

Localizing Multiple Odor Sources in a Dynamic Environment Based on Modified Niche Particle Swarm Optimization with Flow of Wind

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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 characteristic is adopted to solve the multi-peak and multi-source problem. Simulations results demonstrate that the new approach is reliable for The Advection-Diffusion odor robotic model. Finally, the statistical analysis shows this new approach is technically sound.

Keywords: Multiple Odor Sources Localization, Modified Niche PSO

1 INTRODUCTION

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 [1-2]. Another problem was the basing system on the assumption of a strong, unidirectional air stream in the environment [3-6]. 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 [1-10].

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 chemotactic and anemotactic theory along with the development of an Advection-Diffusion odor model.

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 [11-13]. 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.

2 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 ($t=1,2,\dots$). In addition, let \mathbf{p}_i and \mathbf{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 \mathbf{p}_i , the best position found by robot i so far. The difference between \mathbf{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 \mathbf{p}_g and the individual's present position \mathbf{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 \mathbf{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 indexing from each population member; and the best performer's index is assigned as the variable g . Thus, \mathbf{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).

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

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

After finding the two best values, the particle velocity and position is updated by means of (1) and (2). The functions $\text{Rand}()$ and $\text{rand}()$ 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;

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

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)

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

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

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 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.

2.1 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:

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

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

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:

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

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:

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

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

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

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

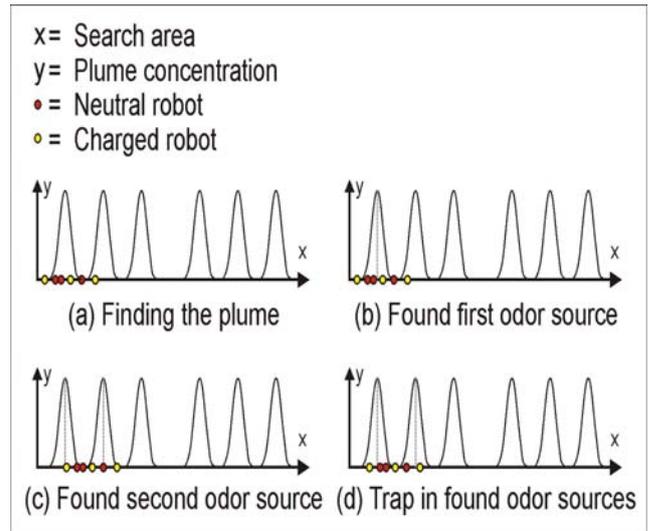


Fig. 1 Demonstration of inability of MPSO solves multiple odor sources.

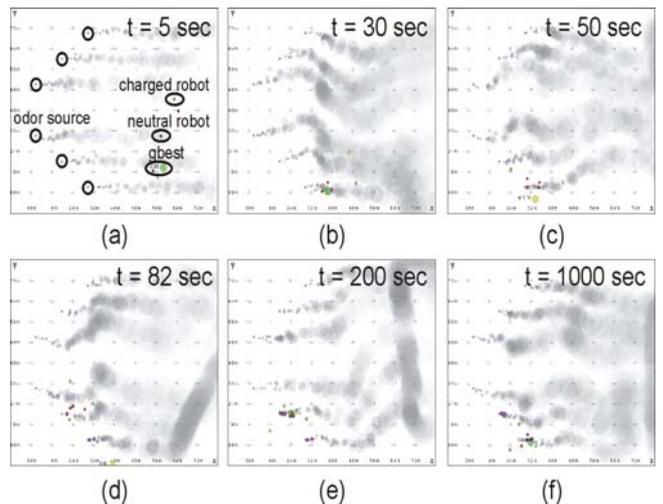


Fig. 2 Demonstration of inability of MPSO solves multiple odor sources.

2.2 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 Fig. 1 and Fig. 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.

3 IMPLEMENTATION FRAMEWORK

The odor source localization problem in the 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.

3.1 Environment

In this paper, we adopted the 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 the chemical diffusion and advective transportation. In addition, the Advection-Diffusion odor model has a key factor approximating the meandering nature of the plume, as the model is sinuous

The Advection-Diffusion model is composed of a large number of advected and dispersed filaments. Given a 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:

$$C(\mathbf{x}_o, t_o) = \sum_{i=1}^M C_i(\mathbf{x}_o, t_o) \quad (13)$$

where C is the concentration of the plume (*molecules/cm³*), 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:

$$C_i(\mathbf{x}_o, t_o) = \frac{q}{\sqrt{8\pi^3}} \exp\left[\frac{-r_i^2(t_o)}{R_i^2(t_o)}\right] \quad (14)$$

$$r_i(t_o) = |\mathbf{x}_o - \mathbf{P}_i(t_o)| \quad (15)$$

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.

3.2 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. The particle swarm concept will be applied to follow the cues determined by the sensed gas distribution. 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 which 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.

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. (13) to (15) 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:

$$t_o + 1 = t_o + \Delta t \quad (16)$$

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

$$t_o = \left\lceil \frac{t}{\Delta t} \right\rceil \quad (17)$$

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

$$S(t) = \begin{cases} C\left(\left\lceil \frac{t}{\Delta t} \right\rceil\right) + e(t) & \text{If } C > \tau \\ 0 & \text{Otherwise} \end{cases} \quad (18)$$

is the sensor's response, C is the gas concentration, e is the random sensor as referred to [12, 17].

4 EXPERIMENTAL EXAMPLE

The main idea of PSO niching is to eliminate solutions described in [14,15]. 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 Fig. 3. and Fig 4. While the logic diagram of odor source closing method is showed in Figure 5.

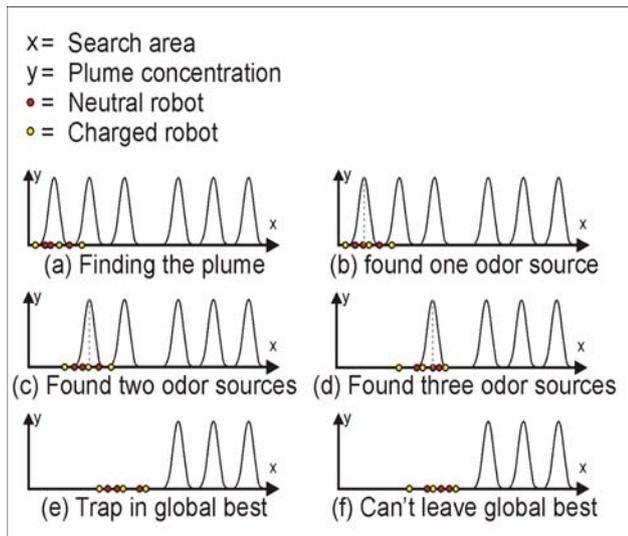


Fig. 3 Demonstration of inability of MPSO with closing method solves multiple odor sources.

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 Fig. 4 where still three sources remain To make robots can find all odor sources; again, we need to modify MPSO.

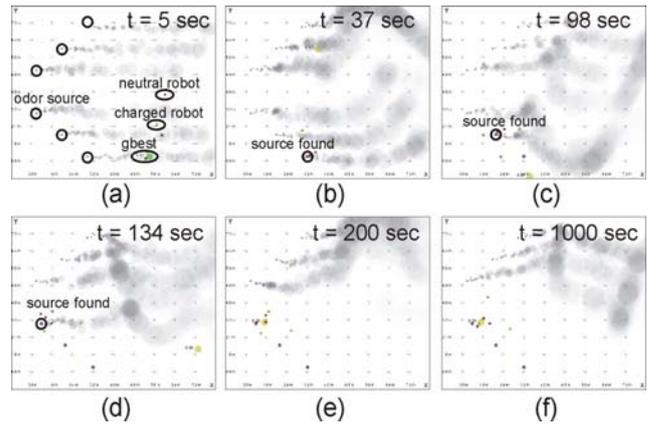


Fig. 4 Screen shoot of demonstration of ability of MPSO with closing method solves multiple odor sources.

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.

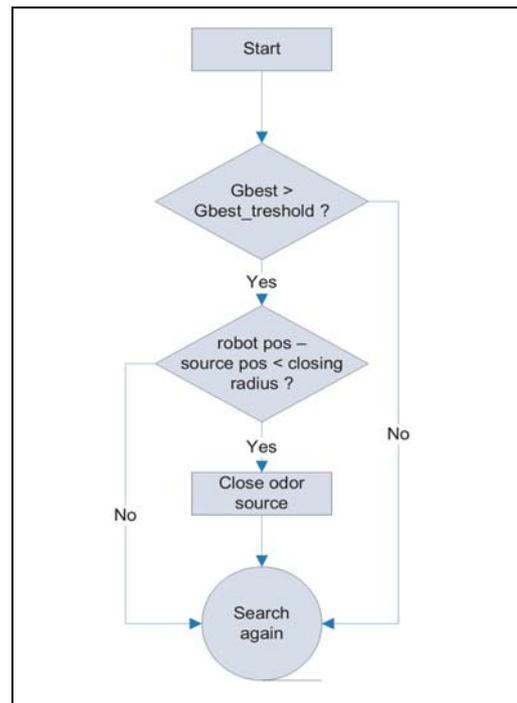


Fig. 5 Logic diagram of closing method.

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 Fig. 6 while the conceptual idea of spread method is shown in Fig. 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 Fig. 8.

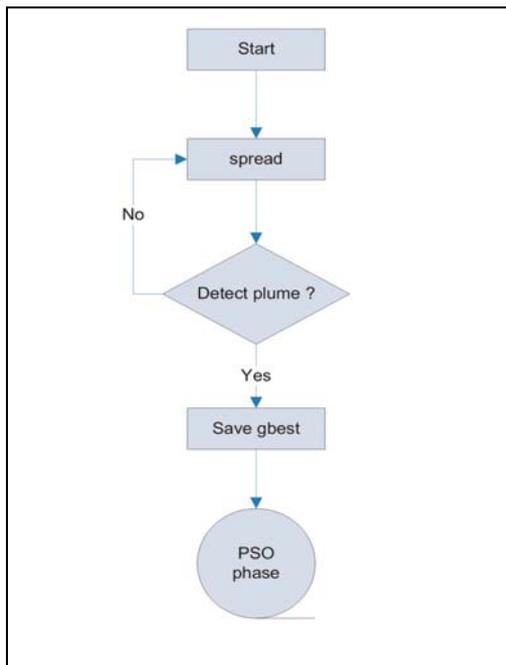


Fig. 6 Logic diagram of spread phase.

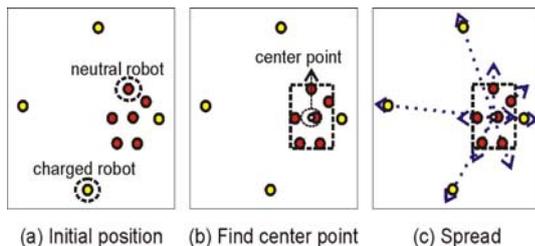


Fig. 7 Robots are spreading using center point of neutral robots only.

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.

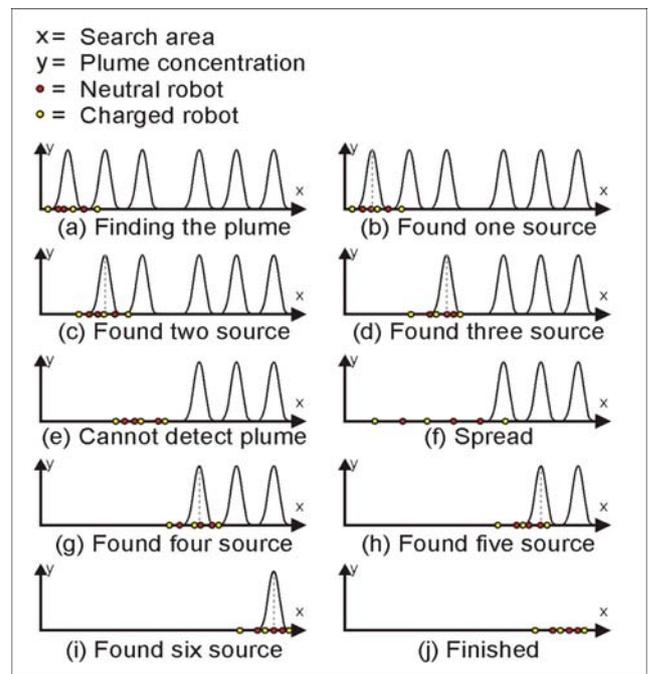


Fig. 8 Screen shot of demonstration of ability of MPSO with closing-spread method solves multiple odor sources.

Conceptual idea of parallel search is shown in Fig 9. Parallel search logically makes searching time faster. Several groups of robot run and find odor sources separately. The comparison between single sub group and parallel are shown in Fig 10.

5 PERFORMANCE ANALYSIS

Solving odor source localization problems in dynamic environments requires hardware and software platforms [11-13, 17,18]. During the initial design stages, software evaluation is preferred because it allows easy comparison of different localization strategies for various environmental scenarios. This paper presents a simulation

implementation that addresses tradeoffs between computational efficiency and inclusion of realistic hardware parameters.

From previous result [11-13], the number of the robots and the width of the area with respect of the iterations step to find the odor source is important. Therefore sample of performance measurement is shown in Fig. 10.

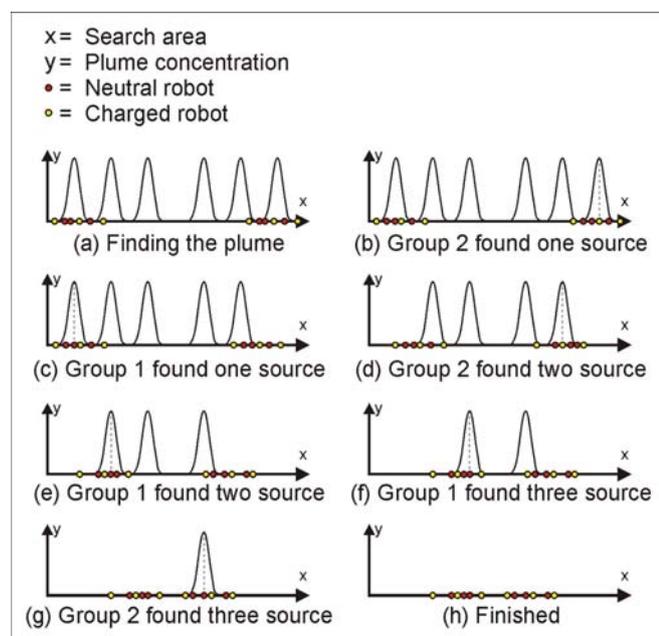


Fig. 9 Screen shot of demonstration of ability of parallel MPSO with closing-spread method solves multiple odor sources.

For more detail analysis, the ANNOVA software, which based on Least Significant Difference (LSD) is used. The purpose of using LSD measurement is to know the significance of the amount of the resource comparing the result or performance the system to search or localize the sources. For example, if we compare using thirty robots and twenty robots in the same scenario, but the performance of thirty robots is not more than LSD performance of twenty robots. Hence, we can decide of using twenty robots is more preferable.

And also the number of group is analyzed by LSD method. The detail of the result using LSD method is shown in Table 1. For example in width area $5 \times 5 \text{ m}^2$ to find 5 sources, the best combination of resource is using twenty robots with three of sub groups (parallel). The experiment shows that using thirty and forty robots the performance is not significant in term of LSD measurement method.

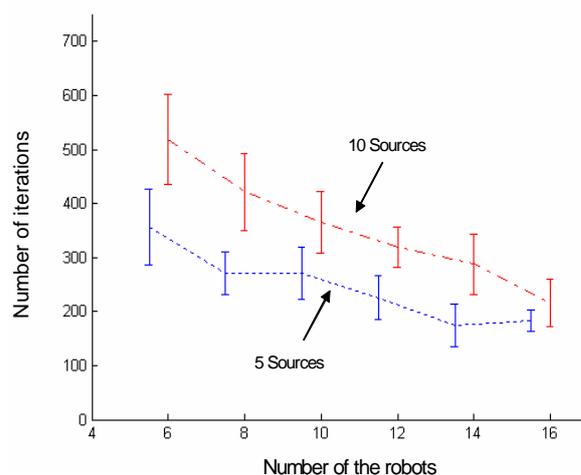


Fig. 10 Comparison of performance according to the number of the robot, across 25 runs. (Width area is $5 \times 5 \text{ m}^2$). Error bars indicate standard deviation and lower values indicate better performance.

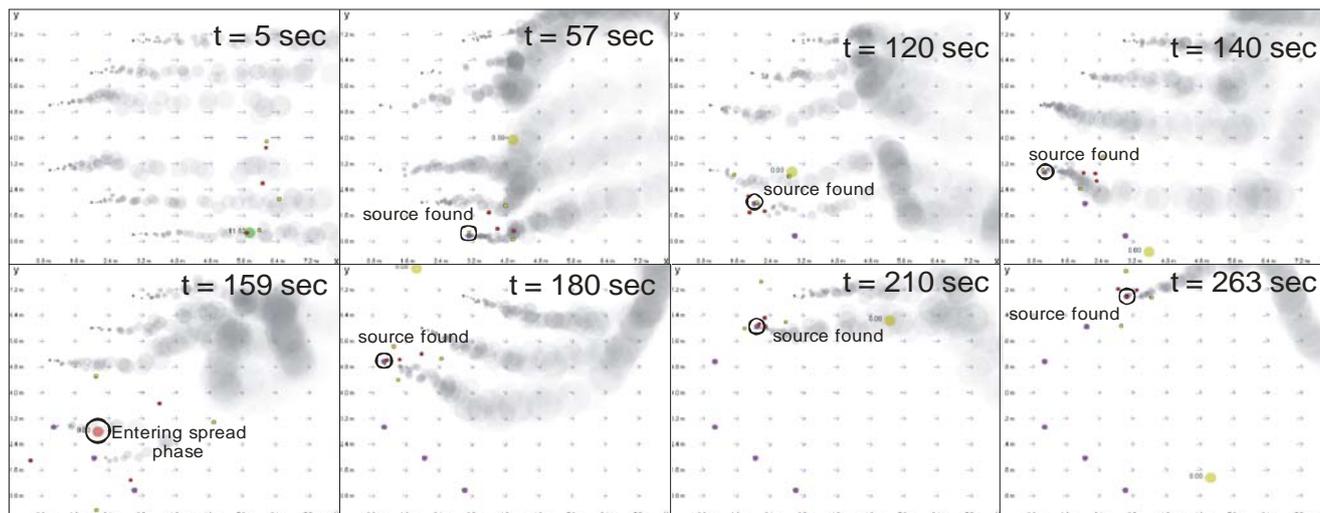
6 CONCLUSIONS

The variant of Niche MPSO was implemented for solving multiple odor source localization problems. The proposed simulator based on MPSO approaches can solve such dynamic environment problems. On the other hand the measurement of the measurement done through the LSD statistical theory.

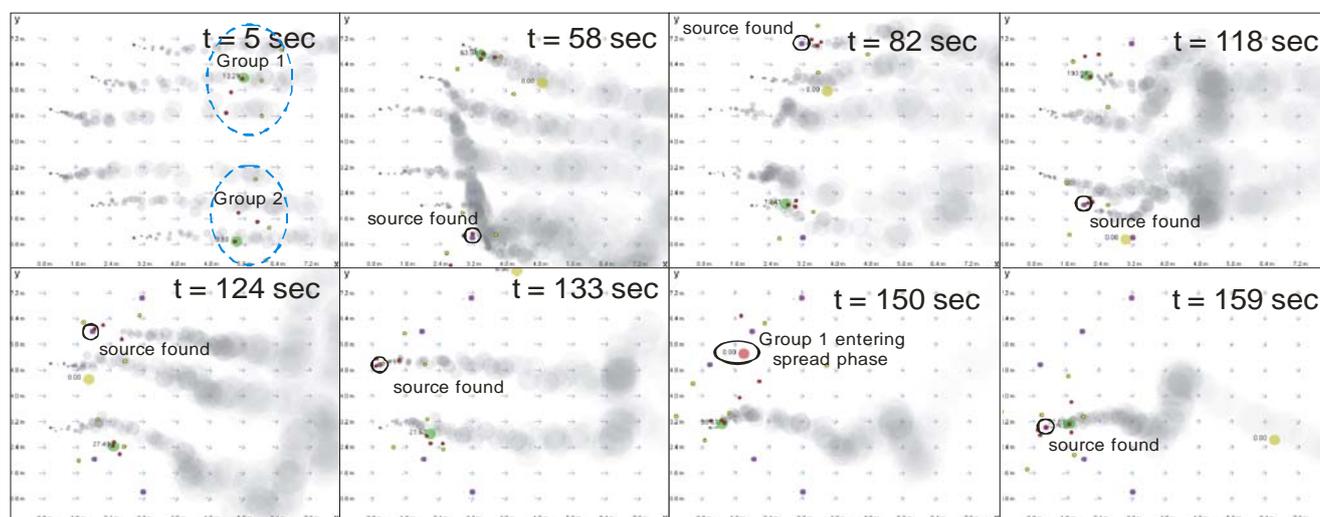
However in practical, for real natural environment, the robot will find various situations related with multi study from biology, physical chemistry, engineering and robotic. Unresolved problem still find in implementation phase. Most of those could be grouped into one of the following categories: Environments, Performance Analysis, Algorithm Optimization and Real Hardware Implementation. We also try to analyze the feasibility conjectures referred to above, in future work.

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(a) Multiple odor source localization with spreading method



(b) Multiple odor source localization with spreading method and parallel search with 2 robot groups

Fig. 11. Screen shoot of demonstration of ability of parallel MPSO with closing-spread method solves multiple odor sources.

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Table 1 Analysis for parameter relationship

Dependent Variable: Mean

Source	Sum of Squares	df	Mean Square	F _{Calc}	F _{Tabel}	Sig.
Corrected Model	64804116.958(a)	191	339288.570	100.521	1.00	.000
Intercept	161867221.542	1	161867221.542	47956.378	3.84	.000
Area	21350598.277	3	7116866.092	2108.513	2.60	.000
Source	24577352.973	5	4915470.595	1456.306	2.21	.000
Robot (R)	2346056.539	2	1173028.269	347.533	3.00	.000
Niche (N)	6782592.603	2	3391296.302	1004.739	3.00	.000
Area * Source	4987334.722	15	332488.981	98.506	1.67	.000
Area * Robot	508385.225	6	84730.871	25.103	2.10	.000
Source * Robot	817757.164	8	102219.645	30.285	1.94	.000
Area * Source * Robot	795158.328	24	33131.597	9.816	1.52	.000
Area * Niche	931027.584	6	155171.264	45.973	2.10	.000
Source * Niche	1365569.769	10	136556.977	40.458	1.83	.000
Area * Source * Niche	705616.653	30	23520.555	6.968	1.46	.000
Robot * Niche	17432.426	4	4358.106	1.291	2.37	.271
Area * Robot * Niche	312197.735	12	26016.478	7.708	1.75	.000
Source * Robot * Niche	297325.213	16	18582.826	5.506	1.65	.000
Area * Source * Robot * Niche	709315.470	48	14777.406	4.378	1.37	.000
Error	5832520.500	1728	3375.301			
Total	232503859.000	1920				
Corrected Total	70636637.458	1919				

a R Squared = .917 (Adjusted R Squared = .908)

Table 2 Analysis for searching best combination using LSD method (performance vs cost)

Sources	Range of Searching Area			
	5 x 5 m ²	7 x 7 m ²	10 x 10 m ²	12 x 12 m ²
5	G ₃ R ₂₀ (62,6)	G ₃ R ₂₀ (129,7)	G ₃ R ₃₀ (67,9)	G ₃ R ₃₀ (116,4)
10	G ₃ R ₂₀ (98)	G ₃ R ₃₀ (130,2)	G ₃ R ₃₀ (171,2)	G ₂ R ₃₀ (215)
15	G ₃ R ₂₀ (139,6)	G ₃ R ₂₀ (201,7)	G ₃ R ₃₀ (227)	G ₃ R ₃₀ (312)
20	G ₃ R ₂₀ (165,8)	G ₃ R ₃₀ (212,4)	G ₂ R ₃₀ (412,1)	G ₃ R ₄₀ (282,1)
25	G ₃ R ₄₀ (121,8)	G ₃ R ₄₀ (207,8)	G ₃ R ₃₀ (345,2)	G ₃ R ₄₀ (380,2)
30	G ₃ R ₃₀ (210,7)	G ₃ R ₃₀ (222,6)	G ₃ R ₄₀ (358,9)	G ₃ R ₄₀ (434,5)

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