow the changing of environment in advance turbulence environment.

5. Conclusions and Future Work

In this paper, we have presented two types of Particle Swarm Optimization modification approaches to control autonomous vehicle robots to search for odor source in dynamic environment. The Detect and Respond PSO can solve the odor source localization problems however the drawback is with the arbitrary nature of the detection and response algorithms. Particle Swarm with charge need no further adaptation to cope with dynamic scenario due to the extended swarm shape.

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. Beside that, our understanding of the solving odor source localization, particularly in dynamic environment, is still in its infancy. In real natural environment the robot will find variety of situation which related multi study from biology, physic-chemistry, engineering and robotic. Unresolved problem still find in implementation phase. Most of those could be grouped into one of the following categories:

1. Environment:

   Environment with various obstacles, as a result, the environment become more realistic and complicated. And also the changing of wind direction, yet, the changes in wind's direction are very are very limited (only 40 degrees) in comparison to the changes possible in natural environment (up to 180 degree).

2. Algorithm optimization:

   The common problem using PSO is a tuning parameter for find the optimal solution. Most of the researcher use, a cross validation or try and error tuning parameter. Further algorithm development in simulation will include online learning (parameter) which system can learn from environment. As our experience used EA in another problem of odor-sensing implementation, that is artificial odor discrimination system [1, 2].

   Considering an application to robots, a decision making architecture, which synthesizes interactions for odor source detection and cooperative mobile behavior under constraints (i.e. error model for GPS sensors), has to be present. Another important factor in PSO is neighborhood topology. In our approach we used fully connected neighborhood topology. In the paper by Kennedy [11], other topologies are described as: 1) Circle Topology and 2) Wheel Topology. We also try to analyze the feasibility conjectures referred to above, in future work.

3. Real Hardware Implementation:

   An important near-term focus will be on porting the simulation to actual robots (MK-01) in a laboratory experiment. Multiple autonomous mobile robots developed by Fuji Heavy Industries Ltd.

will use for actual robot experiment. This robot can move autonomously, that has 16 middle range infrared sensors, eight close range infra red sensor, two actuators, a microcontroller. Additionally, a robot can communicate each other by wireless LAN. 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. Via the ad-hoc wireless LAN, each robot can collect the gas concentration value and choose the best one. Then the position of the robot can be determined covering camera.

Acknowledgments

The authors are grateful to Prof. J. A. Farrell from University of California, Riverside, U.S.A., for his support advance turbulence environment source-code.

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