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PSO ALGORITHM FOR SINGLE AND MULTIPLE ODOR SOURCES LOCALIZATION PROBLEMS: PROGRESS AND CHALLENGE

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Abstract- Odor sensing technology in robotic research introduce two research field namely odor recognition and odor source localization. Odor source localization research also includes the odor recognition ability with localization method. This paper shows some experiment had been done to localize odor source using single agent and multiple agents. Experiment shows that single agent can't be used in dynamic environment, hence also can't be used in real life application. This paper promotes an algorithm known as Particle Swarm Optimization (PSO) to solve these problems. The experiment

conducted using PSO shows that PSO able to localize the odor source in the same condition where single agent failed. However, PSO still need to be modified before it can be use widely. This paper shows modification that has been proposed by the authors to enhance it's ability. The research also has been push to solve multiple odor sources using parallel localization. To verify proposed method, software simulator was used. Results from these experiment show that Modified PSO is able to localize all four odor sources in dynamic environment in 651.900 seconds within 7 x 7 meters search area. The modification being applied in this research not limited by searching technic but also creating two types of robot.

Index terms*:* Particle Swarm Optimization, PSO, Modified PSO, Odor Source Localization, Al-Fath, Multiple Odor Sources Localization, Multiple Robots, Dynamic Environment, Parallel Localization

I. INTRODUCTION

In recent years, there have been a rapid growth in odor-sensing technology applications in robotics. Odor-sensing technology applications could be categorized into two groups: artificial odor discrimination system and odor source localization using autonomous mobile sensing system. Artificial odor discrimination system is utilized to recognize and also categorizing aromas, vapors and gases. Normally, odors could only be recognized and differentiated by a specially trained person based on their human sensory. Their ability has been used in various fields such as food and cosmetics. However, the result from the human sensory test will vary depending on health conditions and the personal mood of the inspector. The limitation of using human sensory could be overcome when using artificial odor discrimination.

In one of our previous research, odor sensor is used to distinguish fruits by its aromas [1, 2, 3]. This artificial system is made up of many chemical sensing system and also a pattern recognition system. In the first research [1], artificial odor discrimination with 4-quartz resonator sensors array are used. This configuration is combined with Back Propagation Neural Networks (BP NNs) for pattern analysis. This combination could recognize various single odors. However the system could not classify the odor mixture [4]. In order to overcome these problems, many improvements were needed in both hardware and pattern analysis software. As for the hardware, the system replaced four-quartz resonators (10 MHz) with 16-quartz resonators (20 MHz). In this software, the original pattern classifier is BP NNs. It is then changed to a variance of Back

Propagation, probabilistic Neural Networks, and Fuzzy-Neuro Learning Vector Quantization (FNLVQ). To increase the accuracy of the FNLVQ, a Matrix Similarity Analysis was proposed. This improvement makes the system usable to recognize two odor mixtures. This is not the final stage, as there's still a chance to produce higher capability by adding further improvements to the system. Our last research shows that utilizing Particle Swarm Optimization (PSO) method to select the best codebook vector it will influence recognition rate [3]. PSO is used to replace fuzzy vector position for recognition analysis.

Our previous researches have utilized PSO for several purposes. Firstly, research conducted by Aprinaldi et al [5] in 2014. This work focus on the detection of ellipse which represents embryo in in vitro process. The PSO algorithm was empowered to optimize the arc's mathematical function. Secondly, research conducted by Aprinaldi in 2015 [6]. This work focused on the sperm tracking by using PSO algorithm which is combine with smoothing stochastic sampling on low frame rate video. Finally, research conducted by Jatmiko et al in 2015 [7]. This work concerned on the prediction of cell growth. He employed multilayer perceptron (MLP) which is optimized by Canonical PSO to predict time series dataset of algal growth.

Another primary area of odor-sensing technology using robotics application is autonomous mobile system for odor source localization [8]. In the early stages, odor source localization is frequently used for gas leakage and locating fire sources. Another challenge of this primary area is that the search space of the odor localization could be very large. The search area is typically a warehouse or a factory that replaced the fixed smoke detection sensors with these robots as an attempt to lower the build and maintenance cost of the warehouse/factory. In addition, there have been several cases where the search area is a room with a ventilated window, as conducted by [9]. The ability to sense our target odor is needed to locate odor source, hence, this topic provides more challenges. The robots should also be equipped with accurate positioning systems [10, 11]. There also several environment conditions that contributes in increasing the complexity of this problem, such as wind and molecule behavior [12, 13, 14]. However, because this topic has high importance level, the attractiveness of this research also increased.

There are many researchers who have tried to propose a method for solving odor source localization problem. In 2007, Martinoli et al [15] proposed odor localization by using a single agent mobile robot. More sophisticated localization methods using many agents is proposed by Hayes [12, 16]. There are also several researches that proposed ant colony algorithm to locate odor source [17, 18]. Most of these methods are only able to find the source in simple environments where the dynamic factors are being ignored. Some of these methods have tried using experimental setups that minimize the influence of turbulent transport. This is done by either minimizing the source-to-sensor distance [19, 20] or assuming a strong unidirectional air stream in the environment [4, 12, 21, 22, 23].

The problem in these previous researches is that the assumptions that are being introduced in the experiment are creating a big gap between the real world environment and experiment environment. Therefore, the proposed methods are not feasible to be implemented and applied in a real world situation. At the very least, there are other two factors that must be brought to the calculation, these are the unstable wind behavior and odor spreading behavior, which is dominated by turbulence rather than diffusion [24]. Under these circumstances, the robots will face a very complex situation, hence, increasing the failure rate of the odor localization.

In 2005, we tried a new approach using a single robot to deal with a single odor source [4]. Although the result was good enough, the environment was still simple. We experimented in an indoor environment and in stable odor concentration. We knew that our development of robotic applications for odor source localization is still at an early stage and it has yet to be developed into the application stage. We still could not handle the two main problems that have been notified earlier.

To handle two main problems that we had in earlier research, we proposed a new approach using Particle Swarm Optimization (PSO) [24, 25, 26, 27]. These proposed method is being proved using simulation software and real world implementation. The results showed that even though the PSO cannot localize all of the sources, PSO is still feasible to be used. This result is the main foundation of the research explained in this paper.

The result of PSO feasibility in odor source localization shows that there is a great possibility that the PSO can be used in real life problem. However, it cannot be claimed until additional research has been preformed. This paper will present research results in order to enhance PSO potency to handle environmental changes. First, to give essential proof that PSO is feasible to be used in natural environments, simulation software has to be developed. This development delivers a two-dimensional simulation software that become the core foundation for further research. To create a dynamic environment in the simulator, wind and plumes behavior must be implemented in the simulation software. Farrell et al in [28] provides a physics model that can be used to mimic natural behavior of wind and molecule that needed. The simulation result shows that PSO can be used in dynamic environment.

Based on this result, the development of real robot could begin. Robot experiments will verify the result obtained from the simulation software. This will also verify that there’s a large possibility to push PSO even further. One of the approach proposed is detect and respond [29] which promotes PSO ability to escape from the local optimum. Because the robot is not trapped in the local optimum, the reasearch continued to applied PSO to localize multiple odor sources. At this point, PSO sometimes failed because of it convergence behavior, hence a new method to maintain robot diversity have to be implemented. Blackwell at [30] proposed to add magnetic behavior in robots, known as charge robots. Since the charge robots had magnetic behavior, it means that there won’t be any robots that are to close to other robots. This mechanism gives robots ability to avoid collision and at the same time maintain their diversity. This approach increased the ability of PSO in multiple odor sources environment, but it’s still prone to failure to localize all sources because the robot can’t detect any plumes. Nugraha in [31] proposed a new method to overcome this problem, this method is called spread phase. Spread phase will make robots spread from the center point of the group, hence, increasing the possibility to detect undetected plumes. In order to speed up the search time needed to find all the source, parallel niche is being applied.

The next step in PSO research is to minimize the gap between real world and simulation world by creating a three-dimensional simulation with physics behavior. The development was done with *Open Dynamic Engine* library, which simplifies 3D modeling and automated physics calculation. Some new enhancements are also being implemented such as implementing new types of robot that are called Main Robot, Main Spread, and Draft. These proposed methods are applied to avoid local optima and optimizing nearby robots. However there’s still a possible unwanted condition such that a niche will only have one member due to the draft behavior. This is the problem that is the main objective to be solved with the implementation of limit movement for charge robot and modification in main spread algorithm. Both these methods were aimed to ensure that there’s no niche that consist of only one robot.

This paper presents all of the modification that had been done to enhance PSO ability to search single odor source and multiple odor sources. This paper also presents the algorithm proposed earlier to search single odor source using a single agent. Each development stage will be presented with each analysis and improvement to develop agent(s) ability. This paper will explain the odor source localization using single agent and then follow by odor localization using PSO. The rest of the paper will be discuss about modification had been carried out to enable PSO handle multiple odor sources.

II. MOTIVATION

Odor source localization has become one of the interesting topics in odor sensing research. Theoretically, odor source localization can be solved by following three principles: search for target odor in the search space, tracking the odor to the source, and then declaring the odor source. However, in reality this is not as easy as stated in the principles.

They are many progress and methods that have been proposed, which can be generally categorized as single and multiple-agent odor source localization. An algorithm that is commonly used in odor source localization is Particle Swarm Optimization Framework (PSO). Usually, PSO is only suitable for handling problems in a static environment. This is because real world problems are dynamic and the convergence characteristic of PSO makes this algorithm unsuitable for application in the real situation. Dynamic problems are defined as time-dependent problems [32]. However, certain research has shown that PSO is able to adapt in dynamic environments, hence, also makes PSO possible to be used in odor localization. Previous researches also showed that PSO can be modified and pushed the algorithm’s limit to handle multiple odor sources problems.

III. SINGLE ROBOT APPLICATION

Although it is possible to implement odor source localization in various interesting applications, the realization of it is quite difficult. The main causes of this difficulty are the unstable wind and the turbulence-dominated odor molecules distribution. Therefore, real world implementation of autonomous mobile system for odor localization is still very limited and very hard to find.

The first implementation done by us was using single robot to find the odor source. The implementation had implemented three subtasks to localize the source that were suggested by Hayes et al [12]. It is divided into plume finding, plume traversal and source declaration. In plume finding, robots can move freely or use any method to cover every search area until they find the odor stream. If environment had stable wind direction, robots can use wind direction information to minimize the searching time. Usually when the wind is stable, wind direction and odor distribution gradient vector have the same direction as the result robot will move crossing the wind direction and find the gradient of odor distribution.

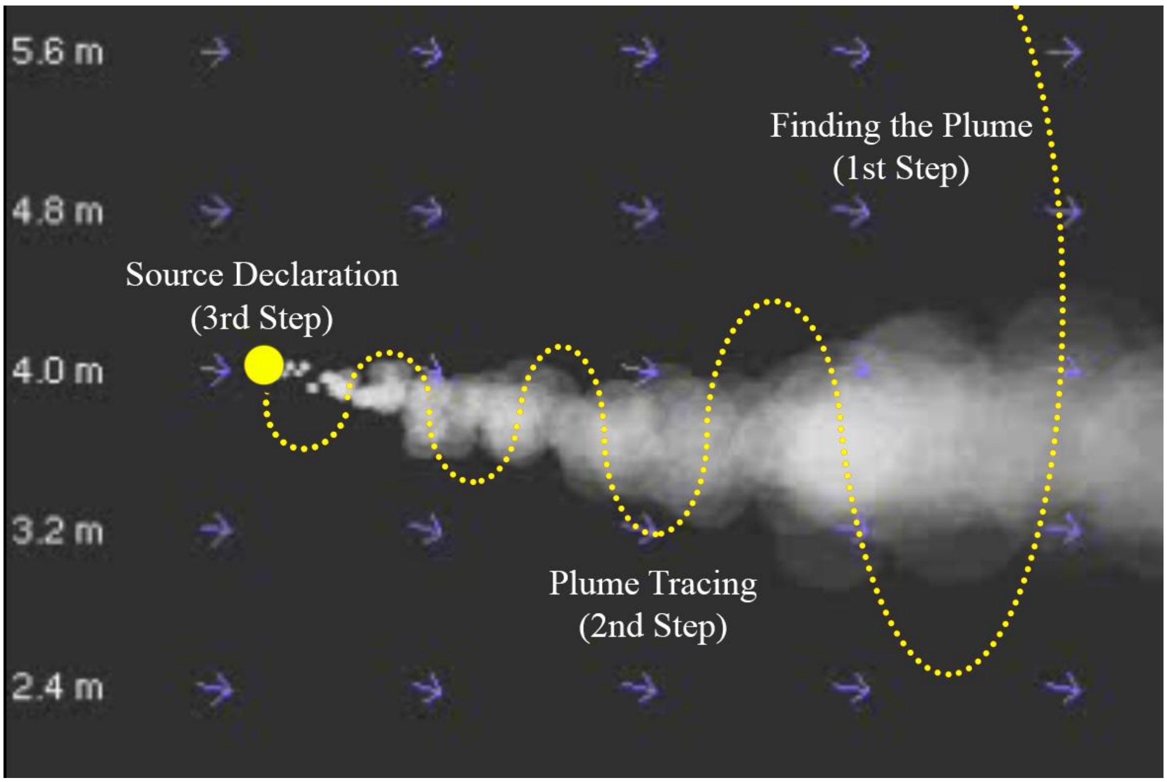


Figure 1. Three Steps to Find the Source.

After the odor stream has been found, information about the odor stream would be used to search the odor towards the source. This step requires more specialized behavior, so that the robot could consistently keep in contact with the plume and also to maintain the progress in the direction of the odor source. The algorithm in the plume traversal step is zig-zag algorithm. When breeding season arrives, flies used this simple method to reach their mate. What they do is repeated traversal movement towards the source of the gas produced by their partners. Further searching is done by moving against the wind direction every time the fly is doing traversal movement. The wind direction angle affects the required time to find the odor source. However, by implementing adaptive strategies the search time can be reduced to obtain a better result [15].

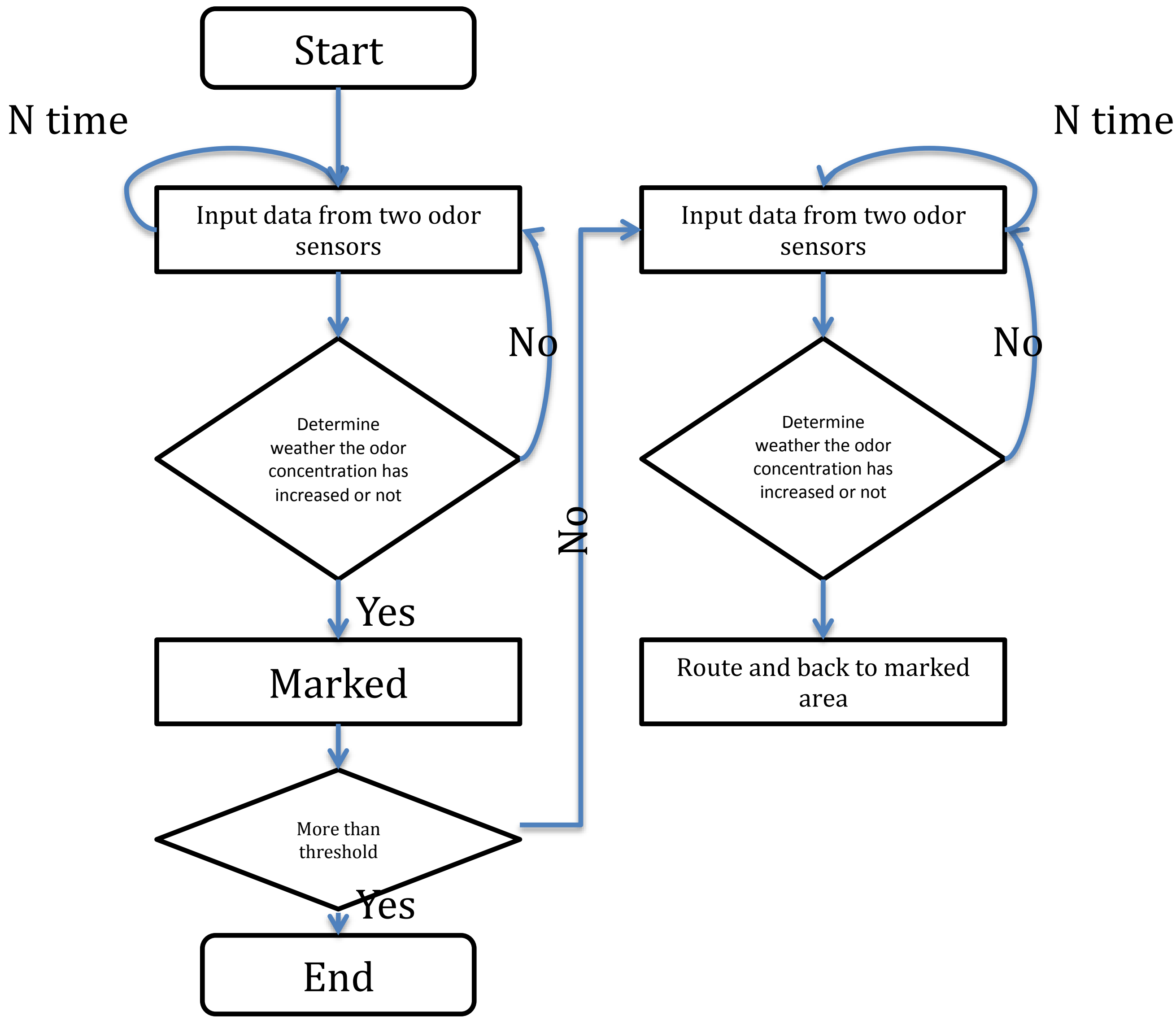


Figure 2. Flowchart for a Single Robot.

The final task in this method is source declaration, which determines with certainty that the gas source has been found. The task does not necessarily have to be done based on odor information. This is because usually, odor sources can be sensed via other forms from a short range. The important factor is how choosing the convergent parameter. Figure 1 shows how single robot can find the source with the three steps given by Hayes.

Implementation of three steps with Zig-Zag Algorithm were done by trying to mark some area where the odor flow passed through it. To mark the area, first we have to make sure that the area is really passed through by the odor flow. It is done by checking the odor concentration n-time in every area that were passed by the robot. If the concentration has increased, which is recognized by the increasing odor concentration from n-time sample, then the area is marked.

After the area has been marked, the robot continues its search with the same pattern as before. This time, an action is done whenever the concentration has decreased. That action is back to the marked area. This procedure is done until there is an area where the odor concentration is more than the threshold. The robot movement has to be set to fight the wind direction in order to reach the source. The flow of the implementation can be seen in Figure 2.

Implementation was done in a real world environment. The robot consists of three parts, namely: tracking module system, data processing module system and modem radio system. Tracking module system is used to collect data from the environment and to approach the odor/gas source. Data processing module is used for storing the data that is gotten by the tracking module. Data processing module is also used to calculate the next position that should be approached by tracking module. Tracking and data processing modules communicate using modem radio. The architecture can be seen in Figure 3.

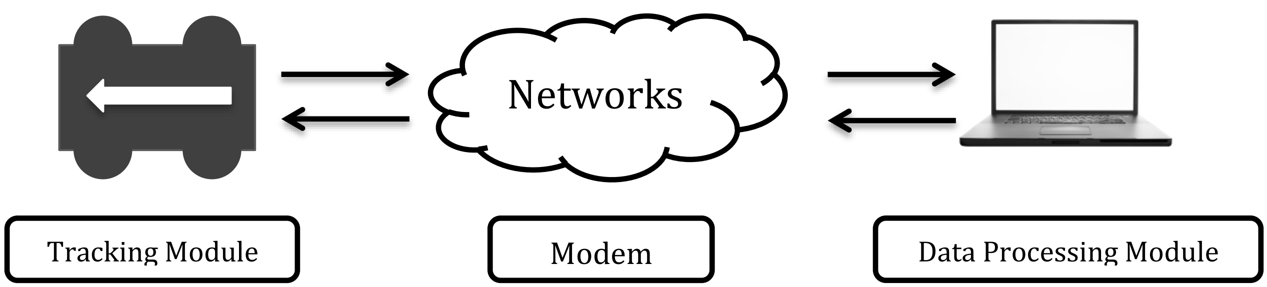
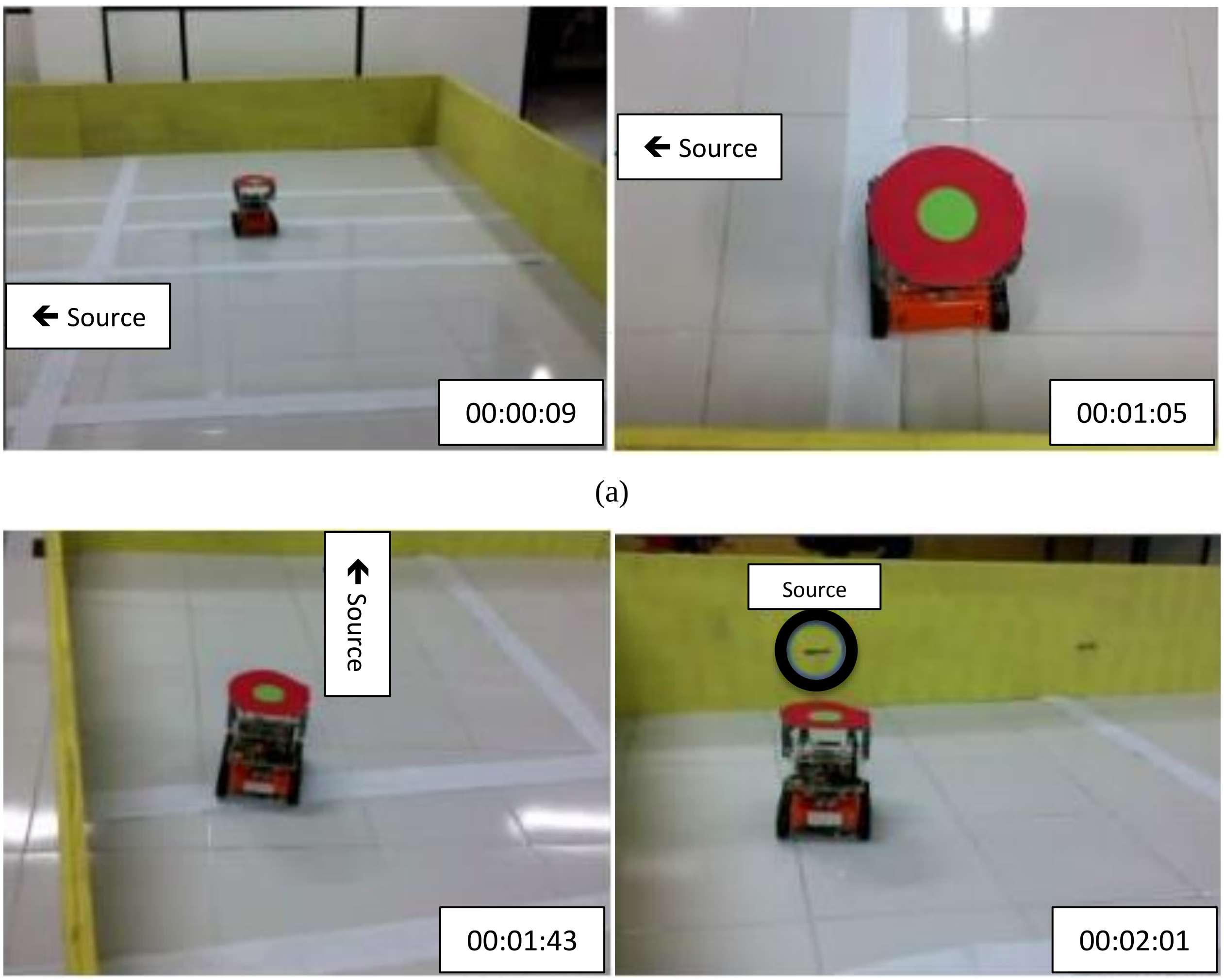


Figure 3. Single Robot Architecture.

Results showed that the agent could localize the source as close as possible. However, this odor source localization system could work only in an indoor environment and in a stable odor concentration as can be seen in Figure 4. Figure 4.a. shows the robot searching the odor source in the first minute. The second minute and the moment when the robot have successfully localize the odor source are shown on figure Figure.4.b. Both in hardware implementation and in simulation results showed that the single agent could not handle the problem that was caused by the influence of unstable wind. In the simulation, the robot's chance to locate the source in this condition was almost zero as can be seen in Figure 5. Figure 5 a shows the robot in the plume finding phase and succeeded in finding it (shown on Figure 5.b.). The robot failed to trace the plume due to the wind changes and shown in Figure 5.c. Finally, the robot could not recover and failed to find the source, this is shown in Figure 5.d. However, in reality, it still had a chance to locate the source even though the chance was low. Figure 6.a shows how the single robot agent failed to locate the odor source at an unstable wind condition. After 5 minutes, the robot still fails to localize the source of the odor due to the wind changes, as shown on Figure. 6.b.



(a)

(b)

Figure 4. Single Robot Implementation.

In the cases where the odor distribution is complex and unpredictable wind directions, the movement of the robot will be unpredictable. This is because of the algorithm it used. The solution to handle this problem without affecting the algorithm is wait for the wind to be stable again. However, the time needed to wait until the wind becomes stable again is unpredictable. To address these problems, multiple robots with a communication between them are considered as an option. Using multiple robots also means there's more ground covered, hence increasing the chances for adapting with unexpected situation. There are many algorithms that enables searching with multiple agents, one of them is Particle Swarm Optimization (PSO). This algorithm is appropriate for solving odor localization problems because it has several properties that needed to solve these problems, which will be explained in the next section.

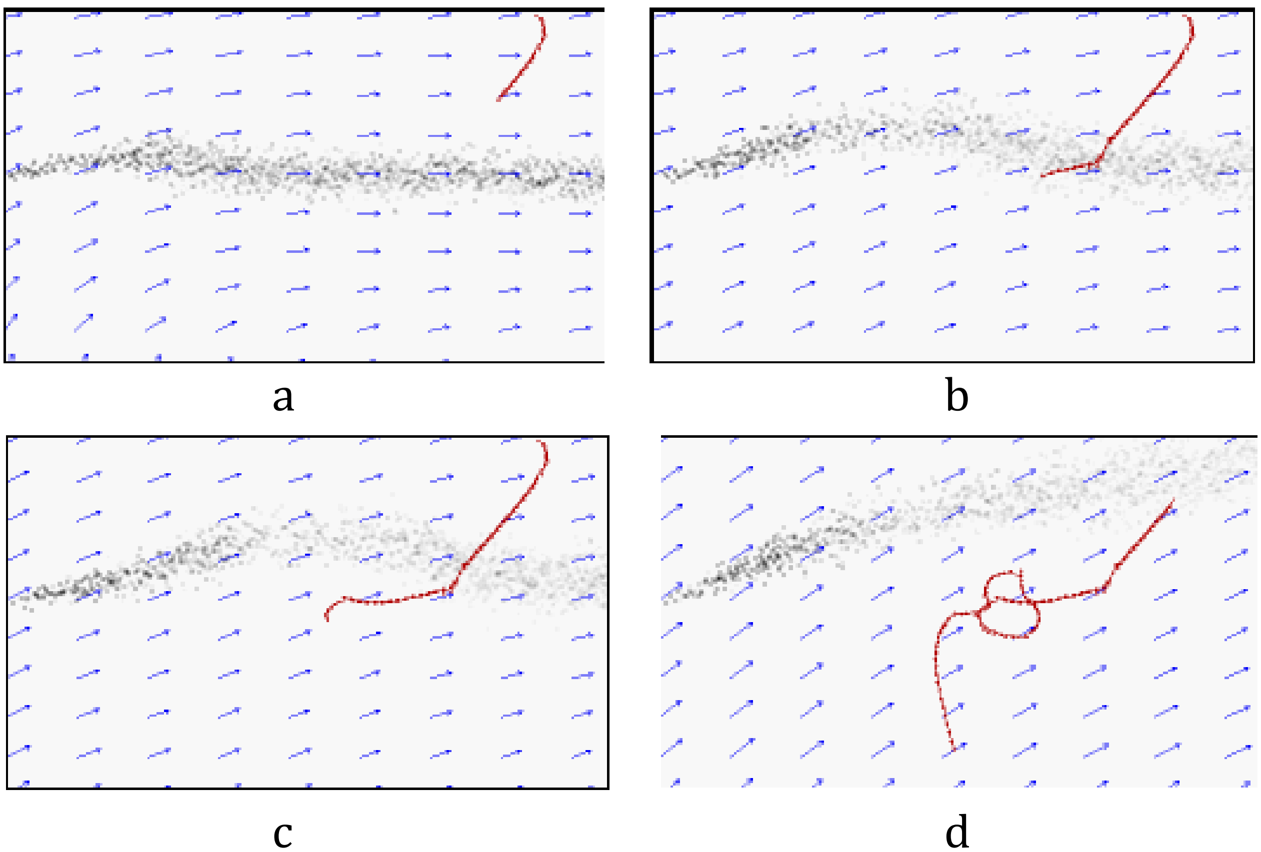
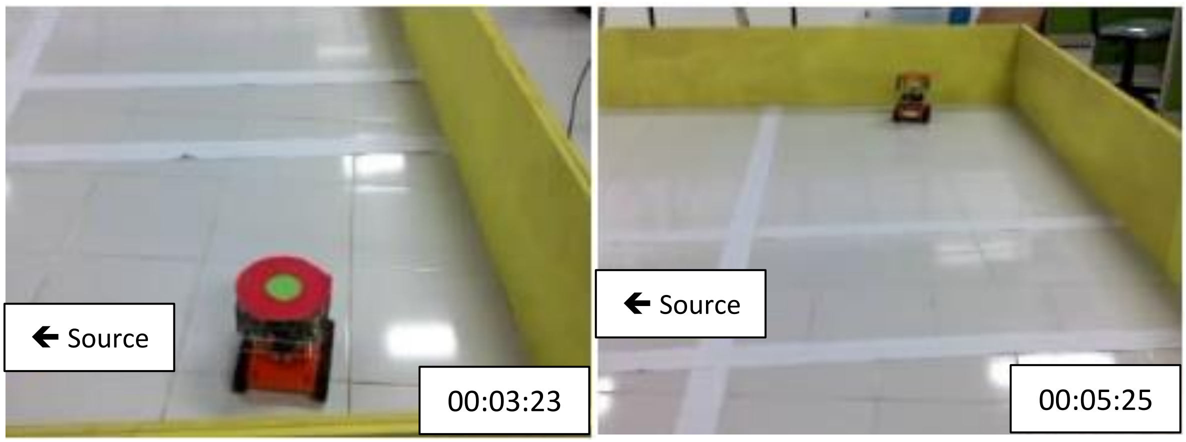


Figure 5. Single Robot Failure in Simulation

(a)



(b)

Figure 6. Single Robot Failure in Implementation

IV. PARTICLE SWARM OPTIMIZATION (PSO) CONCEPT

Particle Swarm Optimization (PSO) is one of the fields of Evolutionary Algorithm. PSO is usually utilized to deal with optimization problems. This method has been particularly effective in static, dynamic, as well as stochastic optimization problems [33, 34, 35]. This algorithm adopts animal formations and techniques when finding food in a group. They are particularly successful because the algorithm considers several measurements to deal with real-world uncertainty. Each individual in PSO will be assumed as a particle. In the case of odor source localization with robots, robots represent those particles and odor source location represent food location. The behavior of each particle will follow Eq. 1.

$$\boldsymbol{V}_i^{n+1} = \chi\left(\boldsymbol{V}_i^n + c_1 \cdot rand() \cdot (\boldsymbol{p}_i^n - \boldsymbol{x}_i^n) + c_2 \cdot rand() \cdot (\boldsymbol{p}_g^n - \boldsymbol{x}_i^n)\right) \quad (1)$$

$$\boldsymbol{X}_i^{n+1} = \boldsymbol{X}_i^n + \boldsymbol{V}_i^{n+1} \quad (2)$$

$\boldsymbol{X}_i^n$ is a position vector for the *i*-th (*i* = 1,2,3,) particle on the *n*-th iteration (*n* = 1,2,3). Vin is a velocity vector for the *i*-th (*i* = 1,2,3,) particle on the *n*-th iteration (*n* = 1,2,3). χ is a constriction factor which has a value of less than one, c_1 and c_2 are acceleration factors which manages the distribution for cognitive component and social component, p_i is the local best value and p_g is the global best value. $Rand()$ is a random number ranging from 0 and 1. Particle position is a result from previous position added with current velocity as a vector.

Velocity calculation with Eq. 1 determines the robot's position for the next step. The value of this velocity is obtained by using information from the particle itself and other particles in that area. Information from the particle itself is called the cognitive component where the value is attained from the distance difference between the current particle position and its best location over time. That position is known as the local best (p_i). From the population of local best, there is a local best which has a value better than the other. This value is called as the global best (p_g). Global best represents social information shared among particles in this population. c_1 and c_2 can influence the value of local best and global best when one of them is greater than the other. Suppose we have a condition where the value of c_1 is greater than c_2. The particle will have a tendency to move towards its local best position. On the other hand, when c_1 is less than c_2, the particle movement tends to move to the global best position.

To evaluate the current position of the robot, we used a fitness function. Position is measured based on domain vector position. A Closer position to solution has a better value. The fitness function could the compare each and every position that were explored by the robot to obtain a knowledge of the position which is the closest to the solution. Every problem has its own fitness function. After a period of time every particle will converge to one point, which is its global best. Sometimes it is not the optimum point for the solution. Convergence in this context is that the PSO has reached an equilibrium point. If this happens, every calculation involving PSO becomes inefficient because particles only move around its position. When it happens, determination to stop or not is done. This behavior determine whether the solution which is found successfully or not.

V. PSO CONCEPT PROOFING

The concepts above raise a possibility that Particle Swarm Algorithm might be possible to be implemented for Odor Source Localization. The PSO used multiple robots and enables communication between them. It simply suits with the characteristic that needed. However, this algorithm needs to be proved before further development. The proofing was divided into two steps. The first step was software implementation to confirm the possibility. The second step was real-hardware implementation to prove that this algorithm has a high possibility of being implemented to solve real world application.

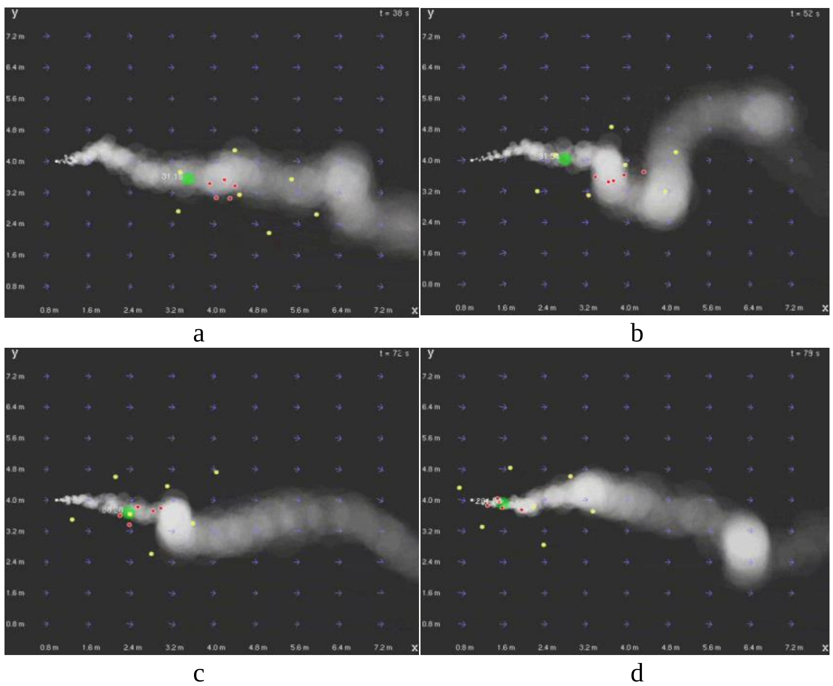


Figure 7. OSL Simulation Using Standard PSO in a 2D Environment

a. Software Implementation

The first step in PSO implementation was developing a 2D simulator. The goals of this simulation were to evaluate the performance of PSO for odor source localization. Simulation used odor source and wind using Advection-Diffusion Odor model [36]. This model is the important factor in odor source localization because it gives an odor-winding movement in such a way that the resulted environment is more dynamic and realistic. This simulation assumes that the search is done in closed room, no objects in the search space, and the wind is always blowing.

This 2D simulator use robots that have been embedded two sensors, odor and wind sensors. Each robot in this simulator is represented as circles, and so does the odor source and plumes. The circle shape was chosen because its collision characteristic that is easy to be simulated. In addition, a circle makes collision computation easier. The other benefit is the simulator does not have to know which is the front or the back, so when two robots collide they will just be bounced like billiard balls. To provide the bounce effect, we also assume that the robot have had omni-wheels to move in every direction. The robot was also assumed have a GPS to get information about itself. Figure 7 shows the 2D visualization of the simulator and PSO ability when tracking plumes. Figure 7.a. shows the initial position where the robots are finding the plume. Figure 7.b and c shows the process of plume tracing by the robots to the source of the plumes. Figure 7.d. shows the discovery of the source by the robots (source declaration).

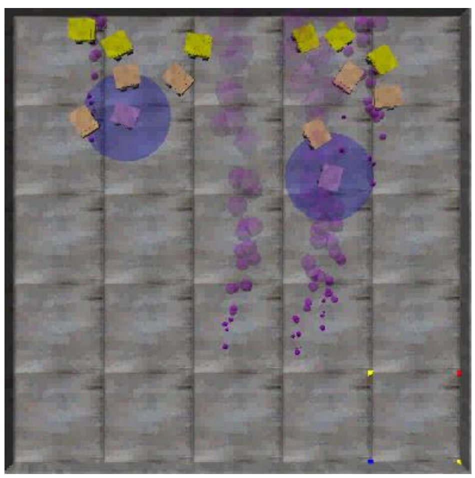


Figure 8. Simulation OSL Using Standard PSO in 3D Environment

In order to reduce the gap between simulation environment and real world environment, a 3D simulator had been developed. Every assumption used in 2D simulator is also applied in this 3D simulator, except the assumption about GPS and robot model. 3D simulator is built using Open Dynamic Engine (ODE). ODE is a C/C++ library that helps modeling physics calculation such as friction, impact, and normal force. The robot model used in this simulation is follows the real robot that would be used in real-hardware implementation.

Figure 7 and Figure 8 shows how implementation of PSO either in the 2D environment or in the 3D environment. Experiments using simulation software has proofed that the PSO are quite useful approach for odor source localization in limited area. Demonstration with real-world setting is used to follow up the successful experiment in 2D simulator.

b. Hardware Implementation

The robots used in this implementation named Al-Fath were built based on the Traxter II platform. Al-Fath is equipped with compass, sonar ranging sensor, incremental encoder, wireless communication device and a pair of odor-sensors. The main processor used in this robot is Atmels AT-MEGA 2560. For left motor and right motor odometry and speed control, two Atmels AT-MEGA 8 are used for each side. In order to obtain the robot's position in the search field, sets of web cameras is used as local GPS. Mounting color signature is also added on the top of robot to help simplify recognizing process. Figure 9 shows Al-Fath shape from the best angle.

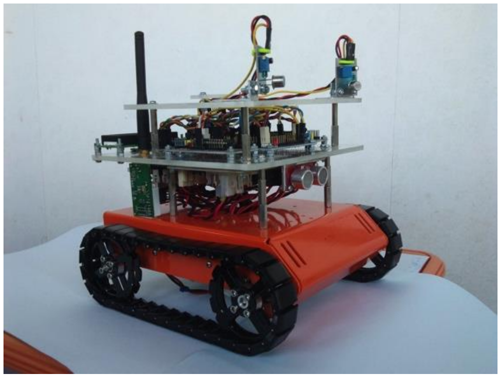


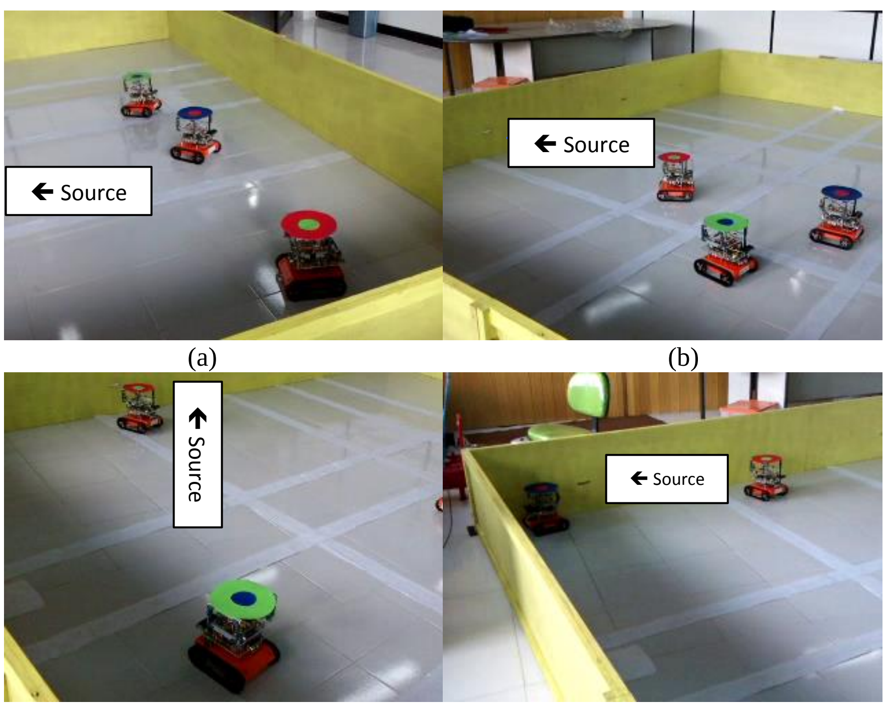
Figure 9. Al-fath Robot

In the experiment, a 488 by 488 area is used with a 50cm high wall that surrounds this area. An odor source is mounted on one wall. Liquid ethanol is used as the source of odor stored in the ethanol storage. The advantage using ethanol is ethanol evaporates quite easily on room temperature. To distribute the gas into the entire field, we have utilized an air compressor, which could be controlled in the horizontal axis to represent a dynamic odor flow. Sample of the experiment can be seen in Fig. 10. In Figure 10 a, the robots are in the initial position. In figure b, the robots are searching the source using the PSO algorithm. In the c figure, the robots are closing in on the source, and in figure 10.d. the robots have successfully localized the odor source.

Table 1 shows the results of PSO experiments. From four out of six experiments, three Al-Faths were able to locate the odor source. Two failures in this experiment were caused by the convergence nature of PSO, so Al-Faths could not locate the source within six minutes. Using standard PSO, the robots can possibly be trapped in a specific global best position. Therefore, a more advanced PSO, such as PSO detect and response is needed to avoid the trap.

Table 1: Experiment Outcome

Scenario	Search Time
Opposing the source, Static wind	219(Success)
Opposing the source, Static wind	315(Success)
Opposing the source, Dynamic wind	241(Success)
Opposing the source, Dynamic wind	360(Fail)
Parallel to the direction of exhaust, Static wind	234(Success)
Parallel to the direction of exhaust, Static wind	360(Fail)



(a) (b) (c) (d)

Figure 10. Single Odor Source Localization Using Standard PSO

VI. PSO MODIFICATION FOR SINGLE ODOR SOURCE LOCALIZATION

The experime nt done using real hardware has shown that PSO can be used in odor source localization. However, experiment result also shows that some modification have to be taken in order to increase PSO capability. This section will discuss some modification that is proposed to solve single odor source localization. These and further modifications discussed in this paper were tested using simulation software that was described in the previous section. Simulation software enables us to do simulation using large number of robots and wider search area. Using simulation can also help us testing and modifying the proposed method faster than testing it using real hardware. However, the importance of hardware verification cannot be ignored. Unfortunately this have to wait due to cost of building the robots is not cheap. In real hardware verification, large search area also can become a problem. All these reasons make the software verification become more feasible and faster solution for the moment.

a. Wind Utilization

Under normal PSO algorithm, there is no guarantee that robots will keep on following the plume until it finds the sources. However, this could be managed if we use a plume data called odor-gated rheotaxis (OGR) [37]. Animals commonly use this method to find their food. This research uses wind data (anemotaxis) to determine particle movement [33] because movement of the plumes will be same with the wind movement. If the particles move against wind movement then distance between robot and source will decrease over time. Whenever a particle lost contact with the plumes, the particle will move towards last direction until they can detect the plumes again. To apply this methodology, we require information about the wind direction. By knowing the direction of the wind, the angle between the wind direction and the particle movement can be calculated. It will be used as parameter to determine the next movement.

Consider the robots could detect the change of the wind $\boldsymbol{W}(t)$ each time and that the velocity is an intermediate velocity $\boldsymbol{V}_i^*(t)$. The direction that the robot will move to could be calculated by knowing the angle (θ) between robot's intermediate velocity vector $\boldsymbol{V}_i^*(t)$ and the wind direction vector $\boldsymbol{W}(t)$. Because the angle is dependent on the wind direction, it is a relative direction. The robot will then follow the concentration of the wind and follow the upstream of the wind. Equation 3 and 4 will define $\boldsymbol{V}_i^*(t)$ and $\boldsymbol{W}(t)$ respectively.

$$\boldsymbol{V}_i^*(t) = v_x\boldsymbol{e_x} + v_y\boldsymbol{e_y} \tag{3}$$

$$\boldsymbol{W}(t) \ = w_x\boldsymbol{e_x} + w_y\boldsymbol{e_y} \tag{4}$$

The angle between $\boldsymbol{V}_i^*(t)$ and $\boldsymbol{W}(t)$ is computed two-dimensionally. This problem then can be solve using inner product which defined as: The angle between $V_i^*(t)$ and $W(t)$ is computed two-dimensionally. This problem then can be solve using inner product which defined as:

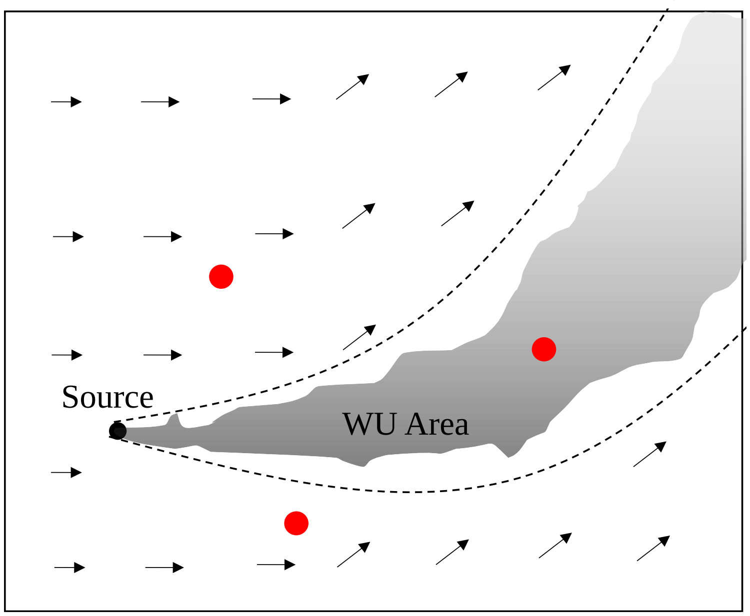


Figure 11. Area where WU is applied

$$\theta \ = \cos^{-1}\left(\frac{\boldsymbol{V}_i^*(t)\cdot\boldsymbol{W}(t)}{\|\boldsymbol{V}_i^*(t)\|\|\boldsymbol{W}(t)\|}\right) \tag{5}$$

a.i Wind Utilization I

One method that can be employed for the utilization of the angle (θ), is to create restricted area where cannot be entered by robots. The above-mentioned area is named forbidden area. The forbidden area indicates an area on which the robots most likely searching in the wrong direction. If the angle (θ) is covered by forbidden area, it means that some action have to be taken in order to avoid robot entering area (i.e. let $\boldsymbol{V_i}(t) = 0$). Modified PSO with Wind Utilization and Forbidden Area concept is described in Eq. 6 - 7.

$$\boldsymbol{V_i}(t) = \begin{cases} 0 & if\ \theta < |\theta_{forbidden}| \\ \boldsymbol{V}_i(t) & Otherwise \end{cases} \tag{6}$$

$$\boldsymbol{x}_i(t) = \boldsymbol{x}_i(t-1) + \boldsymbol{V}_i(t) \tag{7}$$

The conceptual idea of this implementation, with various forbidden areas is depicted in Fig. 12.

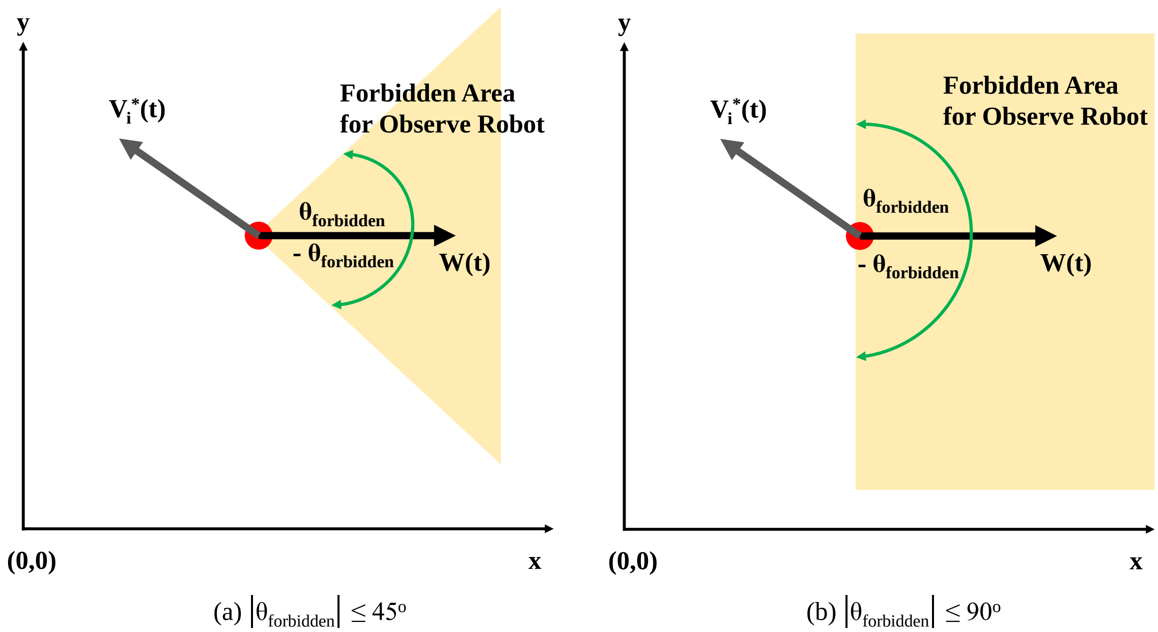


Figure 12. Basic concept of forbidden area in wind utilization (x-axes is downwind direction).

a.ii Wind Utilization II

The controlling parameter (χ) can also be used to utilize the angle (θ). The controlling parameter can be employed to foresee the robots' velocity. After obtaining the robots' intermediate velocity ($\boldsymbol{V}_i^*(t)$), the angle (θ) will be calculated by Wind Utilization (WU) algorithm (Eq. 5). Afterwards, the value of controlling parameter, χ_θ, can be found. The continuation function to find the value of the controlling parameter χ_θ is defined in Eq. 8.

$$\chi_\theta(\boldsymbol{W}(t), \boldsymbol{V}_i^*(t)) = \frac{1}{2}\left(1 - (\boldsymbol{W}(t), \boldsymbol{V}_i^*(t))\right) \tag{8}$$

The Wind Utilization II's (WUII's) basic concepts as a modification of standard PSO are defined in Eq. 9 and Eq. 10.

$$\boldsymbol{V}_i(t) = \chi_\theta \cdot \boldsymbol{V}_i^*(t) \tag{9}$$

$$\boldsymbol{x}_i(t) = \boldsymbol{x}_i(t-1) + \boldsymbol{V}_i(t) \tag{10}$$

The implementation of Wind Utilization would likely to boost up the time required for localization. With wind utilization II, whenever the robot will move to the wrong direction which is seen from its θ, their velocity will be decreased. It prevents the robot to go far away from the source by preventing the robot movement to the wrong direction. The relation between the controlling parameter (χ_θ) and the angle (θ) can be seen in Fig. 13. However, every time robots applied WU, it's also means that more calculation is being taken into account and hence more time needed for the computation.

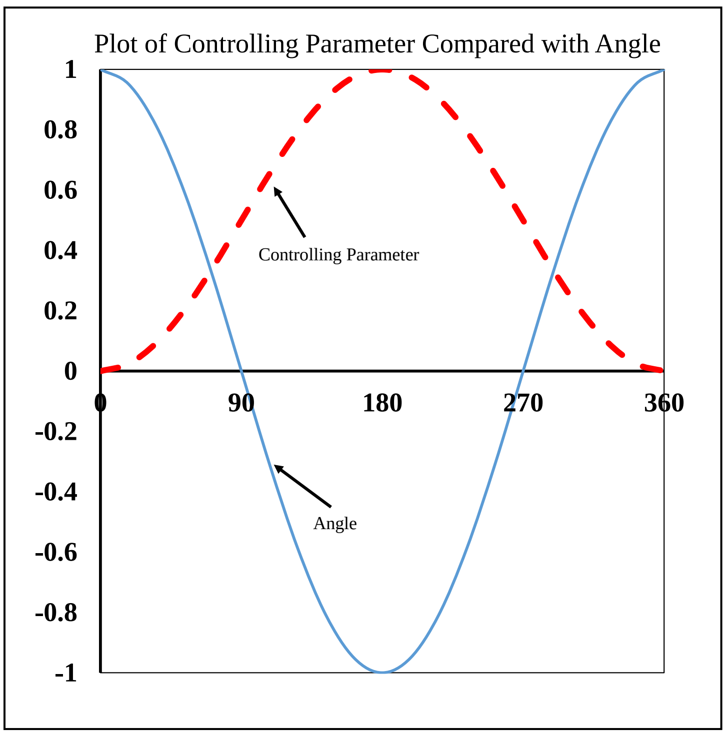


Figure 13. Controlling parameter function's delineation of robots' velocity.

In Fig. 11, the source is in the same direction with the wind. In accordance with WU concept this will make the robots move slowly. This condition causes the search using WU become inefficient. To prevent this condition, WU uses information about plumes (OGR). If the particle can detect plume, then it means that robot is on the right track and WU can be applied. Otherwise, WU would not be applied.

Besides those two methods, there is also a method proposed by Gong [38] which altered two constants in the PSO algorithm based on wind dynamics. It affected the value of both social term and self-recognition term.

b. Detect and Response Algorithm

This is the first approach that was applied in the PSO algorithm to make PSO adaptive in dynamic environment. This modification involved the implementation of limit memory method and local search methods. The first method will be run when robot detect changes in the environment. Limit memory will trigger each particle to change their local best position and then erases their memory of the previous search [29, 33]. Local search [34] tries to adapt the changeover in the environment by searching around the optimum position. This method assumes that more optimum position, can be found near current optimum position. This method is triggered if every particle converge to the optimum position.

By combining the limit memory and the local search methods, a new method to handle changing in environment arises which is called detect and response. Detection is conducted when changes in the environment are detected, while response is done to counteract this condition. This algorithm used global best as measurement parameter in order to acknowledge if there's any changes in the environment. It is assumed that if after several PSO iterations the global best value remains constant, then it indicates that particles are trapped in local optimum. Therefore, robots must do the appropriate response. Response is conducted by resetting global best value in population and local best value for each particle. Detect and Response can help robot avoid being trapped in local optimum.

The successful approach of detect and respond method makes the research to be pushed even further. The next step is to modify the simulation software so that users can put more than one odor source in the search field. This feature is useful in real life application since it cannot be predetermined the number of odor sources in the search field. Unfortunately, the experiment results show that this method was only efficient to be used when localizing single odor source.

VII. PSO MODIFICATION FOR MULTI ODOR SOURCES LOCALIZATION

Although it looks identical, multiple odor sources localization problems is quite different with the single odor source problems. Odor plumes is one of many element that contribute to makes the different become more challenging. Although in both cases the odor plumes move dynamically, when dealing with single source, robots can be sure that every plumes came from the same odor. This kind of assumption cannot be applied in multiple odor sources. Moreover, the plumes of different sources can fuse and makes robot cannot confirm plumes origin. The fused plumes will also drastically increase the target odor concentration on that location. If the location of odor sources are close, then odor concentration from that area will also increase. This will gives robot difficulty, since the odor cannot be distinguished from one source to the other.

This section will discuss the modifications which are applied to PSO, such as charge robot concept, main robot concept, drafting, spreading, parallel niching, and adaptive niching. All these method can be turned on and off as necessary, which enabling various modification combination to PSO. Experiment results of these various combination are shown in the end of this section.

a. Declare and Close Sources

The major challenge in multiple odor sources localization is the interferences of plumes. Tracking plumes to the source in multiple odor source environment is a hard-work, but continue searching the rest of the sources after find one of them is another hard-work. Due to the convergence properties of PSO, after niche found one of the source, niche become converge to that particular source. Hence this properties hold niche from finding the rest of the sources.

In this research, declare and close source method is proposed. This method assume that every time a robot declare that a source has been found then that robot will close the source. The closed odor source means no more plumes generated from that particular source, hence minimize the interference.

b. Charged Robot and Spread Phase

As stated in PSO modification for single source, PSO-DR can be used to maintain diversity at a moment, but it can’t be used to maintain PSO diversity at all time. This is due to the fact that PSO DR is triggered only when environmental change detected. It is in the nature of PSO to have convergence behavior. Which mean in order to maintain robot diversity, a new method have to be embedded to PSO in order to keep robot diversity.

There are many researchers proposed a method to keep particle diversity. Around 2002, Blackwell et al proposed a method by applying Coulombs law [30, 36, 39] to the particle. The application of this, makes each particle have repulsive area to every particle in the search area. This introduce a charged swarm robot. Charged swarm robots are the robots that actively maintain diversity of their positional distribution. As a bonus, the diversity properties can prevent robots from being trapped in the local maximum. Implementation of this method in the simulation software means that there are now two different types of robots i.e. charged and neutral robots. Neutral robots are robots which have no repulsive force work on them. On the other hand, charged robots are defined as robots whose mutual repulsive force among others with similar type. Figure 14 shows repulsive force area for one charge robot. The charge robot is the one that colored by yellow, while the red one is the neutral robot. The repulsive force between robot-*i* and the robot-*l* where ($i \neq l$) is defined in accordance with the relative distance (Eq. 11).

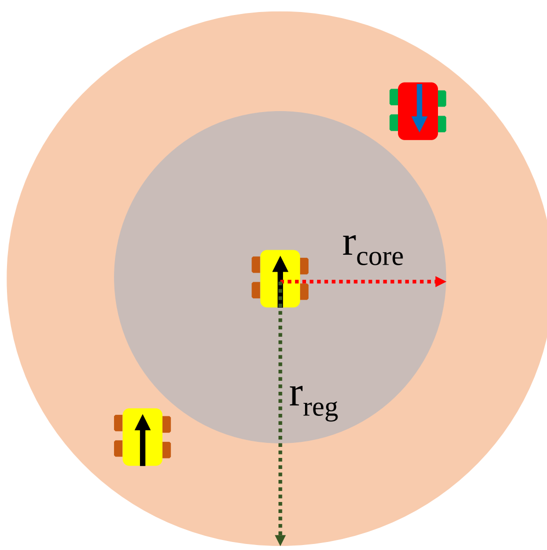


Figure 14. Charged robot force area.

$$\boldsymbol{a}_{il}(t) = \begin{cases} \frac{Q_i \cdot Q_l \cdot (\boldsymbol{x}_i(t) - \boldsymbol{x}_l(t))}{r_{core}^2 \cdot |\boldsymbol{x}_i(t) - \boldsymbol{x}_l(t)|} & if\, |\boldsymbol{x}_i(t) - \boldsymbol{x}_l(t)| < r_{core} \\ \frac{Q_i \cdot Q_l \cdot (\boldsymbol{x}_i(t) - \boldsymbol{x}_l(t))}{|\boldsymbol{x}_i(t) - \boldsymbol{x}_l(t)|^3} & if\, r_{core} < |\boldsymbol{x}_i(t) - \boldsymbol{x}_l(t)| < r_{reg} \\ 0 & if\, |\boldsymbol{x}_i(t) - \boldsymbol{x}_l(t)| > r_{reg} \end{cases} \tag{11}$$

$\boldsymbol{a}_{il}(t)$ denotes the repulsive force of robot-*i* towards robot-*l* at time-*t*. Notation $\boldsymbol{x}_i(t)$ denotes the robot-*i*'*s* position at time-*t*, the same goes to $\boldsymbol{x}_l(t)$ only this is the notation for robot-*l*. Q denotes the point charge of robot. r_{core} denotes the core diameter. In that area, the strong repulsive force is applied. Meanwhile, r_{reg} denotes the range of robot's repulsive force can still be recognized. Therefore, there will be no repulsive force applied for both if the distance *r* is larger than r_{reg},. On the contrary, if $r_{core} < r < r_{reg}$ or $r < r_{core}$, the repulsion force depends on the mutual distance. The repulsion force will be greater if robots mutual distance is smaller than r_{core}. The repulsion force applied to robot-*i* is defined as summation of the mutual repulsion force (Eq. 12).

$$\boldsymbol{a}_i(t) = \sum_{p=1}^{N} \boldsymbol{a}_{ip} \tag{12}$$

Where $\boldsymbol{a}_i(t)$ denotes total repulsive force applied to robot-i and *N* denotes the number of the robots. Eq. 13 and 14 represent the behavior of the charged swarm robot.

$$\boldsymbol{V}_i^{n+1} = \chi\left(\boldsymbol{V}_i^{n+1} + c_1 \cdot rand(\quad) \cdot (\boldsymbol{p}_i^n - \boldsymbol{x}_i^n) + c_2 \cdot rand(\quad) \cdot \left(\boldsymbol{p}_g^n - x_i^n\right)\right) + \underbrace{\boldsymbol{a}_i(t)}_{repulsive\ force} \tag{13}$$

$$\boldsymbol{X}_i^{n+1} = \boldsymbol{X}_i^n + \boldsymbol{V}_i^{n+1} \tag{14}$$

The first part of Eq. 13 is standard PSO equation which responsible to find and converge to the optimal solution. The second part of the equation, mark with 'repulsive force' text, is responsible to maintains diversity of swarm distribution. Please note that this equation only applied to charged robot. If there is no charged robot in the swarm, the Charged PSO (CPSO) becomes standard PSO as defined in Eq. 1 and 2.

Both theory and the experiment show that the implementation of charged robot gives PSO certainty that there exist a minimum area which is watched for each period. However, a new problem arises when PSO dealt with multiple odor sources that makes PSO cannot localized all sources. There is a chance when robots cannot get near the flow of source, especially when particles have converged to one point. The PSO algorithm developed in the manners that if there's no plumes, then particles got nothing to track, so it's safe to claim there's no more source in the field. To handle this problem, re-initializing particle position method is used. Re-initialization of particle position is done by moving particles to another position. With this method, searching can be repeated to handle changes in the environment. The drawback of this method is that particles have to search from the beginning. The condition when the robots have to re-initialize their position is called the spread phase.

The implementation of spread phase add two additional phase to PSO algorithm, these are normal (PSO) phase and critical phase as seen in Figure 15. Define that n is number of PSO entering critical phase and n_{max} become the maximum number that PSO allowed to enter this phase. Let's defined that m_{max} is maximum number of the iteration where PSO can have the same global best value. Every time value of global best does not change for m_{max} times, PSO will enter critical phase. Critical phase will makes robots reset their global best value and restart their search, this also increase the value of n. Resetting the global best value will result in eliminating PSO convergence for a time being and let robots search for new possibilities. If n is over the value of n_{max}, PSO will enter spread phase. This mechanism can minimize unnecessary search, thus can also save power.

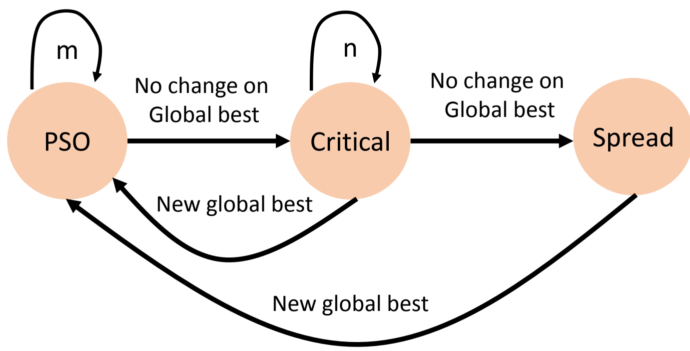


Figure 15. PSO – Critical – Spread Phase.

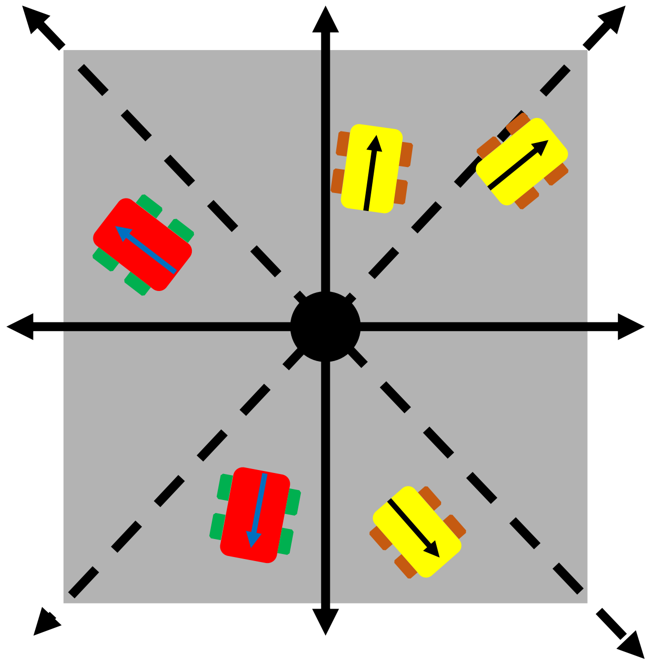


Figure 16. Spread from the center for all robots.

Result of combining PSO-DR with charged ability makes finding odor source becomes easier, which means minimize the search time required to localize all sources. As shown in Fig. 17, charged robots maintain diversity to find the sources faster. Detect and response ability work when the particles are trapped in optimum point. Sometimes the search could be stopped because particles are trap in local optimum, these will triggered spread phase. Figure 17 point (f) shows that with the spread phase, the particles can find the other optimum point and search can be continued.

c. Parallel PSO Niching

Typical PSO algorithm will perform badly in multiple odor sources problems. Particles have to find sources sequentially, hence made search PSO in multiple sources run longer than the search for single source. This trends will also applied when using PSO-DR and Charged PSO simultaneously. This is why the parallel searching becomes an option to reduce the search time. Parallel PSO is done by using more than one groups of robots tasked to find all odor sources. There will be many groups that consist of many robots. Each group will run their own PSO algorithm and this calculation is not affected by other groups. PSO's method that runs in parallel is called PSO parallel Niching and the groups of robots is called as the niche.

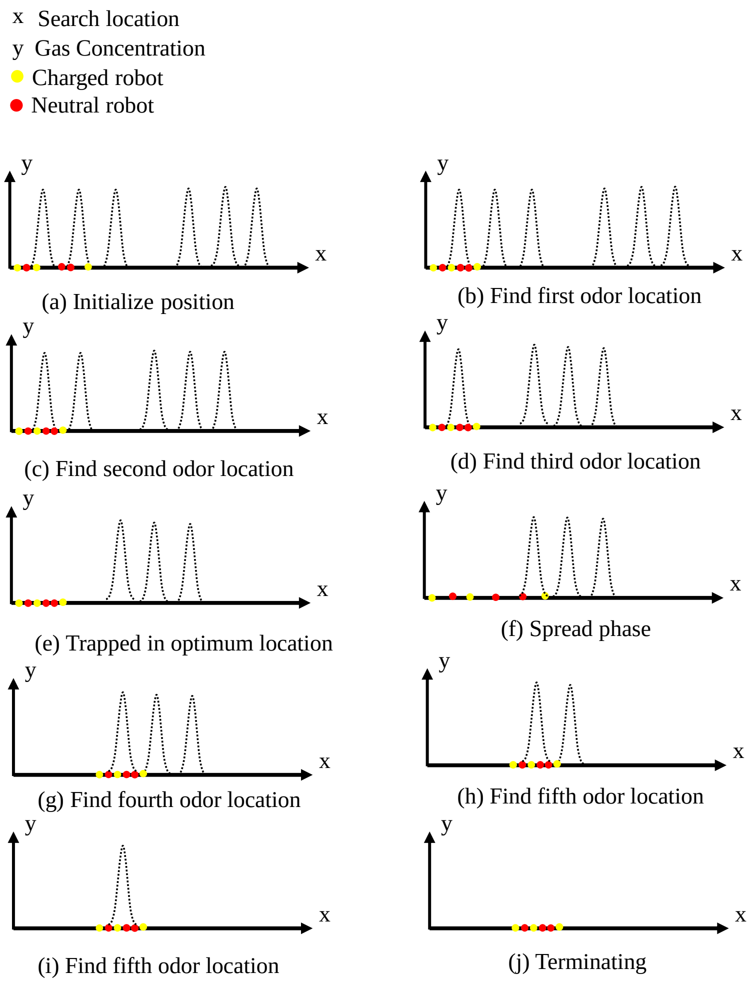


Figure 17. MPSO handling multiple odor sources.

Each group or niche run their own PSO calculation, hence each of them has their own global best. It's commonly known that global best which is defined as the best of all the local best from that group, hence there is only one global best for each group. This also means that each niche is not going to find out information from others. In addition, the information of local best on each robot will only flow into its own niche.

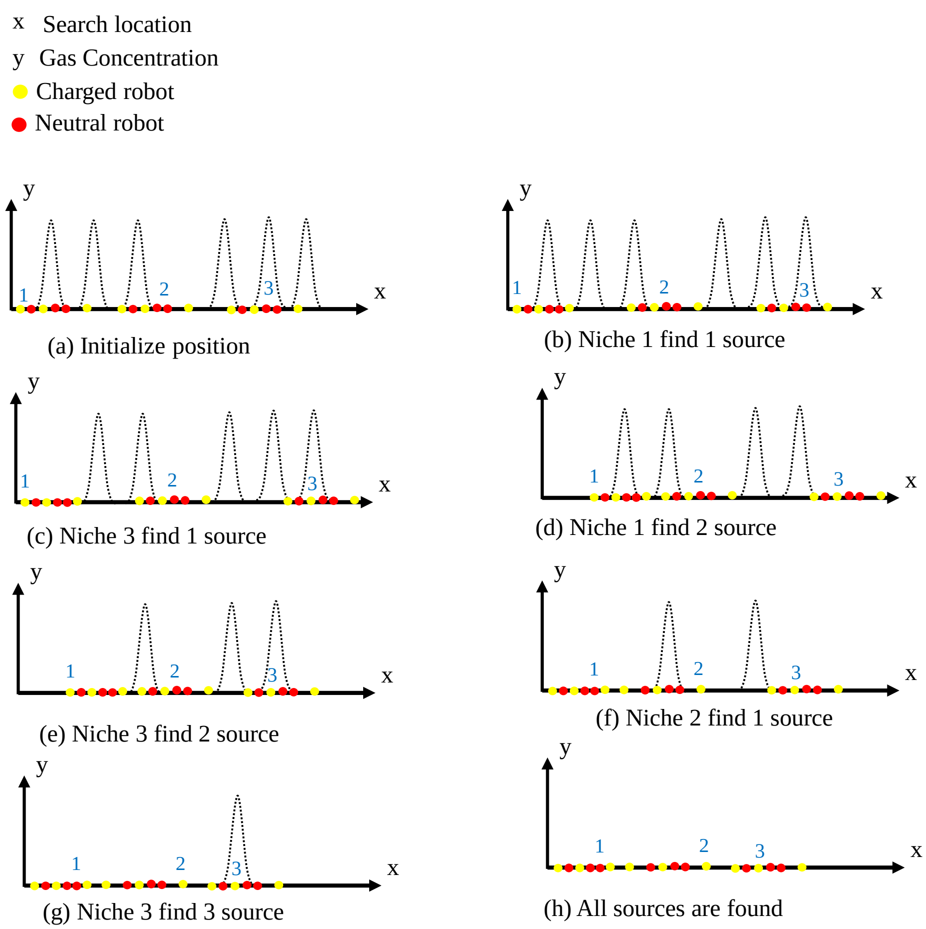


Figure 18. Localize concept with multiple sources and three niches.

Parallel search will provide a faster results than sequential search. Figure 18 shows that with three groups of niche, the search can be start at various position and hence also cover bigger area. As seen in Figure 18, parallel niching enabled finding more than one source at the same time. This is surely speed up the search time needed to complete the search. However, there is a chance where more than one niche moving to the same source. Condition when two niches or more try to find the same source is illustrated in Fig. 18 point (f). This considered as a waste of time and energy, because theoretically when there are n niche in the search area, it means it can search for n odor source at the same time. By make sure each niche go after different odor source, the search time can be reduced. In order to enable this property in PSO, main spread algorithm is introduce and will explained later in this section.

d. Main Robot an Draft-Niche PSO

In the Parallel PSO Niching, there is a chance when more than one niche going to the same source. When this condition occurs, the separation of these two niche has to be carried out in order to fully utilize both niches. Unfortunately, the separation can only be done if two global bests collide. If there is no collision, then the separation between two niches would never happen. The implementation of charged robot and spread mechanism also can't provide PSO with the ability to utilize each niche to pursue different sources. In order handle this problem, a new type of robot and a displacement method are offered.

d.i Main Robot and Draft-Niche PSO Implementation

The new type of robot offered is called main robot. The main robot from hardware view point is the same robot but with some additional properties, such as repulsive force between main robot and attract area. Both of those properties will be explained in the next sub-section. Each niche will be given one main robot. The main robot name is given because this robot is expected to lead the niche to distinct source.

It's in the definition of main robot as a leader of their niche. From this definition, it's safe to assume that to increase niche divergence, one should only maintain the divergence of each main robot. This is the reason that the concept applied in charge robot also being applied in main robot. The value repulsive force applied to each main robot will follow Eq. 12 while each repulsive force from each main robot can be calculated using Eq. 15. Main robot movement will follow Eq. 17, where *x* indicates robot current position and *p* indicates current global best position.

$$\boldsymbol{u}_{jk}(t) = \begin{cases} \frac{Q_j \cdot Q_k \cdot \left(\boldsymbol{x}_j(t) - \boldsymbol{x}_k(t)\right)}{r_{core}^2 \cdot \|\boldsymbol{x}_j(t) - \boldsymbol{x}_k(t)\|} & if \left|\boldsymbol{x}_j(t) - \boldsymbol{x}_k(t)\right| > 2 \cdot r_{core} \\ 0 & if\ Otherwise \end{cases} \quad (15)$$

$$\boldsymbol{V}_i^{n+1} = \chi\left(\boldsymbol{V}_i^{n+1} + c_1 \cdot rand(\quad) \cdot (\boldsymbol{p}_i^n - \boldsymbol{x}_i^n) + c_2 \cdot rand(\quad) \cdot \left(\boldsymbol{p}_g^n - \boldsymbol{x}_i^n\right)\right) + \underbrace{\boldsymbol{u}_i(t)}_{repulsive\ force} \quad (16)$$

$$\boldsymbol{X}_i^{n+1} = \boldsymbol{X}_i^n + \boldsymbol{V}_i^{n+1} \quad (17)$$

As can be seen in Eq. 15, this equation includes two properties which are owned by main robot, called r_{core} and $r_{attract}$. Please see Fig. 19 to simplify the explanation of both properties. As delineated in the figure, main robot has an area which is marked in light brown color and labeled as attract area. Attract area function will be explained later, but notice that this area is created by

$r_{attract}$. Outside attract area there is another ring colored by white. This area are limited by r_{core} and function as the core of repulsive area for main robot.

The main robot has an attract area where the neutral robot or the charged robot from the other niche enter this area will become a member of this niche. Suppose there's a neutral robot which is a member of niche 2 and move toward inside the attract area of main robot from niche 1. As soon as the neutral robot enter the attract area, its membership will change. Now the neutral robot become the member of niche 1, this method called draft. This method only applied to neutral and charged robot, not to main robot. Moreover, there's repulsive force being applied to main robot and since the r_{core} is wider than attract area, the possibility of main robot being inside another main robot attract area can be considered as zero. The area of interest of the main robot can be changed as needed.

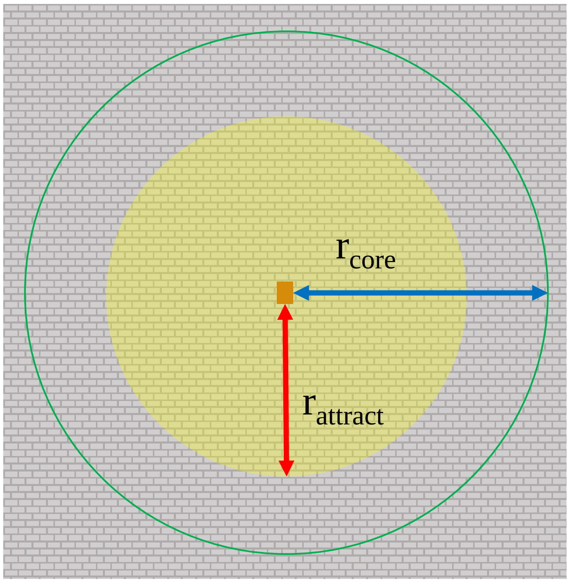


Figure 19. r_{core} and $r_{attract}$ of the main robot.

d.ii Modified Main Robot Movement

The base idea that creating main robot type is to lead niche to distinguish odor source. The core of this modification is to ensure the main robot always try to get closer to the existing global best position. This can be done by eliminating the cognitive factor in the calculation of the PSO for the main robot, hence the movement will only consider the current global best position. This makes the calculation of the PSO for the main robot follow Eq. 18.

$$\boldsymbol{V}_i^{n+1} = \chi\left(\boldsymbol{V}_i^{n+1} + \overbrace{c_2 \cdot rand(\quad) \cdot \left(\boldsymbol{p}_g^n - \boldsymbol{x}_i^n\right)}^{social}\right) + \underbrace{\boldsymbol{u}_i(t)}_{repulsive\ force} + \underbrace{\boldsymbol{b}_i(t)}_{area\ of\ interest} \quad (18)$$

Value of b_i in the equation is used to provide distance between the main robot and the global best. Therefore, the robot can still move around it despite of being close to the global best. If b_i is not included in the equation, then the position of the main robot will always be the same as the global best position. Approach used in this algorithm is to make the odor source in the area around the global best. This modification also comply with the global best concept in PSO which is always point global best to the best location that has high probability of odor source.

e. Main Spread and Modification

Another interesting technique that can be added as the implementation of main robot is Main Spread. This method proposed to handle two or more niche going after the same source, which considered wasteful. Besides explaining the Main Spread concept, here will also be explained the modification taken to handle unexpected condition from Main Spread action.

e.i Main Spread

Main Spread will be triggered when two niches are too close, which means both niches lead to the same source. Two niches will be considered too close if the global best of both niches are too close. If this condition fulfill, then spreading must be taken into action. The spreading must be done by main robot who have the smallest global best value between conflicted niches. Suppose that niche X and Y global best is too close. Niche X global best value is m, while Y is n. Suppose that m is smaller than n, it means that main robot from niche X must move itself to another position and start over the search from it’s new position.

e.ii Modified Main Spread Modification

The main spread algorithm have a simple bug because when main robot do the spread, the rest of robot from the same niche is not following main robot. This bug can make main robot become the one and only robot in that niche. Obviously, when main robot become the only robot, PSO cannot be applied anymore to that niche. Remember that PSO is swarm algorithm, this algorithm is always works in group, not in single agent. The modification that being added to the main spread algorithm is to makes all member of the same niche follow main robot to their new position.

f. Charged Robot Movement Limit

The existence of the displacement of membership in Draft Niche-PSO algorithm raises the possibility that there will be a niche that lost all of its members. Some modification with Draft Niche-PSO needs to be done to handle this problem. Area restriction for the charged robot is proposed to reduce niche lost problems.

In order to understand the concept of area restriction for charged robot algorithm easily, consider Fig. 20. Area indicated by the grey color is the attract area owned by the main robot. In the outer area of interest, there is another area colored in green. This area is the limit range of motion of the charged robots from the main robot called safe area. As seen in the figure, charged robots that belong to main robot niche are in the safe area. If there is a charged robot outside this area, then the robot will actively restore itself into the safe area. Area restriction for charged robot can also guarantee that all robots from the niche to be used by other niche.

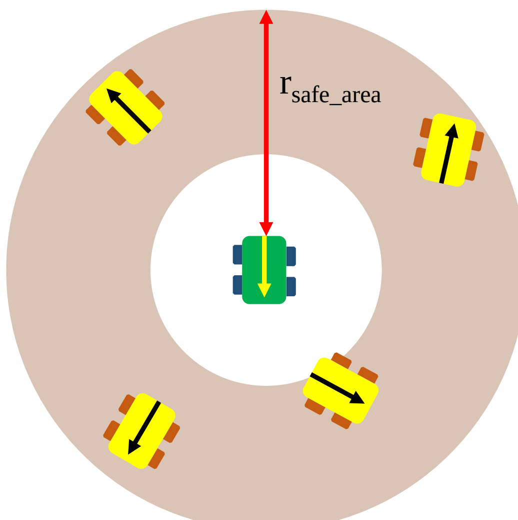


Figure 20. Maximum distance charged robot from main robot.

To increase effectiveness of safe area and to take advantage of privileges owned by the charged robot. Minimum safe radius of the area must satisfy Eq. 19 and 20. Eq. 19 ensures that the safe area is an area larger than the attractive area. Eq. 20 is aimed to give charged robots their respective areas which are not affected by repulsion from others. But it would be better if the radius meets the Eq. 19 and Eq. 21 because Eq. 21 guarantees the charged robot to move more freely than Eq. 20. With these equations, the charged robots have a mechanism to follow their main robot whenever the main robot moves to the other directions even when the niche faces the spread condition.

$$r_{safe\_area} \geq r_{attractive\_area} \tag{19}$$

$$r_{safe\_area} \geq d_{charged\_robot\_area} \cdot 2 \tag{20}$$

$$r_{safe\_area} \geq d_{charged\_robot\_area} \cdot n_{charged\_robot} \tag{21}$$

g. Range Multi-Niche PSO

The previous odor source localization methods using PSO niches methods prove to be successful in finding multiple odor sources. However, this method is very challenging and difficult to be implemented in the real world. First, the niche must have a prior knowledge of the number of odor sources that is in the search area. This is very impractical, as in the real world scenario we don't have a prior knowledge to that. Moreover, the main task of these robots is to actually localize those odor sources. The next problem that is very difficult to be implemented in the real world is the process of closing the odor source by the robots. This process is actually a separate problem from the localization of the odors, as it requires some knowledge on how to deal with the leakage. So, in practice, we must assume that the robots will move on to find another source once it has find a source of gas.

In the previous method, it is stated that the membership of the robots inside a niche could be changed once it has entered an area of another niche. Upon further investigations, it is possible that if this membership is applied, a niche will have only the main robot. Another peculiar occurrence is that when the main robot is doing the main spread process; there is a chance that the main robot is farther than the other robots in its niche. In order to solve these issues, Hafizh et al. proposed a method called Ranged Multi-Niche PSO [40]. This method will be focused in solving the problem of when more than one niche is looking for the same source. Another problem that this method is trying to solve is how to make the robots move on to another source once it has found an odor source. This is done without using any closing mechanism of the odor.

Basically, the Ranged Multi-Niche PSO changed the formation of the niche. This method proposed the niche to not be centered by a main robot. The main robot will be a neutral robot inside the niche area. The center of the niche will be determined based on the left-most, right-most, bottom-most, and top-most neutral robot inside a niche. To further understand the proposed formation, please see Fig. 21 along with the center of the formula in Eq. 22.In Eq. 22, x_c, y_c is the center of the niche, replacing the main robot. . $\boldsymbol{x}_{left}$, $\boldsymbol{x}_{right}$, $\boldsymbol{y}_{bot}$, $\boldsymbol{y}_{top}$ determines the left-most, right-most, bottom-most, and top-most neutral robots respectively.

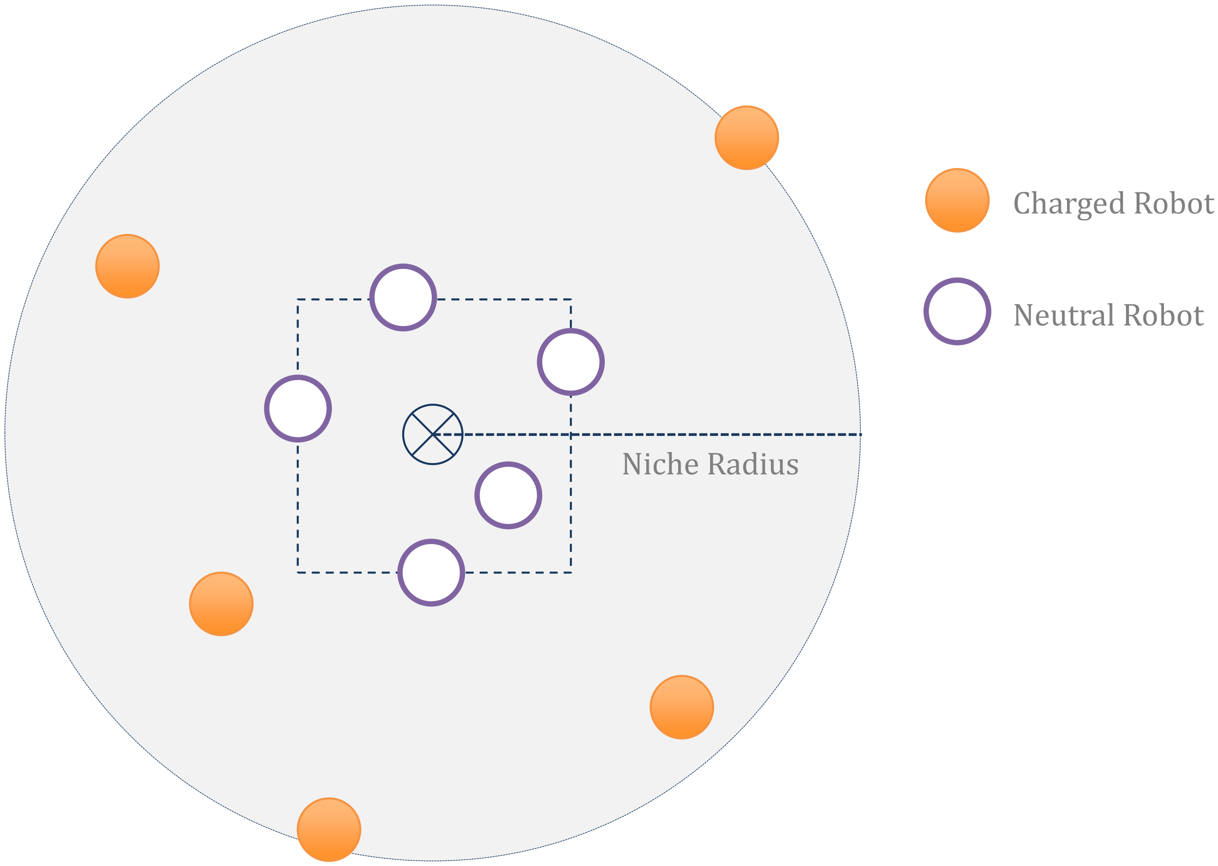


Figure 21. The proposed formation of the niche of Multi-Niche PSO

$$(x_c, y_c) = (x_{left} + \frac{x_{right} - x_{left}}{2}, y_{bot} + \frac{y_{top} - y_{bot}}{2}) \tag{22}$$

To prevent two niches getting close with each other, which could result in two niches searching for the same source a repelling force is applied with charged niche. Each niche have the same charge, therefore they repel each other. There are several consideration that determines which niche is the one that moves (being repelled). Suppose there are two niches, niche A and niche B. When niche B moves to an area where it is smaller than niche A's radius, the repelling force will be calculated. First, it will calculate which niche is closer to the global best. If, for example, niche A's global best is smaller than niche B's, than niche A will be repelled by B's force. Equation 23 will further explain this concept.

$$\boldsymbol{a}_{A,B}(t) \begin{cases} \frac{Q_A - Q_B}{|\boldsymbol{C}_A(t) - \boldsymbol{C}_b|^3} (\boldsymbol{C}_A(t) - \boldsymbol{C}_b) \ , if\ r_{A,B} \leq r_A + r_B\ and\ gbest_A(t) \leq gbest_B(t) \\ 0\ , otherwise \end{cases} \tag{23}$$

$a_{A,B}(t)$ is the repel force between niche A and niche B. C_A and C_B is the center of niche A and niche B. The charge of niche A is Q_A, whereas the charge for niche B is Q_B. r_A, r_B, and $r_{A,B}$ are the radius of niche A, radius of niche B, and distance between the centers of niche A and B respectively. After the repel force for each niche is calculated, the search space of the niche is re-initialized with the following equation:

$$\boldsymbol{V}_{i,A}^{n+1} = \chi\left(\boldsymbol{V}_{i,A}^{n} + c_1 \cdot rand() \cdot \left(\boldsymbol{p}_{i,A}^{n} - \boldsymbol{x}_{i,A}^{n}\right) + c_2 \cdot rand() \cdot \left(\boldsymbol{p}_{g}^{n} - \boldsymbol{x}_{i,A}^{n}\right)\right) + \sum_{B=1}^{n} a_{A,B}(t) \tag{26}$$

Notice that the 24 is the standard velocity of PSO. This show that the repel force for each niches are considered into the calculation. After the velocity of the PSO have been calculated, it is the added to the distance of the niche.

$$\boldsymbol{X}_{i,A}^{n+1} = \boldsymbol{X}_{i,A}^{n} + \boldsymbol{V}_{i,A}^{n+1} \tag{26}$$

In the previous methods, if a member of a niche is to close to another, new niche, it will switch membership and join the new niche. This creates a problem, where there will be an instance where the main robot inside a certain niche lost all its members to other niches. A solution to this problem is to give all the member of the niche a certain charge. This charge will be different for each niches, so that two robots from a different niche do not come close to each other. Another solution is to create a boundary so that every member of the niche do not wander too far from the niche. 26 will further explain this concept.

$$\boldsymbol{V}'_{i,A}(t+1)\begin{cases}\boldsymbol{C}_A(t) - \boldsymbol{X}_{i,A} & ,if\ |\boldsymbol{C}_A(t) - (\boldsymbol{X}_{i,A} + \boldsymbol{V}_{i,A}(t+1))| \le r_{restrict} \\ 0 & ,otherwise\end{cases} \tag{26}$$

The next problem that Hafizh et. al tackles is to create a restricted zone on the discovered odor source perimeter. As mentioned before, the closure of odor source is not practical in the real world environment. To substitute the source closure, this method proposed a restricted area to be created around the source of the gas. The robot that tries to enter the area will be diverted. This is further explained in equation 27, that explains the i-th particle for niche A to divert from source src. S_{src} denotes the postion of source src.

$$\boldsymbol{V}_{rep,i,A,s}(t)\begin{cases}\boldsymbol{X}_{i,A} & ,S_{src}\ ,if\ r_{i,A,src} \le r_{src} \\ 0 & ,otherwise\end{cases} \tag{27}$$

This method has been successful in preventing many niches searching the same area. Form the experiment results, it could be derived that a wider search area could increase the search time of the robots. The number of sources also impacts the search time for these niches. Using the restricted area as a substitution for closing the source still has several flaws. The niche could still be stuck searching for a detected source. This is because the odor is still coming out of the source, therefore, confusing the niches.

h. Adaptive Niching

h.i Modification of Niche Behavior

In the previous research, the member of niche is predetermined and fixed. In 2014 Zhang et al. [41] proposed new method in which the niche size is dynamically altered. The aforementioned method was proffered to increase the ability of algorithm to localize as many odor sources as possible. In the early stage, while the global best position of the robots still far from the global optimum position, large number of robots required to accelerate the localizing of odor source. As the position of global best position of robots is getting closer to global optimum position, the number of robot in that niche should be reduced. The reduction is needed to increase the efficiency of searching process. If the size is reduced the removed robot can be allocated to help the main swarm to localize the other odor sources.

Using multiple niche formation, the exploration capability of each individuals could increased and therefore the population could be very diverse. This could solve complex problems, such as multi-modal optimization problems [42]. Typically, a niche formation could use the following techniques: crowding, fitness sharing, clustering, objective fitness stretching, speciation, and multi-swarm [43–47].

Zhang proposed three consecutive modifications of niche behavior, i.e. niche formation, niche evolution, and niche cooperation. In the beginning, the main swarm which contains all the robot in the search area is not divided into niches. Main swarm will search for plume randomly. After one robot find plume whose concentration exceed the threshold (C_{th}) the niche would be established. The size of the niche is prescribed to be the neighbor robots of the above-mentioned robot which have position inside the certain radius (R_i) from the robot which finds plume. Figure 28 illustrates the niche formation algorithm.

The second proposed method is niche evolution. As previously elucidated that the size of the niche is dynamically altered. The change of the niche size depends on the aggregation degree (m_i) which is influenced by robot position (x_{robot}), global best position (x_g), niche size (N_i), and certain parameter (β) as shown in equation (29).

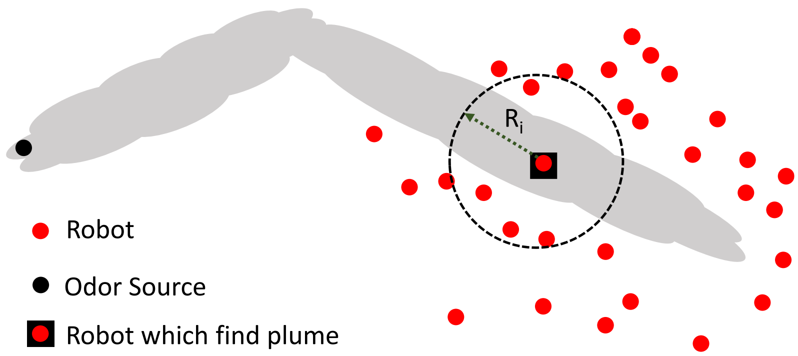


Figure 22. Niche formation

$$m_i = \sum_{k=1}^{N_i} \left(1 - \left(\frac{d_{gk}}{R_i}\right)^{\beta}\right) \tag{28}$$

$$d_{gk} = x_g - x_{robot} \tag{29}$$

In the early stage the value of d_{gk} is large and m_i small. After the robots converge, the value of d_{gk} is getting smaller and cause the reduction of m_i. In the evolution phase, the niche size is dynamically change by means of $\rho_i(t)$ (equation (30)). If the niche size exceed the threshold (m_o) the farthest $\rho_i(t)$ robots would be returned to the main swarm. In the beginning when the value of m_i is small, its value is small as well, thus the robots returned to the main swarm is small. More robot is required to find the plume for the first time. On the contrary, after the convergence increases, the value of mi is large which lead to the larger $\rho_i(t)$ value. Therefore, there would be more robots returned to the main swarm to localize other odor sources.

$$\rho_i(t) = \left[N_i \lambda \left(\frac{1}{1+\exp\left(-(t-t_0)\cdot\left(\frac{m_i}{N_i}\right)\right)} \right) \right] \tag{30}$$

The third proposed method is niche cooperation which minimize the possibility of searching in the found odor source. After odor source is found, a circle with certain radius will be created and set as a taboo area. When robot enter the taboo area, the direction of the robot movement will be altered, hence it will avoid the odor source which has been previously found. Moreover, Zhang also proposed niche merging. This method will occur when there are two niche aiming for similar odor source. Equation (31) shows the condition which must be met to activate the aforementioned algorithm. This method was proposed to prevent an odor source locate by more than one niche.

$$\begin{cases} \left\| \boldsymbol{x}_{g,1} - \boldsymbol{x}_{g,2} \right\| < R_1 + R_2 \\ \boldsymbol{v}_{g,1} \cdot \boldsymbol{v}_{g,2} > 0 \end{cases} \tag{31}$$

VIII EXPERIMENTS FOR MULTIPLE ODOR SOURCES LOCALIZATION

The experiment are taken using 3D simulator software. There are eight scenario being tested in search area size of 7 x 7 meters. Inside search area there are 4 odor sources. The search robots consist of 2 niches each with 3 or 4 for both neutral and charged robots. There are eight scenarios involving every modified algorithms proposed in this paper, these scenarios are described in Table 2. Results of this experiment are used as a benchmark for real-world implementation using Al-Fath as an agent. Each scenario elapsed time are shown in Figure 23.

Figure 23 illustrates that the best combination of PSO modification is the combination being used in fourth scenario. This scenario combine PSO DR, Charged PSO, WU I, WU II, Declare and Close Source, Draft Niche-PSO, Modified Main Robot Movement, and Charge Robot Movement Limit. Some combination even need more time compare to base algorithm to finish their search, such as the third and seventh scenario.

IX CONCLUSION AND CHALLENGES

a. Conclusion

This paper shows that in both simulation and real world implementation, robots can be used as agents in odor source localization. The algorithm to utilize these robot known as Particle Swarm Optimization (PSO). PSO has successfully been proven to handle single odor source in acceptable time. It's in the nature that PSO had convergence behavior which can lead PSO being trapped in the local maximum. However, in this research, local maximum traps can be avoided by modified the PSO with various algorithms known as Modified PSO (MPSO). These modification is tested and implemented in real robot which proven the feasibility of PSO.MPSO makes robots capable to handle environmental changes so robots not trapped in the local maximum, while PSO DR + Charged + WU accelerates the localization process because it uses information about the wind direction.

Table 2. Experiment scenarios

Scenario	Algorithm
Based Algorithm	PSO DR, Charged PSO, WU I, WU II, Declare and Close Source, Draft Niche-PSO
Scenario 1	Based Algorithm, Modified Main Robot Movement

Scenario 2	Based Algorithm, Charge Robot Movement Limit
Scenario 3	Based Algorithm, Modified Main Spread
Scenario 4	Based Algorithm, Modified Main Robot Movement + Charge Robot Movement Limit
Scenario 5	Based Algorithm, Modified Main Robot Movement + Modified Main Spread
Scenario 6	Based Algorithm, Charge Robot Movement Limit + Modified Main Spread
Scenario 7	Based Algorithm, Modified Main Robot Movement + Charge Robot Movement Limit + Modified Main Spread

Beside the single source localization problems, in this research the experiment also conducted to solve multiple source problems. Multiple odor localization problems is more challenging than single source. This result in the next modification of MPSO which focusing in parallel MPSO. Some algorithm in association with parallel searching is implemented such as Parallel PSO Niching, Draft Niche-PSO and Modified Draft Niche-PSO can be added to the previous algorithms to find sources faster. The experiment shows that the combination between Modified Main Robot Movement and Restriction Area for Charged Robot in Modified Draft Niche-PSO can find the sources faster than the other combination. However this research is not complete yet, the multiple source localization problems still considered as open problem.

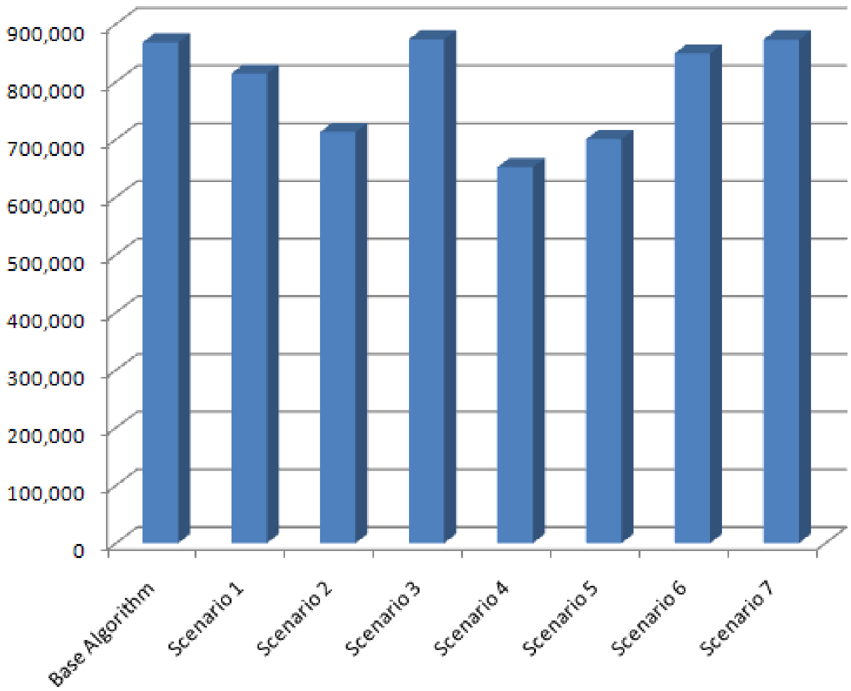


Figure 23. Experiment results.

b. Challenges

Before robots that implement this algorithm can be used to solve real world problems, several intensive experiment must be conduct. The final goal of this research is to develop a whole system, constituting software and hardware implementation, that quick and robust in localizing odor. The algorithm must be improve to enhance time needed to localize all source. The further algorithm development could include online learning in which system can learn from the environment. There's also communication topics since PSO deals with multiple agents. The last is the dynamic changes and environment factor, such open search area, search area size, obstacle, multiple room environment, or non-flat ground that need to be considered.

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REFERENCES

[1] Wisnu Jatmiko, T. Fukuda, F. Arai, and B. Kusumoputro, *Artificial Odor Discrimination System Using Multiple Quartz Resonator Sensor and Various Neural Networks for Recognizing Fragrance Mixtures*, IEEE Sensors Journal, vol. 6. no. 1, pp. 223233, Feb. 2006.

[2] B. Kusumoputro, H. Budiarto, W. Jatmiko. *Fuzzy-neuro LVQ and its comparison with fuzzy algorithm LVQ in artificial odor discrimination system*. ISA Transaction 41, pp. 395-407. 2002.

[3] W. Jatmiko, Rochmatullah, B. Kusumoputro, K. Sekiyama, T. Fukuda. *Fuzzy Learning Vector Quantization Based on Particle Swarm Optimization For Artificial Odor Dicrimination Sys- tem*. WSEAS Transaction on System, Issues 12, Volume 8. 2009.

[4] W. Jatmiko, T. Fukuda, T. Matsuno, F. Arai and B. Kusumoputro. *Robotic Applications for Odor-Sensing Technology: Progress and Challenge*. WSEAS Transaction on System:Issue 7, Volume 4, July 2005.

[5] Aprinaldi, I. Habibie, R. Rahmatullah, A. Kurniawan, A. Bowolaksono, W. Jatmiko, B. Wiweko, *ArcPSO: Ellipse Detection Method using Particle Swarm Optimization and Arc Combination*, in: Proceedings of the International Conference on Advanced Computer Science and Information Systems (ICACSIS), Jakarta, 2014, pp.408–413.

[6] Aprinaldi, G. Jati, A. A. S. Gunawa, A. Bowolaksono, S. W. Lestari, W. Jatmiko, *Human Sperm Tracking using Particle Swarm Optimization combined with Smoothing Stochastic Sampling on Low Frame Rate Video*, in: Proceedings of 26th International Symposium on Micro-NanoMechatronics and Human Science, Nagoya, 2015.

[7] W. Jatmiko, D. M. J. Purnomo, M. R. Alhamidi, A. Wibisono, H. A. Wisesa A. Bowolaksono, and D. Hendrayanti, ArcPSO: *Algal Growth Rate Modeling and Prediction Optimization Using Incorporation of MLP and CPSO Algorithm*, in: Proceedings of 26th International Symposium on Micro-NanoMechatronics and Human Science, Nagoya, 2015.

[8] H. Ishida, Y. Wada, and Matsukura, H. (2012). Chemical sensing in robotic applications: A review. *Sensors Journal, IEEE*, 12(11):3163–3173.

[9] F. Li, Q. H. Meng, J. G. Li, etal.,P-PSO *algorithm based multi-robot odor source search in ventilated indoor environment with obstacles*, Acta Automatica Sinica 35(12)(2009)1573–1579.

[10] P. Neumann, M. Bartholmai, and V. H. Bennetts, V. (2012a). *Adaptive gas source localization strategies and gas distribution mapping using a gas-sensitive micro-drone*. In Proceedings of the 16th ITG / GMA Conference, pp. 800– 809.

[11] Z. Liu and T.F. Lu (2008). Odor source localization in complicated indoor environments. In *Control, Automation, Robotics and Vision, 2008. ICARCV 2008. 10th International Conference on*, pages 371–377. IEEE.

[12] A. T. Hayes, A. Martinoli and R. M. Goodman. *Distributed odor source localization*. IEEE Sensors Journal, vol. 2, no.3, pp 260-271, June 2002.

[13] H. Ishida, T. Nakamoto, T. Moriizumi, T. Kikas and J. Janata, *Plume-Tracking Robots: A New Application of Chemical Sensors*, Biol. Bull. 200: 222-226. (April 2001).

[14] W. Jatmiko, B. Kusumoputro, and Yuniarto, *Improving the Artificial Odor and Gas Source Localization System Using the Semiconductor Gas Sensor Based on RF Communication*, Proc. of IEEE APCASS, October 2002.

[15] T. Lochmatter, X. Raemy, A. Martinoli. *Odor Source Localization with Mobile Robots*. Ecole Polytechnique Federale Lausanne, Info Science, 2007.

[16] A. T. Hayes, A. Martinoli and R. M. Goodman. *Swarm robotic odor localization: Off-line optimization and validation with real robots*. Robot- ica, 21(4):427-441, 2003.

[17] Y. Zou, D. Luo, and W. Chen, (2009). Swarm robotic odor source localization using ant colony algorithm. In *Control and Automation, 2009. ICCA 2009. IEEE International Conference on*, pages 792–796. IEEE.

[18] M. L. Cao, Q. H. Meng, X. W. Wang, B. Luo, M. Zeng, and W. Li (2013). Localization of multiple odor sources via selective olfaction and adapted ant colony optimization algorithm. In *Robotics and Biomimetics (ROBIO), 2013 IEEE International Conference on*, pages 1222–1227. IEEE.

[19] M. Wandel, A. Lilienthal, T. Duckett, U. Weimar, and A. Zell. *Gas distribution in unventilated indoor environments inspected by a mobile robot*. In Proceedings of the IEEE International Conference on Advanced Robotics (ICAR03), 2003.

[20] X. Cui, C. T. Hardin, R. K. Ragade, and A. S. Elmaghraby. *A swarm-based fuzzy logic control mobile sensor network for hazardous contaminants localization*. In Proceedings of the IEEE International Conference on Mobile Ad-hoc and Sensor Systems (MASS04), 2004.

[21] Ishida, H. Nakayama, G. Nakamoto and T. Moriizumi, T. *Controlling a gas/odor plume tracking robot based on transient responses of gas sensors*, IEEE Sensors Journal, Vol. 5. No.3. June 2005.

[22] D. Zarzhitsky, D. Spears, and W. Spears. *Distributed Robotics Approach to Chemical Plume Tracing*. Proceedings of the IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS'05), 2005.

[23] R. A. Russell and A. H. Purnamadjaja. *Odor and airflow: Complementary senses for a humanoid robot*. In Proceedings of the 2002 IEEE International Conference on Robotics and Automation, 2002.

[24] Wisnu Jatmiko, K. Sekiyama and T. Fukuda, *A PSO-based Mobile Robot for Odor Source Localization in Extreme Dynamic Advection-Diffusion Environment with Obstacle: Theory,*

Simulation and Measurement. IEEE Computational Intelligence Magazine: Special Issue on Biometric. Vol. 2, Issue 2, pp. 37-51, May 2007.

[25] M. Dadgar, S. Jafari, & A. Hamzeh. *A PSO-based multi-robot cooperation method for target searching in unknown environments*. Neurocomputing, 177, 62-74. 2016.

[26] K. Hassani, & W. Lee, W. *Multi-objective design of state feedback controllers using reinforced quantum-behaved particle swarm optimization*. Applied Soft Computing Journal Vol. 41, 66-76, 2016.

[27] Y. Zhang, J. Zhang, G. Hao, & W. Zhang. *Localizing odor source with multi-robot based on hybrid particle swarm optimization*. In the Proceedings of - International Conference on Natural Computation 2016, pp. 902-906. January 2016.

[28] A. T. Hayes, A. Martinoli and R. M. Goodman. *Swarm robotic odor localization: Off-line optimization and validation with real robots*. Robotica, 21(4):427-441, 2003.

[29] Y. Zou, D. Luo, and W. Chen, (2009). Swarm robotic odor source localization using ant colony algorithm. In *Control and Automation, 2009. ICCA 2009. IEEE International Conference on*, pages 792–796. IEEE.

[30] M. L. Cao, Q. H. Meng, X. W. Wang, B. Luo, M. Zeng, and W. Li (2013). Localization of multiple odor sources via selective olfaction and adapted ant colony optimization algorithm. In *Robotics and Biomimetics (ROBIO), 2013 IEEE International Conference on*, pages 1222–1227. IEEE.

[31] Jay A. Farrel et al. *Filament-Based Atmospheric Dispersion Model to Achieve Short Time-Scale Structure of Odor Plumes*. Environment Fluid Mechanics, vol 2, pp. 143-169, 2002.

[32] X. Hu, R. Eberhart. *Adaptive Particle Swarm Optimization: Detection and Response to Dynamic System*. Proceedings of the IEEE Congress on Evolutionary Computation (CEC), pp. 1666-1670, 2002.

[33] T. M. Blackwell and P. J. Bentley, ”Dynamic Search with Charged Swarms”, In Proceedings of the Genetic and Evolutionary Computation Conference, pp. 19-26 2002.

[34] W. Jatmiko, A. Nugraha, R. Effendi, W. Pam- buko, R. Mardian, K. Sekiyama AND T. Fukuda. *Localizing Multiple Odor Sources in a Dynamic Environment Based on Modified Niche Particle Swarm Optimization with Flow of Wind*. WSEAS Transaction on Systems, Issues 11, Vol 8. 2009.

[35] Branke, J. *Evolutionary Optimization in Dynamic Environments*. Kluwer Academic Publisher, 2002.

[36] A. Carlisle, G. Dozier. *Adapting Particle Swarm Optimization to Dynamic Environment*. Proceeding of the International Conference on Artificial Intelligence, pp. 429 - 434, 2000.

[37] X. Zhang, et al. *Two-Stage Adaptive PMD Compensation in a 10 Gbit/s Optical Communication System Using particle Swarm Optimization Algorithm*. Optics Communications, 231(1- 6):233-242, 2004.

[38] J.P. Coelho, P.B. De Moura Oliveira, and J.Boa Ventura Cunha. *Non-Linear Concentration Control System Design Using a New Adaptive PSO*. In Proceedings of the 5th Portuguese Conference on Automatic Control, 2002.

[39] T. M. Blackwell, ”Swarms in Dynamic Environment”, In Lecture Notes in Computer Science, Proceedings of the Genetic and Evolutionary Computation, volume 2723, pp. 1-12, 2003.

[40] Wisnu Jatmiko, Petrus Mursanto, Benyamin Kusumoputro, K. Sekiyama and T. Fukuda, *Modified PSO Algorithm Based on Flow of Wind for Odor Source Localization Problems in Dynamic Environments*, WSEAS Transaction on System, Issue 3, Volume 7, pp. 106-113, March 2008.

[41] D. W. Gong, C. L. Qi, Y. Zhang, et al., Modified particle swarm optimization for odor source localization of multi-robot, in: Proceedings of the 2011 IEEE Congress on Evolutionary Computation, USA, 2011, pp.130–136.

[42] T. M. Blackwell and P. J. Bentley, ”Don’t Push Me! Collision-Avoiding Swarms”, In Proceedings of the IEEE Congress on Evolutionary Computation, volume 2, pp. 1691-1696, May 2002.

[43] H. Hasrinda, Ranged Multi-Niche Particle Swarm Optimization for Multi Odor Source Localization: Simulation and Analysis, M.Kom. thesis, Faculty of Computer Science, Universitas Indonesia, Depok, 2014.

[44] K.E. Parsopoulos, V. P. Plagianakos, G. D. Magoulas, et al., Stretching technique for obtaining global minimizers through particle swarm optimization, in: Proceedings of the Particle Swarm Optimization Workshop, Indianapolis, 2001,pp.22–29.

[45] S. Das, S. Maity, B. Y. Qu, et al., Real-parameter evolutionary multimodal optimization—a survey of the state-of-the-art, Swarm and Evolutionary Computation 1(2) (2011) 71–88.

[46] D. E. Goldberg, J. Richardson, Genetic algorithm with sharing for multimodal function optimization, in: Proceedings of the Second International Conference on Genetic Algorithms and Their Applications, Hillsdale, 1987, pp.41–49.

[47] J. Kennedy, Stereotyping: improving particle swarm performance with cluster analysis, in: Proceedings of the Congress on Evolutionary Computation, Piscataway, 2000, pp.1507–1512.

[48] K.E. Parsopoulos, V. P. Plagianakos, G. D. Magoulas, et al., Stretching technique for obtaining global minimizers through particle swarm optimization, in: Proceedings of the Particle Swarm Optimization Workshop, Indianapolis, 2001,pp.22–29.

[49] X. Li, Adaptively choosing neighborhood bests using species in a particle swarm optimizer for multimodal function optimization, Lecture Notesin Computer Science 3102(2004)105–116.

[51] R. Brits, A. P. Engelbrecht, F. Vanden Bergh, Locating multiple optima using particle swarm optimization, Applied Mathematics and Computation 189(2) (2007)1859–1883.