RANGED SUBGROUP PARTICLE SWARM OPTIMIZATION FOR LOCALIZING MULTIPLE ODOR SOURCES

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***Abstract-** A new algorithm based on Modified Particle Swarm Optimization (MPSO) that follows is a local gradient of a chemical concentration within a plume and follows the direction of the wind velocity is investigated. Moreover, the niche or parallel search characteristic is adopted on MPSO to solve the multi-peak and multi-source problem. When using parallel MPSO, subgroup of robot is introduced then each subgroup can locate the odor source. Unfortunately, there is a possibility that more that one subgroup locates one odor sources. This is inefficient because other subgroups locate other source, then we proposed a ranged subgroup method for coping for that problem, then the searching performance will increase. Finally ODE (Open Dynamics Engine) library is used for physical modeling of the robot like friction, balancing moment and others so that the simulation adequate to accurately address the real life scenario.*

Index terms: Modified Particle Swarm Optimization, Multiple Odor Sources Localization, Parallel Search, Subgroup, Open Dynamic Engine, Real Life Scenario

I. 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 odor source localization by artificial odor discrimination system and autonomous mobile sensing system [1-10]. This paper would address the second area of application. The Artificial odor discrimination 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.

This paper is organized as follows. Section II explains the motivation of the research III presents the modified particle swarm optimization framework. Section IV ranged subgroup particle swarm optimization while section V implementation framework, then section VI experimental result and finally, section VII presents the concluding remarks.

II. MOTIVATION

The recent advances have been made in understanding biological odor localization and tracking as developed in moths and rats in the air, and lobsters and stomatopods in water. Biology utilizes olfaction for a wide variety of tasks including finding others of the same species, communication, behavior modification, avoiding predators, and searching for food. Animals use a combination of “hardware" (frequency of receptor adaptation, perhaps), “software" (temporal integration and/or spatial integration), and behavioral search strategies (both intrinsic and landmark-based) to locate odor sources. Odor localization is in essence a behavioral problem that varies from animal to animal. While some animals exploit fluid information at different layers (lobster) or different residues on the ground (ants), others can track odors in the air (moths) or use a combination of information (dogs). From an engineering standpoint there are advantages to combining odor tracking with mobile robots, such as in the detection of chemical leaks and the chemical mapping of hazardous waste sites. A necessary initial step is to develop robotic systems that use odor tracking algorithms, multiple sensory modalities (e.g., odometry, anemometry, olfaction), and sensory fusion to search out and identify sources of odor [1-10].

On the other hand, there are many reported of implementation of odor source localization in mobile robot. Most work on chemical sensing for mobile robots can be divided becoming two issues. First issue is assumes an experimental setup that reduces the influence of turbulent transport by either minimizing the source-to-sensor distance in trail following. For example work from [9, 10] which is their robot remains completely within the plume as it is carrying out its tracking behavior. The robot is inactive when outside of the plume, and active when inside the plume. Its behavior is simple, forcing the robot to execute turns when it approaches the edge of a plume, and to walk straight when completely within the plume.

Second issue is assuming a strong air stream in the environment [4, 5]. A strong air stream means that additional information about the local wind speed and direction can be obtained from an anemometer. Thus strategies become feasible that utilize the instantaneous direction of flow as an 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].

On the other hand one popular swarm inspired methods in computational intelligence areas; particle swarm optimization (PSO) which related with multiple agents (robots) has been introduced. Particle swarm optimization (PSO) is a population based stochastic optimization technique developed by Dr. Eberhart and Dr. Kennedy in 1995, inspired by social behavior of bird flocking or fish schooling from biological inspiration. The particle swarm concept originated as a simulation of simplified social system. The original intent was to graphically simulate the choreography of bird of a bird block or fish school. However, it was found that particle swarm model can be used as an optimizer.

But most research in evolutionary computation especially in particle swarm optimization focuses on optimization of static (non changing problems). Many real world optimization problems however are actually dynamic and optimization methods capable of continuously adapting the solution to a changing environment are needed, like odor source localization in dynamic environment.

The main problem with standard evolutionary algorithms (particle swarm optimization) used for dynamic optimization problems appears to be that PSO eventually converge to an optimum and thereby loose their diversity necessary for efficiently exploring the search space and consequently also their ability to adapt to a change in the environment when such a change occurs.

Over the past few years a number of authors have addressed this problem in many different ways, most of those could be grouped into one of the following for categories:

1. The PSO is run in standard fashion but as soon as a change in the environment has been detected explicit actions are taken to increase diversity and thus to facilitate the shift to the new optimum.
2. Convergence is avoided all the time and it is hoped that a spread out population can adapt to changes more easily.
3. The PSO is supplied with a memory to be able to recall useful information from past generations which seems especially useful when the optimum repeatedly returns to previous locations.
4. Multiple subpopulations are used, some to track known local optima, some to search for new optima. The different subpopulations can maintain information about several promising regions of the search space, and thus act as a kind of diverse, self-organized memory.

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 with the current velocity $\mathbf{V}_i(t)$. This causes a change to the trajectory the robot would take at that position. The stochastically weighted difference between the population's best position $\boldsymbol{p_g}$ and the individual's present position $\boldsymbol{x_i}$ is also added to the velocity to adjust for the next time step. This adjustment to the robot's behavior directs the search around the two best positions.

The value of $\boldsymbol{p_g}$ (the best of global position of the gas concentration) is determined by comparing the best performances of all the population members. The performances are defined by indicing from each population member; and the best performer's index is assigned as the variable *g*. Thus, $\boldsymbol{p_g}$ represents the best position found by all the members of the population.

Each robot is equipped with an ad-hoc wireless network and global positioning system (GPS). Through the ad-hoc network, the robot transmits and collects the information about the gas concentration, while the position of the robot is determined by the GPS.

The concept of the standard PSO is described in eq. (1) and (2).

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

$$\mathbf{x}_i(t) = \mathbf{x}_i(t-1) + \mathbf{V}_i(t) \qquad (2)$$

After finding the two best values, the particle velocity and position is updated by means of (1) and (2). The functions *Rand* () and *rand* () which are random functions returning a value between (0, 1). Coefficient χ is constriction factor, which is less than 1. The coefficient c_1 and c_2 are learning parameters, where $c_1 = c_2 = 2$.

The main problem with standard PSO application in dynamic optimization application is the PSO will eventually converge to an optimum and lose the diversity necessary for efficient exploration of the search space.

Applying Coulomb's law, a charged swarm robot is introduced in order to maintain diversity of the positional distribution of the robots and to prevent them from being trapped in a local maximum. This enhances adaptability to the changes of the environment. Suppose that robot *i* can observe the present position of the other robots ($\mathbf{x}_p \neq \mathbf{x}_i$) and has a constant charge Q_i in order to keep a mutual distance away and maintain its position. Two types of swarm robots are defined: *neutral* and *charged* robots. For all *neutral* robots $Q_i = 0$; hence, no repulsive force is 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;

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

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)

$$\mathbf{V}_i(t) = \chi\big(\mathbf{V}_i(t-1) + c_1 rand()(\mathbf{p}_i(t-1) - \mathbf{x}_i(t-1)) \quad (5)$$
$$+ c_2 Rand()(\mathbf{p}_g(t-1) - \mathbf{x}_i(t-1))\big) + \mathbf{a}_i(t)$$
$$\mathbf{x}_i(t) = \mathbf{x}_i(t-1) + \mathbf{V}_i(t) \quad (6)$$

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 navigates "upstream" in the plume to find the odor source. This methodology is well known as odor-gated rheotaxis (OGR) since it is employed by animals to find food.

a. Conceptual Idea

Unless the position and velocity are updated in the PSO algorithm, there is no guarantee the robot direction will follow the plume upstream to the source. To overcome this issue we use wind data. Assume the velocity from the basic PSO becomes an intermediate velocity ($\mathbf{V}_i^*(t)$) from which the robots are able to detect the direction of the wind ($\mathbf{W}$(t)) at every time. The movement of the robot can be controlled by analyzing the angle (θ) between the intermediate velocity vector of the robot and the wind direction vector. Note that the angle is a relative direction depending on the direction of the wind. By this concept, the robot movement is not only to follow the gradient of the chemical concentration but also to follow the direction "upstream" of the wind. As a more detailed explanation, the formulation $\mathbf{V}_i^*(t)$ and $\mathbf{W}$(t) as vectors defined as the following:

$$\mathbf{V}_i^*(t) = v_x\mathbf{e}_x + v_y\mathbf{e}_y \qquad (7)$$

$$\mathbf{W}(t) = w_x\mathbf{e}_x + w_y\mathbf{e}_y \qquad (8)$$

The angle of the two vectors $\mathbf{V}_i^*(t)$ and $\mathbf{W}$(t) in two-dimensional space becomes an inner product and is defined as:

$$\theta = \cos^{-1}\left(\frac{\mathbf{V}_i^*(t).\mathbf{W}(t)}{\|\mathbf{V}_i*(t)\|\|\mathbf{W}(t)\|}\right) \qquad (9)$$

For the implementation the controlling parameter χ_θ is used to predict the velocity of the robot. After receiving the intermediate velocity of the robot, $\mathbf{V}_i^*(t)$, the Wind Utilization (WU) algorithm will calculate the angle (θ) as given in Eq. 9. Then the controlling parameter, χ_θ, can be calculated. The continuation function for the control parameter χ_θ is obtained as follows:

$$\left(\chi_\theta(\mathbf{W}(t), \mathbf{V}_i^*(t))\right) = \frac{1}{2}\left(1 - (\mathbf{W}(t), \mathbf{V}_i^*(t))\right) \qquad (10)$$

The modified PSO with Wind Utilization (WU) concept is described from eq. (11) to eq. (12):

$$\mathbf{V}_i(t) = \chi_\theta\mathbf{V}_i^*(t) \qquad (11)$$

$$\mathbf{x}_i(t) = \mathbf{x}_i(t-1) + \mathbf{V}_i(t) \qquad (12)$$

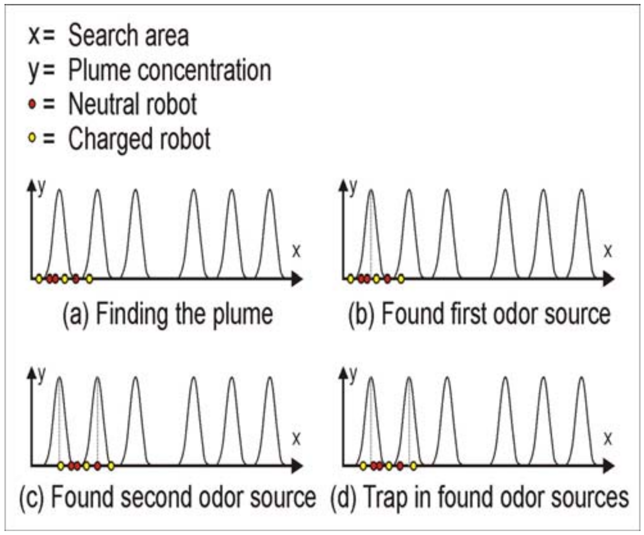


Figure 1. Demonstration of inability of MPSO solves multiple odor sources

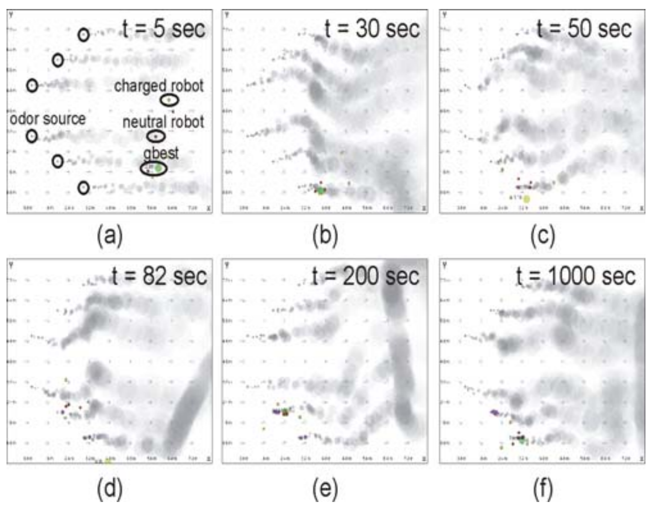


Figure 2. Demonstration of inability of MPSO solves multiple odor sources

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.

Where multiple odor sources localization are a problem the best way is to eliminate these sources and to close them off preventing plume from spreading. Thereby it allows the search devices to locate other odor sources.

The Robot as the principle search device is assumed to have some means to close off extraneous odor sources which is effective within a given range and is closed off within that range. Otherwise, they will continue searching odor source until it can be found and closed.

The closing method itself will not be explained in this paper. We only assumed the robot as searching agents has this capability. For example, if odor source is a fire point that produces plumes, robot will squirt water to stop the fire. The water itself can be squirted as far as certain range, and if the fire point is in its range, the fire point will be closed as shown in Figure 3 and Figure 4. While the logic diagram of odor source closing method is showed in Figure 5.

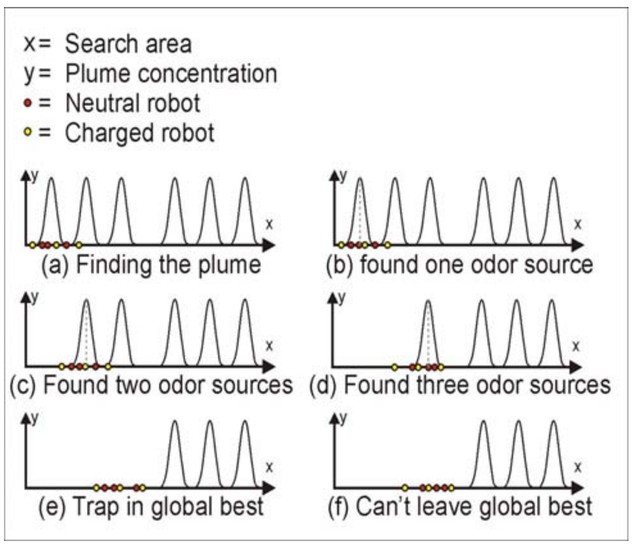


Figure 3. Demonstration of inability of MPSO with closing method solves multiple odor sources

After odor source being closed, robots will be able to find other odor sources. Unfortunately, if the latest odor source position is far enough from odor stream, robot cannot find other sources. It is shown in Figure 4 where still three sources remain. To make robots can find all odor sources; again, we need to modify MPSO.

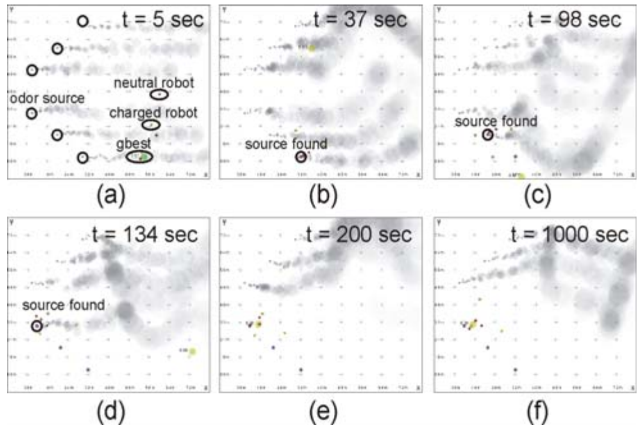


Figure 4. Screen shoot of demonstration of ability of MPSO with closing method solves multiple odor sources

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.

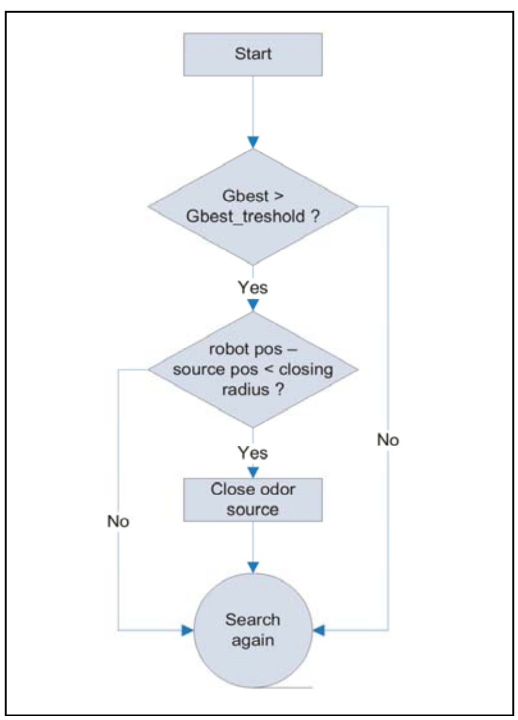


Figure 5. Logic diagram of closing method

The robot spreading method is originally come from detect and response PSO (DR PSO) used in previous research [11-13]. Detect and response mechanism was adopted to make robots be adaptable to the dynamic environment. When environment change, robots can detect changes and response to this new condition so that robots can find their solution. The logic diagram of spreading method is shown in Figure 6 while the conceptual idea of spread method is shown in Figure 7.

Spreading method is used when robots cannot detect any other plume stream. So, spreading method is a response to this unfavorable condition. Spreading method will be used until robots can find plume stream. When spreading method is used, robots enter spread phase. Vice versa, when MPSO algorithm is used, robots enter PSO phase. In the spread phase, the robots will be spreading to all direction. The procedure will be the following:

1. Find center point from all robots' position.
2. Robot will move to opposite direction from center point to its position.
3. Robot will move straight until it collide another robot or collides area's boundary.

The detail of MPSO with closing-spread method solves multiple odor sources is shown in Figure 8.

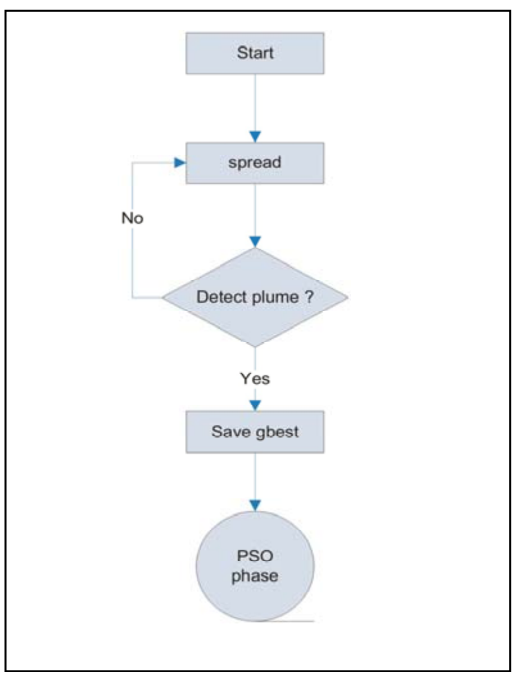


Figure 6. Logic diagram of spread phase

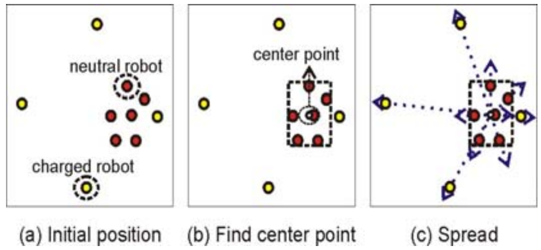


Figure 7. Robots are spreading using center point of neutral robots only

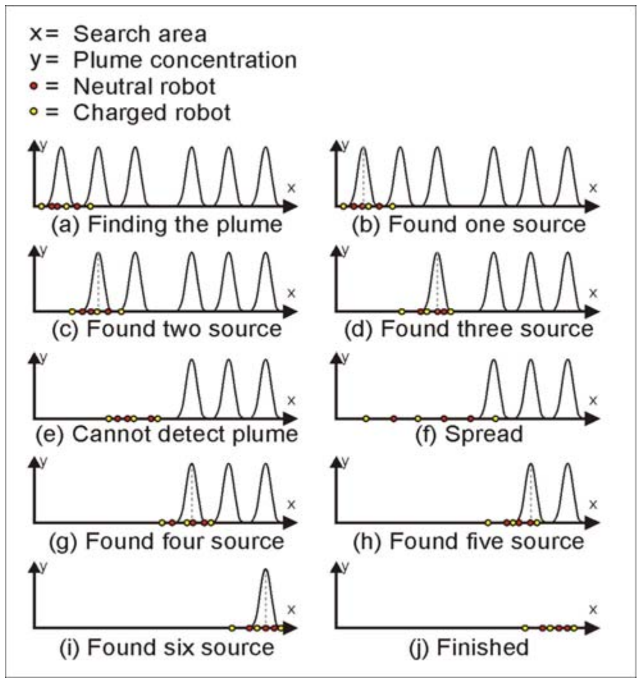


Figure 8. Screen shoot of demonstration of ability of MPSO with closing-spread method solves multiple odor sources

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 separately among each group. When one group is running in spread phase, other may run in PSO phase.

Conceptual idea of parallel search is shown in Figure 9. Parallel search logically makes searching time faster. Several groups of robot run and find odor sources separately

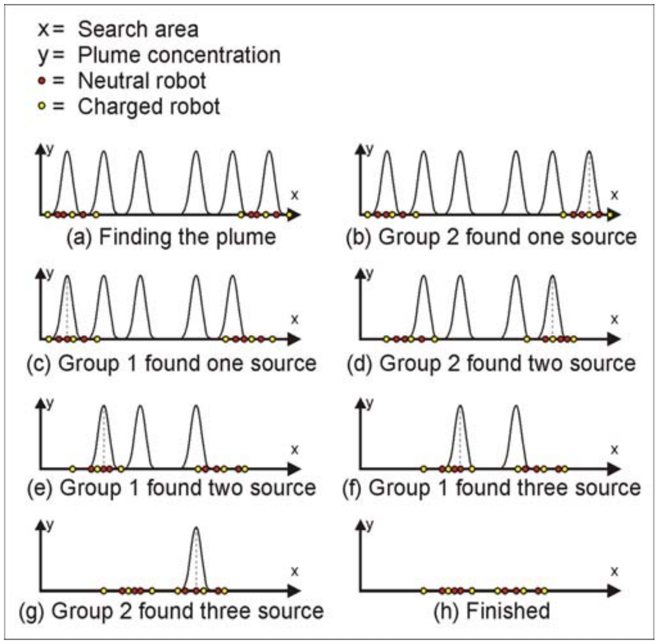


Figure 9. Screen shoot of demonstration of ability of parallel MPSO with closing-spread method solves multiple odor sources

Robot groups run separately and do not transfer any data to each other. It makes one group cannot find the others. Hence, one group will not know if it goes to the same odor source as the others. These groups compete with each other. It is very inefficient. One odor source can be tracked by more than one group. However, each group should track different odor sources. Consequently, number of odor sources found by each group not distribute well. As shown by Figure 2 (b), there are two groups of robot which has found respectively three odor sources all at once. But in Figure 2 (c), there are three groups of robot, group 1 and group 3 found the identical three odor source, but none for group 2. This is not efficient. There are three groups of robot but only two of them run effectively. The other one just get in their way and could not find any.

IV. RANGED SUBGROUP PARTICLE SWARM OPTIMIZATION

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 robot is the rejection character among other main robots. It will guarantee of their positions to be away from each others. This character is also an instrument of collision avoidance and to increase divergence of PSO. There is no rejection character between the main robot and charged robot. The radius of rejection is mentioned by R core value as it is stated in Figure 11. The algorithm for this calculation is depicted in (13). The main robot as a coordinator will receive the information on the local best of its robot member. Based upon those information received, then the global best can be determined and transmitted to its robot members.

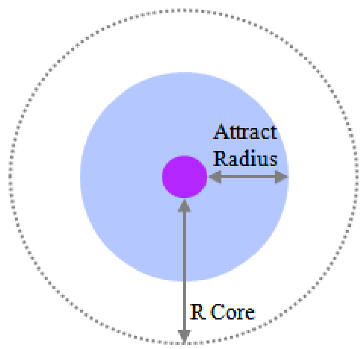


Figure 11. The attract Radius area and R Core of a main robot

$$u_{jk}(t) = \begin{cases} \dfrac{Q_j Q_k (x_j(t) - x_k(t))}{(AttractRadius + R_{Core})^2 \left\| x_j(t) - x_k(t) \right\|} & if \quad \left| x_j(t) - x_k(t) \right| < 2 \times AttractRadius + R_{Core} \\ 0 & if \quad \left| x_j(t) - x_k(t) \right| > 2 \times AttractRadius + R_{Core} \end{cases} \quad (13)$$

Besides all the above mention, the rejection trait can prevent the niches from pursuing the similar odor source simultaneously. The idea is easy to understand by looking Figure 12. The green circle denotes the main robot representing the niche movement under its control. Meanwhile, another circle circling main robot is the area of R core. Then, the purple circle denotes an odor source with a triangle representing the odor movement. Figure 12 (a) is representing the state where two niches are moving to the certain direction which is not significantly different. The movement of niche is denoted by the blue arrow.

At a time both the two niches are moving and reaching a certain position as shown Figure 12 (b). At such state, it is certain that either niche 1 or niche 2 will follow to the odor source 1. The implementation of the algorithm Draft Niche-PSO will enable the main robot of each niche 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).

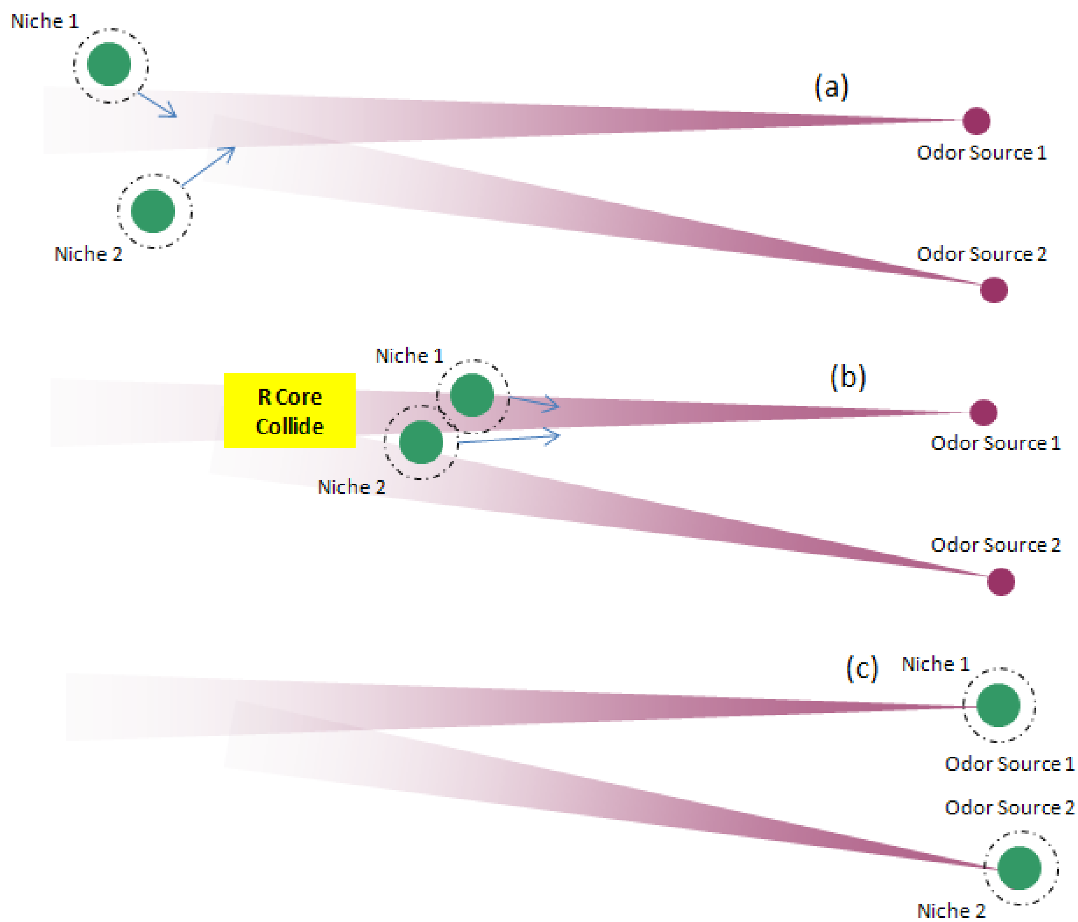


Figure 12. One niche is for one odor source

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 example; if there are two niches of robot where each comprises 6 fellow robots; 2 neutral robots and 4 charged robots. The state of robot is described in Figure 13.

Table 1. The fellow members of robot

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

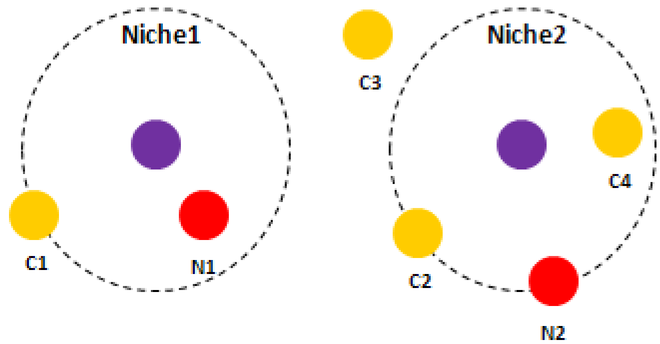


Figure 13. Robots position

The colored circles in Figure 13 are representing robots and denoting their typical character. The yellow one means the charged robot. The red one means the neutral robot and the last the purple one is the main robot representation. The dotted circle illustrates the radius of the attract area of the main robot. The particle C2 is the charged robot belongs to niche 1. The Figure above is depicting the C2 has been in the position within the attract area of niche 2. Thus, C2 is submitted to the niche 2 membership and at the same time it renounces its membership from niche 1. The new listed membership is shown as the followings:

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:

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

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

where q is the amount of odor released, R_i is the parameter controlling the size of the i-th filament; and $\mathbf{P}_i$ is changing positions of the i-th filament. (For further explanation on this model, see [16], section two and three.)

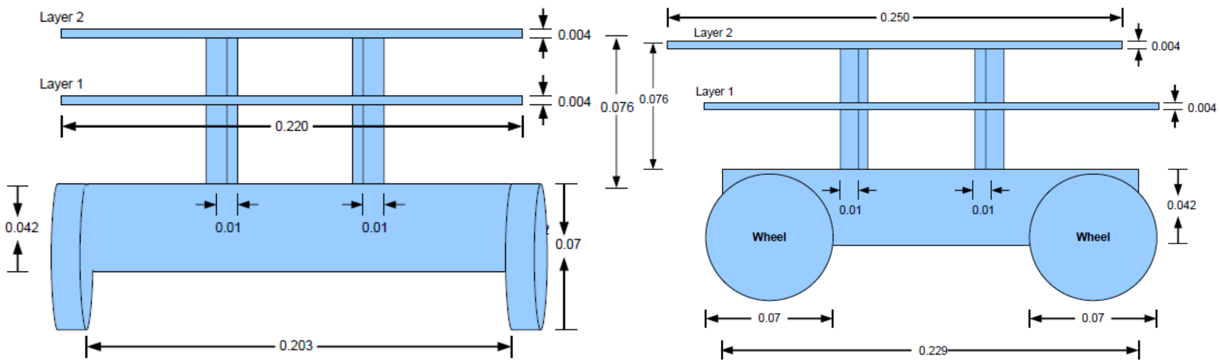
This model generates plumes that meander; in addition, the meander is coherent with the flow fields in the sense that downwind odor distribution from the source is the result of advection by the flow.

b. Robot Behavior

The gas source localization algorithm used in this work can be divided into three subtasks: plume finding, plume traversal and source declaration. Random search is employed until one robot encounters the plume. After finding the plume, the second task of the plume traversal proceeds. Particle Swarm concept will be applied to following the cues determined from the sensed gas distribution toward the source. The last task is the source declaration based on the certainty that the gas source has been found. If a robot senses the gas density that is beyond a certain threshold value, it means that the gas source location is specified; and hence, the searching behavior is terminated. Moreover, the search is terminated if the swarm robots fail to localize the odor source by the maximum iteration time step.

Figure 14. Al-Fath – Robot for odor source localization

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.

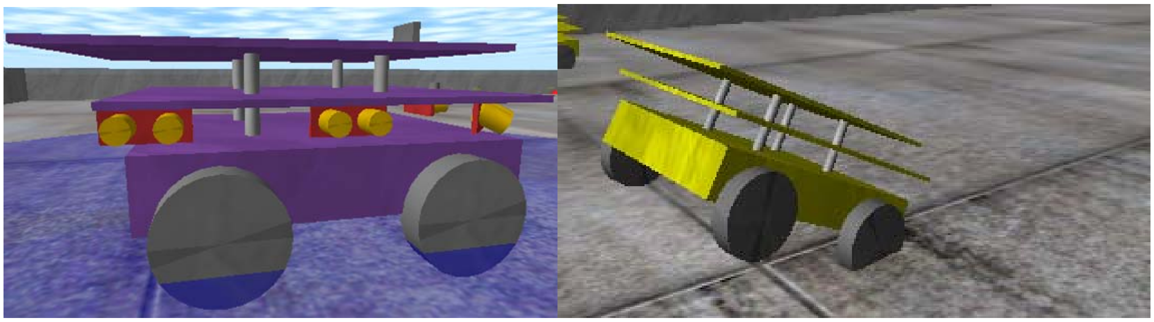


Figure 16. Al-Fath in Simulation.

Secondly, to rotate the whole robot, left wheels and right wheels rotate with direction inverted each other. This method will make robot rotate and robot movement is applied with input at rotation angle and speed in m/s. Robot will rotate as rotation angle and run as shown in Figure 15. In order to incorporate a collision avoidance mechanism, we assume that infrared sensors are equipped on each robot as shown in Figure 17.

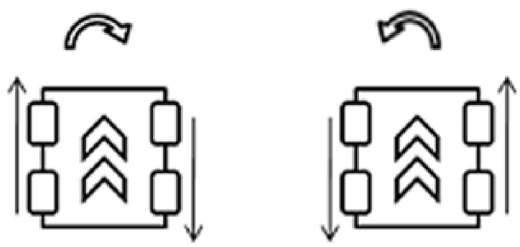


Figure 17. Rotation movement

Then the parameters of sensor noise and threshold value are added to model sensor responses. Assume that iteration time t of the robot in eq. (1) to (6) and iteration time t_o in eq. (14) to (16) is different time step resolution. Time correlation between time step t and time step t_o is explained as follow: The time scale of t has higher resolution than that of time step t_o and count up is represented as:

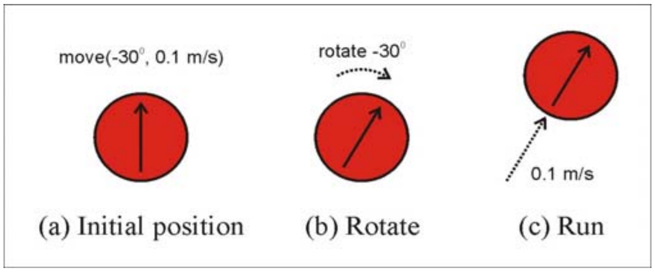


Figure 18. Robot movement

$$t_o + 1 = t_o + \Delta t \qquad (17)$$

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

$$t_o = \left[\frac{t}{\Delta t}\right] \qquad (18)$$

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

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

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

c. Simulator Interface

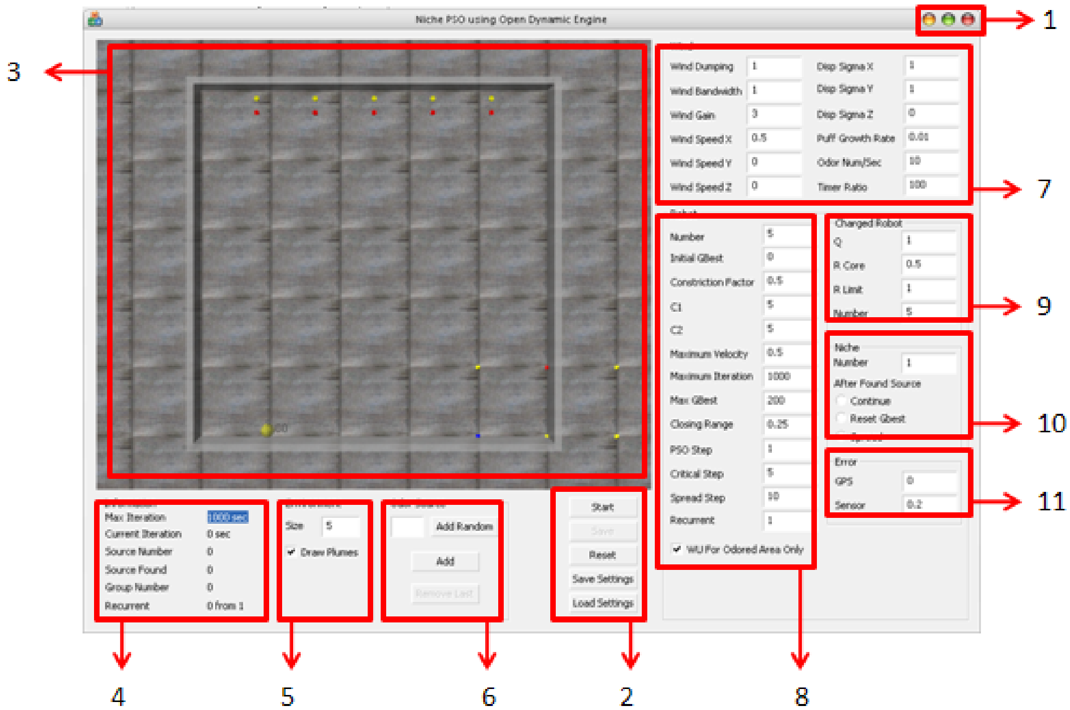


Figure 19. Simulator Interface

Figure 19 the following is the list of descriptions on Layout Simulator for odor source localization:

1. The key Functions provided by Windows TM to minimize and maximize simulator window. To turn off the simulator the “close” button at the top right corner can be activated.
2. Simulator Menu

   This menu comprises 5 buttons functioning to control simulator characteristic including Start/Pause, Save, Reset, Save Setting, and Load Setting. Start/Pause, Save and Reset Buttons are functioning as their label. Reset will set the entire configuration back to the last value stored by the simulator. The save button enable the simulator to read the entire given configuration, so long as the save button has not been activated the entire conversion should be ignored. The Save Setting will enable the simulator store the inputting configuration in a file. This stored data will be read by the simulator by pressing Load Setting button.

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

VI. EXPERIMENTAL RESULT

The research is trying to figure out the effectiveness of the 3 comparative proposed algorithms we have developed recently. Those 3 algorithms are including Modified PSO (MPSO), Parallel MPSO, and Ranged Subgroup MPSO. The experiments are conducted within two steps of application. The first is comparing procedure between MPSO and Parallel MPSO. The second procedure is comparing between the effectiveness of MPSO parallel range alternative algorithm and parallel MPSO. This experiment is carried out in our well developed simulator with some parameters stated below in table

Table 3. General Parameters for the Experiment

Element	**Value**
Initial Gbest	0 ppm
Construction Factor	0.5
Maximum Velocity	0.1
Q	1 coulomb
R Core	0.464 m
Sensor Error Factor	0.2

In order to determine which algorithm will give minimum search time, we use incremental comparison procedure. First procedure is comparing MPSO and Parallel MPSO. The second procedure is to compare the effectiveness of MPSO parallel range alternative algorithm and parallel MPSO. General parameters for first procedure can be seen in Table 4. Each algorithm will be tested in 5x5 m^2 and 10x10 m^2 search area with three and five odor sources. Since Parallel MPSO requires more than a group of searching particles; thereby the total number of robots should be grouped into niches. Therefore, in this procedure, robots in Parallel MPSO will be divided into four colonies (or niche). Each niche comprises five neutral robots and five charged robot. The experiment result based upon the statistical calculation in comparative graphs is shown in Figure 20.

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.

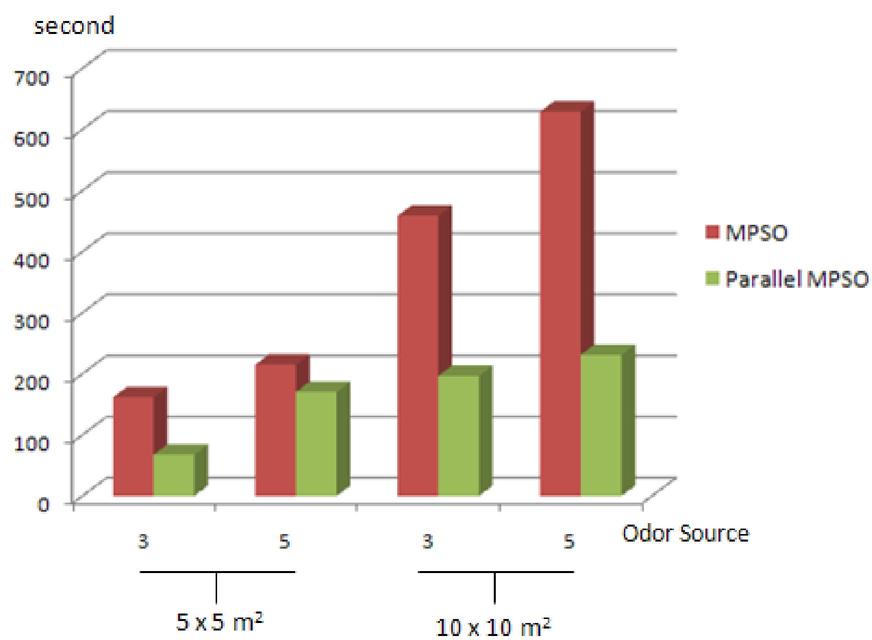


Figure 20. Comparison of the first experimental result

After first procedure, we continue to second comparison procedure. These procedures follows configuration as shown in Table 3 and Table 4. We used two experiments, both in 10 x 10 m^2 with 4 to 5 odor sources that have to be found. Location for each odor source is predetermined. Although there's a difference in total of robot included between scenarios I and II, but total robot for each niche is unchanged. Each Niche comprises four neutral robots and four charge robots, plus one main robot for newly proposed algorithm.

Table 5. General Parameters for Second Comparison

Experiments	I	II
Search Space	10 x 10	10 x 10
Total of Neutral Robots	8	12
Number of Charge Robots	8	12
Number of Niche	2	3
Number of Odor Sources	4	5

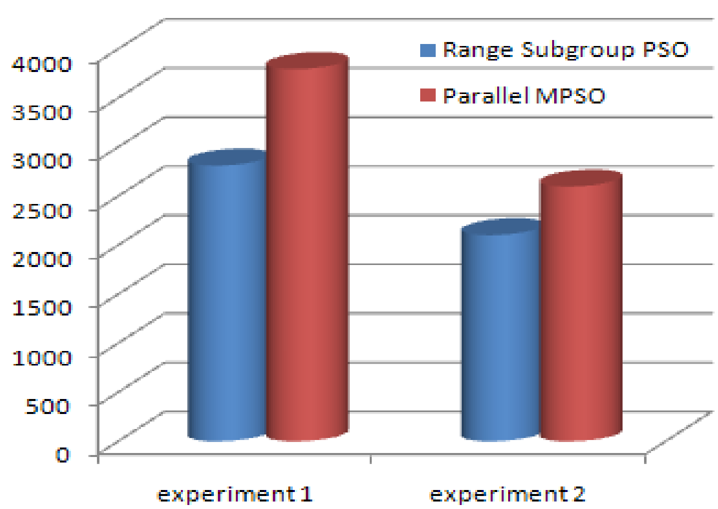


Figure 21. Comparison of the second experimental result

Result for second procedure can be seen in Figure 21. As can be seen in the graphics that Ranged Subgroup PSO is gives faster searching than Parallel MPSO. Under experiment 1, Ranged Subgroup PSO is faster 982.95 seconds or about 16.38 minutes. Both Figure 20 and Figure 21 have shown the increasing time required to localize odor source in a wider search space. The 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.

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