system is being developed for automated detection and classification of aromas, vapors and gases. Conventionally, odors are discriminated by well 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. The second prime area of robotics application for odor-sensing technology is odor source localization system. The odor source localization can be used for various attractive applications, including the search for toxic gas leak, the fire origin at its initial stage, etc [2, 3].

Many obstacles have hindered odor source localization in the past. One of the most common problems was the detection of chemicals with mobile robots. The experiments were setup in which the distance between the source and the sensor following an odor trail was minimized to limit the effect of turbulent transport. Another problem was the basing system on the assumption of a strong, unidirectional air stream in the environment. Meanwhile, little attention is devoted to the issue of odor localization within a natural environment.

The natural environment presents two major problems addressed in this paper. The first is regarding the distribution of odor molecules which is usually dominated by turbulence, rather than diffusion. Another one is the influence of the unstable winds either its force or direction. Thus, when the odor distribution is very complex owing to turbulent flow and wind instability, current mobile robotic odor detection systems are not well performed.

To overcome these natural phenomena, a new approach of exploiting Particle Swarm Optimization (PSO) is presented in the paper. The PSO algorithm here is modified to include chemotaxic and anemotaxic theory along with the development of an Advection-Diffusion odor model [11-13]. The Modified Particle Swarm Optimization (MPSO) is applied by multiple mobile robots to localize an odor source in the natural environment where the odor distribution changes over time. The results showed the MPSO was capable of solving single odor source location. However, facing multi-odor source localization problem, this method failed. Then the niche characteristic will be adopted to deal with the multi-peak and multi-source problems [14, 15]. Moreover the ranged subgroup is introduced for increasing the efficiency of the searching capability. Finally to bridging the gap between real implementation, ODE (Open Dynamics Engine) library is used for physical modeling of the robot like friction, balancing moment and others.

estimate of the source direction by combining gas searching behaviors with periods of upwind movement. Under the assumption of isotropic and homogeneous turbulence, and a unidirectional wind field with a constant average wind speed, it is further possible to model the time-averaged spread of gas. The effect of turbulent air movement can be described in this case with a diffusion-like behavior. Under these assumptions, the effect of turbulent air movement can be described with a diffusion-like behavior ruled by an additional diffusion coefficient. The available wind measuring devices, however, are limited in their applicable range. With state-of-the-art anemometers based on the cooling of a heated wire, the bending of an artificial whisker or the influence on the speed of a small rotating paddle, reliable readings can be obtained only for wind speeds in the order of at least 10 cm/s.

In fact all the system mention above can only solve odor source localization in simple conditions, like stable wind and indoor environment. When odor distribution was very complex and the wind direction was not stable where the odor distribution becoming dynamic or changing every certain time, the robot will be haphazard and desultory. To cope this problem many; in single robot learning was discusses in neutral networks, genetic algorithms, and reinforcement learning, and these learning method currently become useful tools. For example, neural networks provides a well-defined theoretical framework for single-agent learning and was succeed in wide area application, also succeed in electronic nose as a system we mention in previous section.

However, while neural network has accomplished successful result in single-agent system, learning of multi-agent systems is still a challenging research topic now and more promising successful in wide area application especially in dynamic problems. The difficulty on learning of multi-agent systems is caused by the interaction among autonomous agents (robots). For example, in recent years, many research works regarding the multiple robot systems have been done. Its fields involve several issues on cooperation searching, coordination among agents and so forth. Cellular Robotic Systems (CEBOT) is one of such the autonomous distributed robotic systems, which is composed of a number of functionally limited and different robotic units called cell. The CEBOT reconfigures its structure in terms of hardware and software according to the task or working environment. In spite of the fact that some attempts have been made to generate an intelligent behavior from combination of the simple rules, realizing such systems is still a challenging problem and will require years of work to achieve an efficient system [16, 17].

In our case using mobile robot, we must concern about the feasibility with real hardware. As that reason we will use multiple swarms for further discussion. With multiple populations we can maintain the diversity very easy and is possible to implement with a simple algorithm. The idea is use charge particle to add repulsion function to make balancing diversity (like potential field idea). The potential field method is widely used for autonomous mobile robot path planning due to its elegant mathematical analysis and simplicity.

And using PSO model to solve odor source localization problem, we must do some reformulate approach in theoretical frame work in to implement PSO approach. Three steps implementation, there are; (1) representation the solution, (2) fitness function (3) Meaning of dynamic change. Especially the meaning a dynamic problem where the meaning can be the system changes state in a repeated or non-repeated manner. The changes may occur frequently or perhaps even almost continuously. There are several ways in which system can change over time. We must define the changing of odor source localization problem with specific manner. And also concern the relationship parameter with odor dispersion model.

III. MODIFIED PARTICLE SWARM OPTIMIZATION FRAMEWORK

Many complex real-world optimization problems are dynamic, and change stochastically over time. These problems require measurements that account for the uncertainty present in the real environment. Evolutionary algorithms (EAs), especially The Particle Swarm Optimization (PSO), have proven satisfactorily in a number of static applications as well as dynamic and stochastic optimization problems, due to the principle of Natural Evolution (EAs) which is a stochastic and dynamic process.

The interaction of the robot with the PSO algorithm is described as follows: Suppose that a population of robots is initialized with certain positions and velocities; let $\mathbf{x}_i(t)$ and $\mathbf{V}_i(t)$ denote the position and the velocity vector of the *i*-th robot at the iteration time *t* (*t*=1,2...). In addition, let $\boldsymbol{p_i}$ and $\boldsymbol{p_g}$ be defined as the best local and the best global position found in plume distribution being evaluated by the robot, at position $\mathbf{x}_i(t)$. The position and the velocity are revised to improve the fitness function at each time step. When a robot discovers a pattern that is better than any previous one, the positional coordinates are stored in the vector $\boldsymbol{p_i}$, the best position found by robot *i* so far. The difference between $\boldsymbol{p_i}$ and the current position $\mathbf{x}_i(t)$ is stochastically combined

applied to them. For *charged* robots, the mutual repulsive force between robots i and p is defined according to the relative distance, $|\mathbf{x}_i - \mathbf{x}_p|$ as follows;

$$\mathbf{a}_{ip} = \begin{cases} \dfrac{Q_i Q_p (\mathbf{x}_i - \mathbf{x}_p)}{r_{core}{}^2 |\mathbf{x}_i - \mathbf{x}_p|} & |\mathbf{x}_i - \mathbf{x}_p| < r_{core} \\ \dfrac{Q_i Q_p}{|\mathbf{x}_i - \mathbf{x}_p|^3} (\mathbf{x}_i - \mathbf{x}_p) & r_{core} < |\mathbf{x}_i - \mathbf{x}_p| < r_{perc} \\ 0 & r_{perc} < |\mathbf{x}_i - \mathbf{x}_p| \end{cases} \quad (3)$$

where $(i \neq p)$, r_{core} denotes the diameter inside which a constantly, strong repulsion force is applied and r_{perc} denotes the recognition range of robot. Hence, if the mutual distance is beyond r_{perc}, there is no repulsion force between the robots. In the case of $r_{core} \leq r \leq r_{perc}$, the repulsion force is dependent on the mutual distance. Then, taking the summation of the mutual repulsion force, robot i defines collective repulsion force by:

$$\mathbf{a}_i(t) = \sum_{p \neq i}^{N} \mathbf{a}_{ip} \quad (4)$$

where N is the number of the robots included. The charged swarm robot is described in equations (5) and (6)

$$\mathbf{V}_i(t) = \chi\big(\mathbf{V}_i(t-1) + c_1 rand()(\mathbf{p}_i(t-1) - \mathbf{x}_i(t-1)) + c_2 Rand()(\mathbf{p}_g(t-1) - \mathbf{x}_i(t-1))\big) + \mathbf{a}_i(t) \quad (5)$$

$$\mathbf{x}_i(t) = \mathbf{x}_i(t-1) + \mathbf{V}_i(t) \quad (6)$$

Where the first part of eq. (5) is responsible for finding and convergence to the optimal solution, while the second part maintains diversity of the swarm distribution and prevents the robots from being trapped in a local maximum. Also, if all robots are set to the *neutral*, the Charged PSO (CPSO) is reduced to the standard PSO, as described in eq. (1) and (2).

In this section, the integration of chemotaxis and anemotaxis properties to the PSO is introduced. Again, chemotaxis causes the Modified PSO robots to follow a local gradient of the chemical concentration, while an anemotaxis-driven PSO measures the direction of the fluid's velocity and

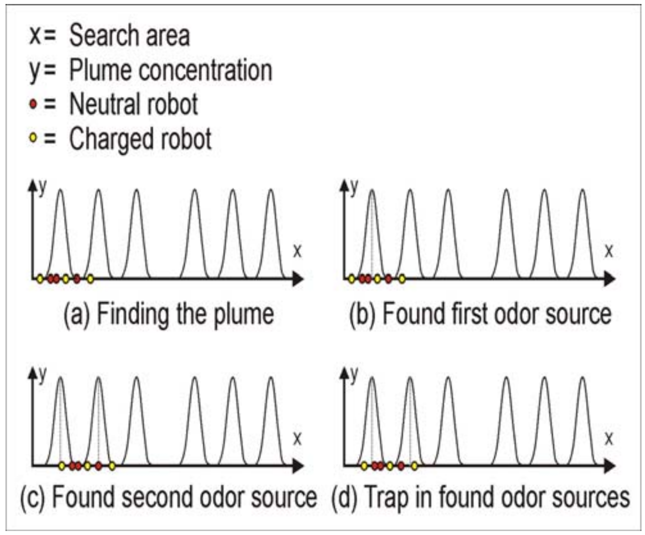


Figure 1. Demonstration of inability of MPSO solves multiple odor sources

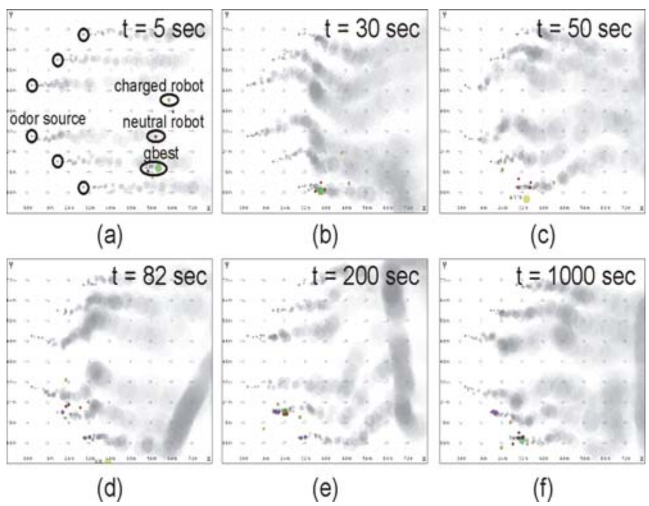


Figure 2. Demonstration of inability of MPSO solves multiple odor sources

b. Dealing with Multiple Source

The limitation of PSO is a premature convergence to a local solution or one solution. This situation is also found in multiple odor source localization problems as shown in Figure 1 and Figure 2. To cope with this kind of existence, niche method with deflection procedure is adopted [14, 15]. The deflection approach operates in multiple odor density function, adapting it to remove or close when the one source is found.

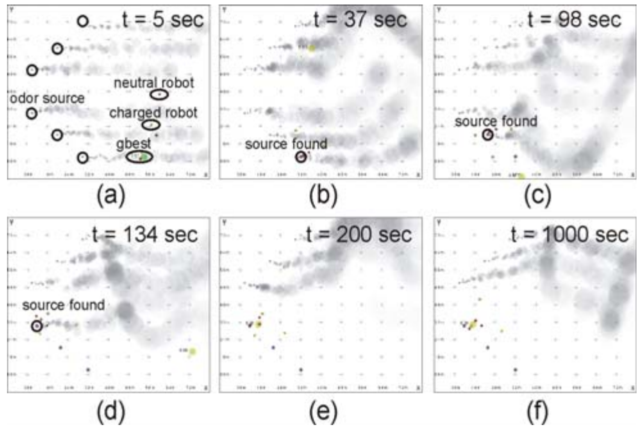


Figure 4. Screen shoot of demonstration of ability of MPSO with closing method solves multiple odor sources

Facing this problem, we need to make robots move so divergent that they could cover all search space. It would not happen as long as robots move toward their global best. We could reset global best to make robot movement is more divergent. But it is useless; in fact that reset global best could not guarantee robots to cover all search space. To solve this shortcoming, then the robot spreading method will be adopted.

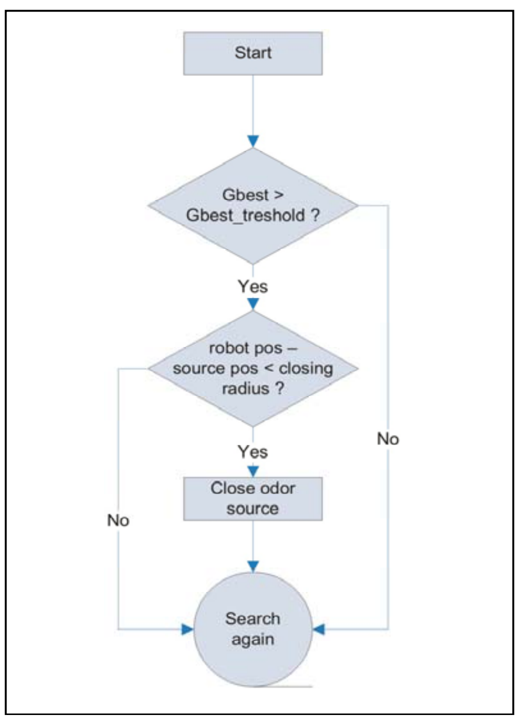


Figure 5. Logic diagram of closing method

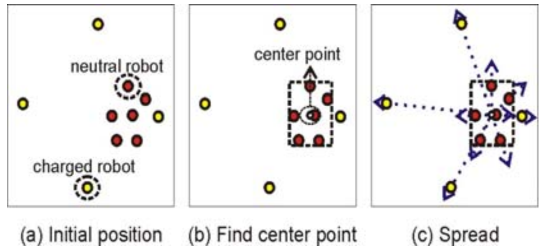


Figure 7. Robots are spreading using center point of neutral robots only

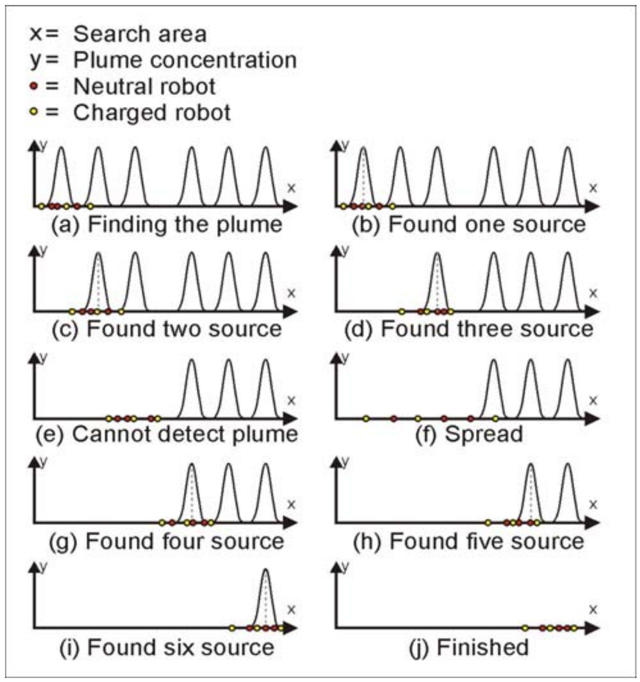


Figure 8. Screen shoot of demonstration of ability of MPSO with closing-spread method solves multiple odor sources

c. Parallel Search

To make searching time faster, we are using parallel PSO niching. Robots are grouped, either in number or member as well. For example we can determine three neutral robots and three charged robots for each group. If we determine two groups, then there is total twelve robot used for multiple odor source localization.

Each group runs by itself. There is no connection between groups. Members of each group can only send and take information among their group. Each group has its global best information which is different and not connected to others. Detect and response mechanism is also run

The next modification we make is to reconfigure a mechanism for optimization of the search robots. In the conducted experiment has shown that an odor source can be pursued by two or more niches of robot as stated in Figure 10. The figure shows a tendency for more than two niches approaching the similar source of odor simultaneously. Meanwhile, the number of source is not the only one but could be more. This is pointless in terms of using robot source and time consume with two niches for only a single source as well. Hence, the delay in searching the next odor can possibly occur. The new proposed modification of range of a sub group PSO should cope with this disadvantage.

Figure 10. The possibility of two niches pursue similar source of odor

An additional range of this sub group PSO enables the niche to possess some new qualities, one of which is the transferring mechanism of robot from one niche to another niche. For instance; a search robot either charged or neutral one belongs to niche 1 can transfer to niche 2 membership. The additional mechanism needs a coordinator agent of niche. This coordinator has some functioning qualities to disseminate information, to receive data and to register robot membership, to manage the transferring process of robot. The experiment creates that agent as a coordinator is identified the main robot.

The main robot possesses all capability as of a neutral one with some additional competence. This Robot is in charged of the transferring fellow membership so that it needs a mechanism on how and when that process being carried out. Upon the implementation all main robots may have the attract function as stated in Figure 11. If a robot position is within the attract boundary of a main robot, it will become the member niche of this main one. All neutral and charged robots can be transferred their membership among the niches. The radius of the attract area is one meter and can be upgraded during the simulation process. Meanwhile, another characteristic of this main

possesses rejection character. The state described in Figure 12 (b) will activate this capability which enables main one of a niche to move back then to find other odor source. Which niche should be defeated to move back is considered by which niche possessing better global best value. For instance; the niche 2 is defeated, so it moves back to search other odor source consequently as stated Figure 12 (c).

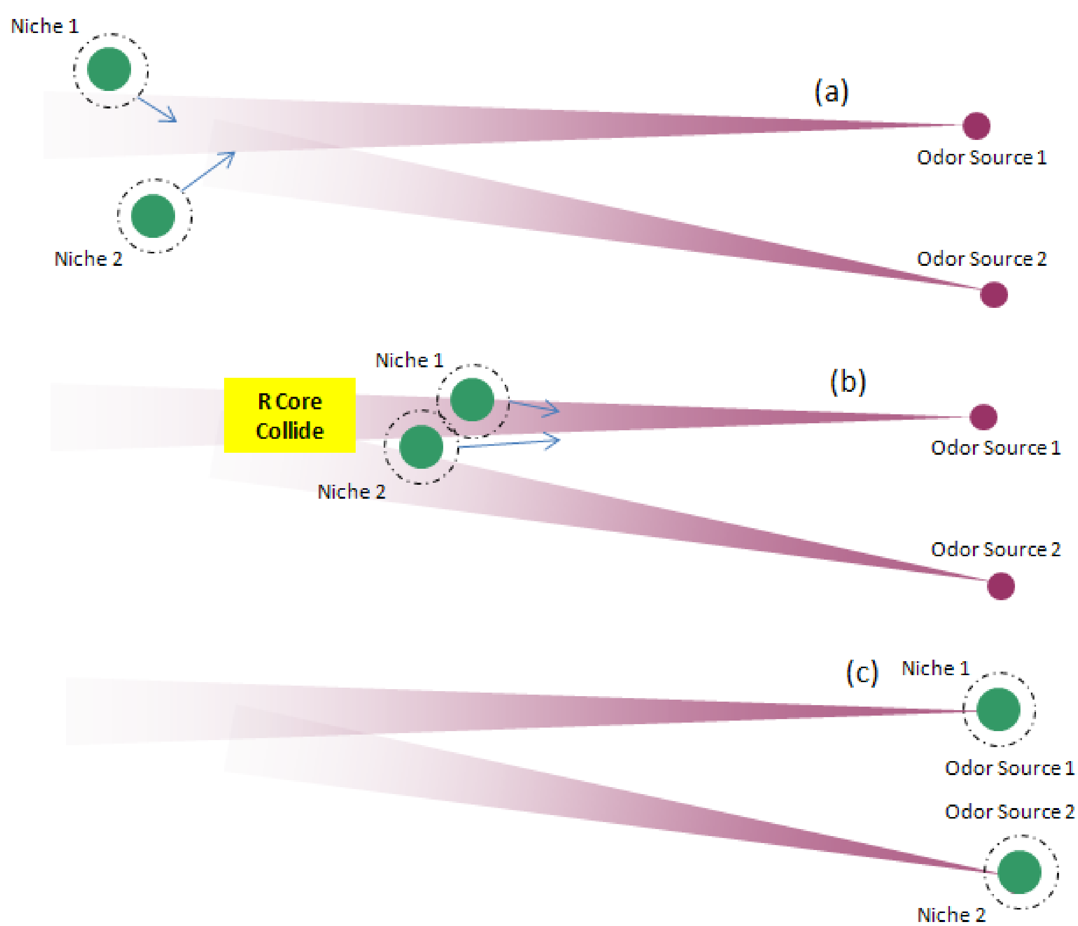


Figure 12. One niche is for one odor source

The existence of a current main robot as a commandant of the niche and the rejection trait among the main robots will boost divergence characteristic of the searching particles to speed up finding another odor source. Moreover, the main robot also possesses the attract radius area which is developed to control and empower its fellow robots both the charged and the neutral. The purpose of this concept initially is to assist the conversion of the membership of robots. For

Table 2. The membership of each robot

Robot Type	Niche 1	Niche 2
Neutral	N1	N2
Charge	C1	C3, C4, C2

V. IMPLEMENTATION FRAMEWORK

The odor source localization problem in dynamic environments is related to several issues from biology, physical chemistry, engineering and robotics. This paper proposes a comprehensive approach to offer a sound technical basis for odor source localization in a dynamic environment.

a. Environment

In this paper, we adopted an extended Advection-Diffusion odor model by Farrell et al. [16] because of its efficiency. It represents time-averaged results for measurement of the actual plume, including chemical diffusion and advective transportation. In addition, the Advection-Diffusion odor model has a key factor to approximate the meandering nature of the plume, in that the model is sinuous

The Advection-Diffusion model is composed of a large number of advected and dispersed filaments. Given a large number of filaments, the overall instantaneous concentration at $\mathbf{x}_o = (x, y)$ is the sum of the concentrations at that location contributed by each filament:

$$C(\mathbf{x}_o, t_o) = \sum_{t=1}^{M} C_i(\mathbf{x}_o, t_o) \qquad (14)$$

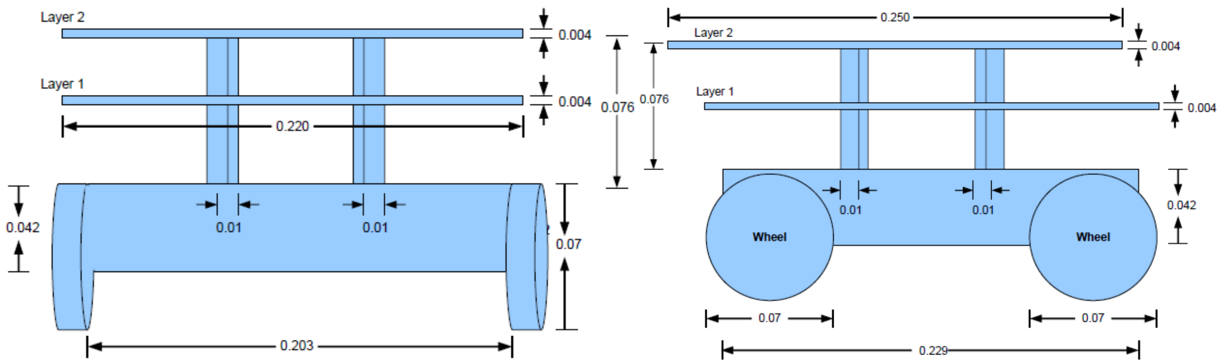
where C is the concentration of the plume (*molecules/cm*^{3}), t_o is the number of iterations, and M is the number of filaments currently being simulated.

The Advection-Diffusion gas concentration at the location $\mathbf{x}_o$ due to the i-th filaments is expressed by:

$$C_i(\mathbf{x}_o, t_o) = \frac{q}{\sqrt{8\pi^3}} \exp\left[\frac{-r_i^2(t_o)}{R_i^2(t_o)}\right] \qquad (15)$$

$$r_i(t_o) = \left|\mathbf{x}_o - \mathbf{P}_i(t_o)\right| \qquad (16)$$

To ensure that the performance of proposed strategies is applicable to the hardware experiments, the simulation must contain the key features of the hardware setup. We design the robot structure based on the actual robot for odor search localization namely Al-Fath. Name Al-Fath means victory in Arabic. This robot first developed to participate in robotic competition which task is to put out fire sources inside a house miniature. Picture of Al-Fath can be seen in Figure 14.



(a) front (b) side

Figure 15. Al-Fath measurement model

Based on this robot, a measurement model created. Figure 15 shows that some adjustment had to be made to robot wheel. Wheels in original robot use rail mechanism just like a tank. However, because the limitation in the simulation engine, robots in simulation use standard round wheels. Surely this consideration will also affect robot behavior, but it can be omitted since all 4 wheels only rotate forward or backward. Beside a basic robot model, some sensor also being model and draw in simulation. These sensors are ultrasonic, odor and wind sensors. All three are important sensors in order to make robot to ability to determine the odor source. Figure 16 shows Al-Fath looks in simulation.

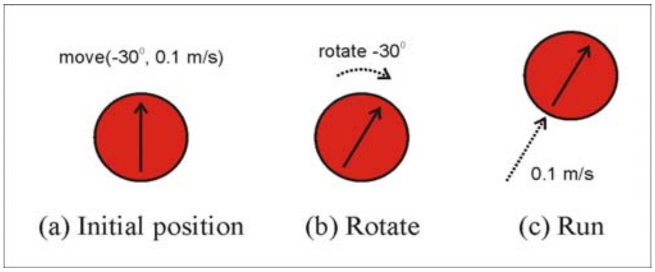


Figure 18. Robot movement

$$t_o + 1 = t_o + \Delta t \tag{17}$$

$\triangle t$ is the interval time step t_o in terms of time step t. Hence; t_o is represented with t by:

$$t_o = \left[\frac{t}{\Delta t}\right] \tag{18}$$

where [X] is the Gauss's symbol. The sensor response is defined by:

$$S(t) = \begin{cases} C\left(\left[\dfrac{t}{\Delta t}\right]\right) + e(t) & \text{If } C > \tau \\ 0 & \text{Otherwise} \end{cases} \tag{19}$$

is the sensor's response, C is the gas concentration, e is the random sensor.

3. Simulation figure of the animation

   This part depicts an animation of odor source localization. The animation comprises searching robots, odor and diffusion, odor source and global best location of each niche.

4. Simulation Information

   This is to provide information on manual and the progress at the certain period of time.

5. Environment Menu

   This is to provide on how to set environmental parameters during the simulation. This section will determine the measurement of search space and whether the odor diffusion will be activated during the simulation program.

6. Odor Source Menu

   This menu is utilized to set the number and the position of the odor source. The simulator is able to add up n number of odor source randomly in search space.

7. Wind Menu

   This menu is utilized to control wind characteristic and its related animation.

8. Robot Menu

   This menu is utilized to control robot characteristic and the number of neutral robot during the simulation process, calculation factors by robot and all the elements related to PSO.

9. Charged Robot Menu

   This menu is utilized to control the quantity of charge and the number of charged robot.

10. Niche Menu

    This menu is utilized to control the niche characteristic and the number of niche or robot colony.

11. Error Menu

    This menu is utilized to control the erroneous factor by the sensor

Table 4. General Parameters for First Comparison

Experiments	I	II
Search Space	5 x 5	10 x 10
Total of Neutral Robots	20	20
Number of Charge Robots	20	20

Figure 20 shows that Parallel MPSO algorithm provide more effective searching algorithm compare to MPSO. As can be seen in the figure, the time needed by Parallel MPSO is decrease greatly. The reason to this accomplishment is because in parallel MPSO there are more than two global best indicating any possibility that the particles pursuing some odor sources at the same time. Meanwhile, MPSO algorithm has the only one global best as the base movement to all robots. There is possibility that global best changes its direction consequently as the searching agent pursue different odor source. These two factors are basically the causes why the searching time is longer than the parallel MPSO somehow.

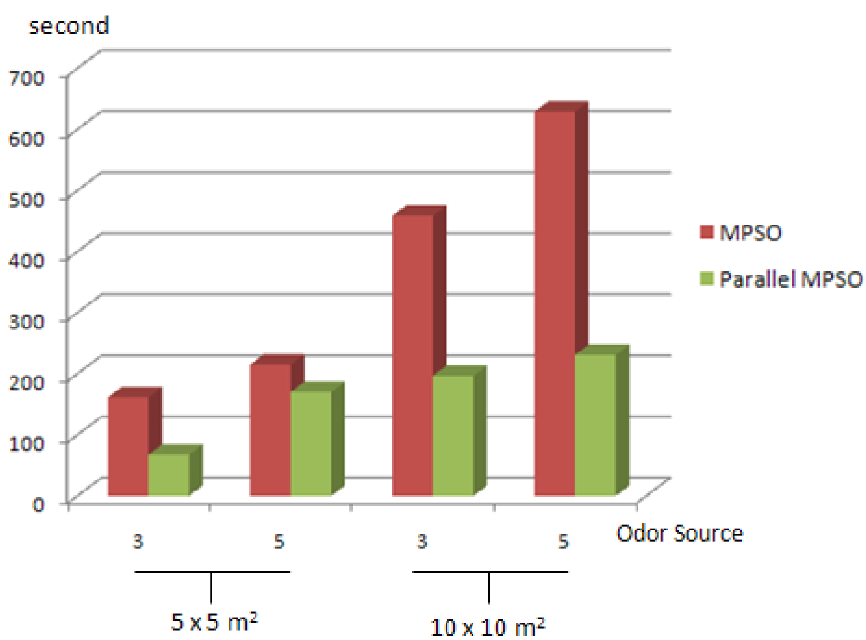


Figure 20. Comparison of the first experimental result

length of time spent is quite significant for 400 seconds. However, Figure 21 proved that the time spending can be overcome by adding the number of niche so that the odor source localizing procedure should be faster somehow.

VII. CONCLUSIONS

After conducting the experiments, the conclusion we may derive from this research is stated as follows:

Odor source localization using some robots as the particle agents should be more effective by grouping them into niches in one process of searching. That supposition is supported by the increasing of the effectiveness shown by running several parallel MPSO. Applying niche robot has promoted divergence characteristic and prompt result. The research is trying to implement all the simulation procedures by ODE, thereby the disparity between the simulation procedure and real application should be minimized especially to support the further research in building hard were prototype. Nevertheless, the verification is still required during the implementation procedure someway.

ACKNOWLEDGMENT

This work was supported in part by the Science and Technology 2007 by Indonesia Toray Science FOUNDATION and the Incentive Research Program 2008 -2009 by the Ministry of Research and Technology Republic of Indonesia. The authors also are grateful to Prof. J. A. Farrell from the University of California, Riverside, U.S.A., for his support in advanced turbulent-environment source-code.

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