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Modified Particle Swarm Robotic Odor Source Localization in Dynamic Environments

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Abstract— **This paper presents a problem of odor source localization in a dynamic environment, which means the odor distribution is changing over time. Odor source localization is an interesting application in dynamic problems. Modified Particle Swarm Optimizationis a well-known algorithm, which can continuously track a changing optimum over time.PSO can be improved or adapted by incorporating the change detection and responding mechanisms for solving dynamic problems. Charged PSO which is another extension of the PSO has also been applied to solve dynamic problems. We will adopt two types of PSO modification concepts to develop a new algorithm in order to control autonomous vehicles in more realistic environment where a speed limitation of the robot behavior and collision avoidance mechanism should be taken into consideration as well as the effect of noise and threshold value for the odor sensor response, also positioning error of GPS sensor of robot. Simulations illustrate that the new approach can solve such dynamic environment in Gaussian and Advection-Diffusion odor model problems.**

Index Terms— **Odor source localization, Modified Particle Swarm Optimization, Dynamic Environment.**

1. INTRODUCTION

INrecent years, many research works regarding the multiple robot systems have been done. Its fields involve several issues on cooperation searching, coordination among agents and so forth. Cellular Robotic Systems (CEBOT) is one of such the autonomous distributed robotic systems, which is composed of a number of functionally limited and different robotic units called cell. The CEBOT reconfigures its structure in terms of hardware and software according to the task or working environment. In spite of the fact that some attempts have been made to generate an intelligent behavior from combination of the simple rules, realizing such systems is still a challenging problem and will require years of work to achieve an efficient system [1, 2].

From the viewpoint of robotic applications, amount of research for odor-sensing technology has grown substantially. This work can be broadly categorized into two groups, namely artificial odor discrimination systems [3] and odor source localization by autonomous mobile sensing systems [4]. The artificial odor discrimination system has been developed for automated detection and classification of aromas, vapors and gases. The second prime area of robotics application to odor-sensing technology is odor source localization. Odor source localization can be used for various attractive applications, including the search of toxic gas leaks and the fire origin at its initial stage. This paper will address the second area of these applications.

Most work on chemical sensing with mobile robots assume an experimental setup that minimizes the influence of turbulent transport by either minimizing the source-to-sensor distance in trail following or by assuming a strong unidirectional air stream in the environment, including our previous work. However, not much attention has been paid to the natural environment problem. This paper focuses on our new approach that exploits particle swarm optimization with multiple robots to solve odor source localization in natural environment where the odor distribution may change over time.

The main problem with standard PSO used for dynamic optimization problems appears to be that PSO eventually will converge to an optimum and thereby lose the diversity necessary for efficiently exploring the search space and consequently the ability to adapt to a change in the environment when such a change occurs [5, 6]. Two ways of improving PSO will be developed to solve this problem. Firstly, PSO is run in standard fashion, but when a change in the environment is detected, explicit actions are taken to increase diversity and thus to facilitate a shift to the new optimum. Therefore, PSO can be improved or adapted by incorporating the change detection and the responding mechanism for solving dynamic problems [7, 8]. Secondly, multiple populations are used in order to track a known local optima, or to search a new optima. Two types of robot swarms, neutral and charged robots, will be used for solving the dynamic problem [9, 10]. Odor source localization is an interesting dynamic problem application. We will adopt these two types of PSO modification concepts as described above to develop a new algorithm to control autonomous vehicles.

2. MOTIVATION

There are several reports on the use of PSO in solving dynamic problem. Many reports are available in the literature on the application of different mechanism, i.e., reinitializing particle positions [7, 8], charged swarms [9, 10], limit memory [11], local search [12], split adaptive PSO [13], fine-grained PSO [14], hierarchical particle [15]. In the case of using mobile robot and multiple sensory modalities (e.g., odometry, anemometry, olfaction), we should carefully consider the feasibility of the hardware [1, 2, 16]. For that reason, in the initial stage, we chose two types of simple mechanism to develop a new algorithm to control autonomous vehicles.

PSO, which incorporates the change detection and the responding mechanism, can be implemented with a simple

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algorithm in an actual hardware. Charged PSO (CPSO), which presumes two types of robots, the neutral and the charged robots, can also be implemented with simple algorithm. Extension to multiple populations will allow maintaining the diversity of the swarm robots. Applying a notion of electric potential field to PSO, a charged swarm is introduced to sustain a balance of diversity. The potential field method has been widely used in the path planning of autonomous mobile robot due to its simplicity for mathematical modeling and analysis. A goal of this model is to make a number of sub-populations explore the best local optima. For this purpose, a part of the population is separated when a local optimum is discovered, and remains close to the optimum for further explorations. The remainder of the population continues to search for new local optima, and the process is repeated as long as new better solutions are found. While the neutral swarm robots continues to optimize, the surrounding charged swarm robots maintain sufficient diversity to cope with dynamic changes in location of the covered peaks.

Evaluation on solving odor source localization problem in dynamic environments requires hardware and software platforms [1, 2, 16]. During the initial design stages, the software evaluation is preferred since such tools allow competing strategies to be evaluated under identical conditions for various environmental scenarios. This paper presents a two-dimensional (2-D) simulation implementation that addresses the tradeoffs between computational efficiency and inclusion of the realistic hardware parameters. The algorithms presented here can be extended directly to the three-dimensional (3-D) problem, but implementation for three dimensions requires significantly increasing computational cost. Another reason using 2-D problem is motivated by the assumption that the plume tracing will occur at nearly constant altitude within a few meters of the ground level.

3. PRIOR APPROACH

The problem of gas source localization in an enclosed 2-D area can be decomposed into three subtasks: plume finding (coming into contact with the plume), plume traversal (following the plume to its source) and source declaration (determining the source is in the immediate vicinity), as shown in figure 1.

There have been several reported implementations of odor source localization by autonomous mobile sensing system. Most work on chemical sensing with mobile robots assume an experimental setup that minimizes the influence of turbulent transport by either minimizing the source-to-sensor distance in trail following [18, 19] or by assuming a strong unidirectional air stream in the environment [20, 21]. However, not much attention has been paid to the natural environment problem.

To the best of our knowledge, there has been no real implementation on a mobile robot that works in the natural environment.The main problem in implementing odor source localization using gas sensor in real world environments is that the distribution of the odorant molecules is usually dominated by turbulence rather than diffusion, the latter of which is known to be a considerably slower transport mechanism for gases in general. The other problem is the influence of

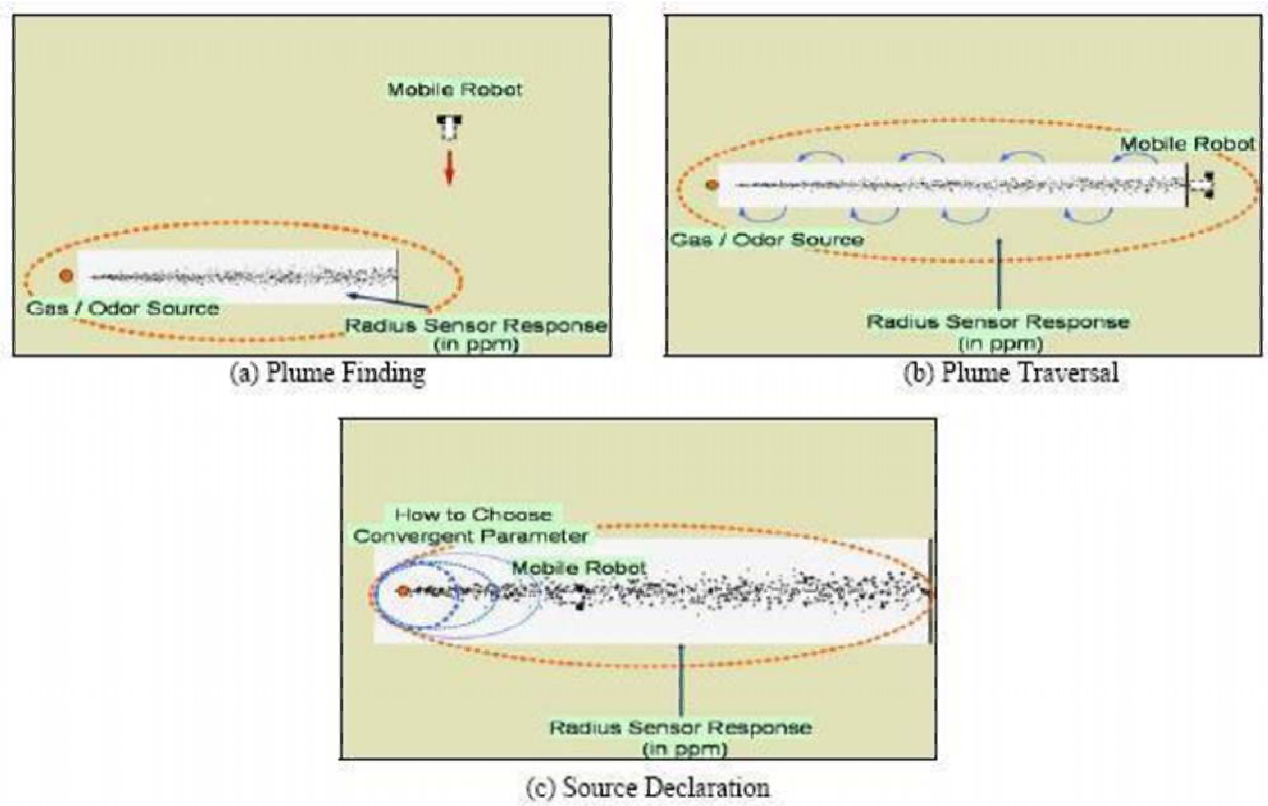

Fig. 1. Visualization of a typical approach for Odor Source Localization with three subtasks

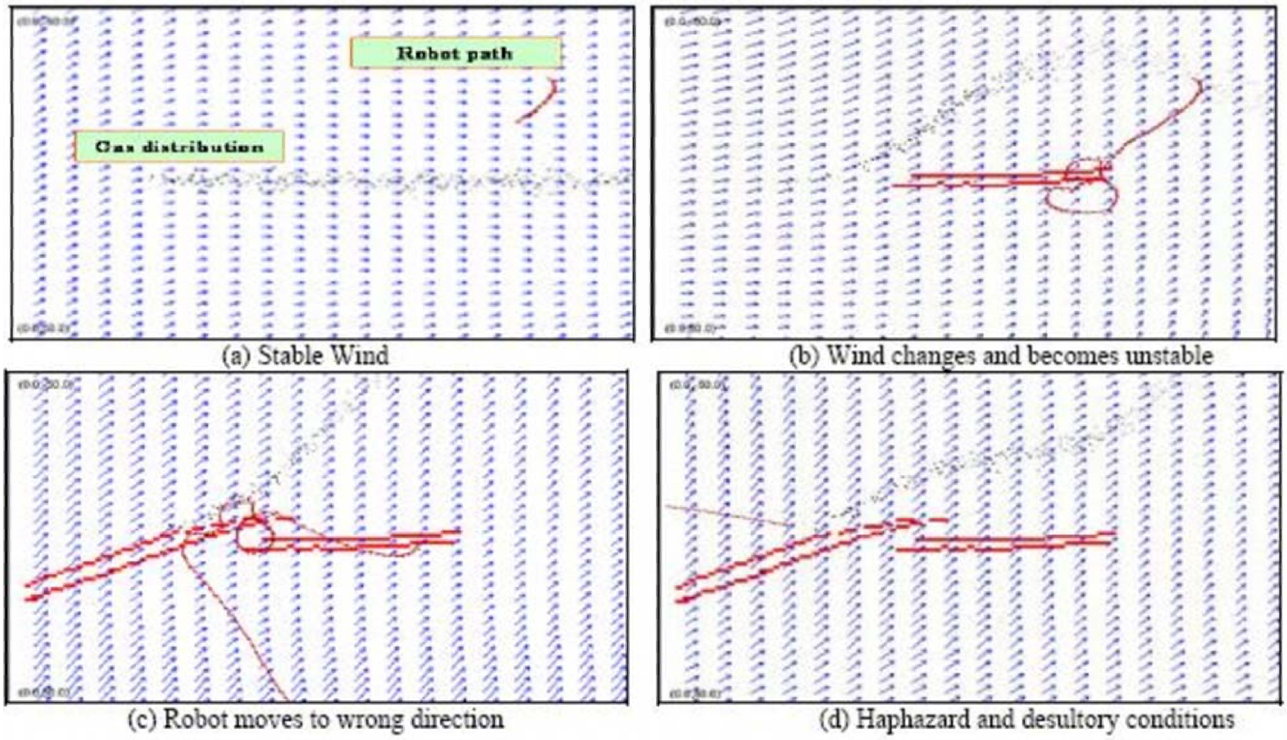

Fig. 2. Conventional approach in natural environment

unstable wind. When odor distribution is very complex and the wind direction is not stable, the robot will be haphazard and desultory, as shown in figure 2. This paper focuses on our new approach that exploits particle swarm optimization with multiple robots to solve odor source localization in natural environment where the odor distribution may change over time, and is an extension of our previous work [22].

4. PARTICLE SWARM OPTIMIZATION FRAMEWORK

4.1. *Particle Swarm and Robot Interaction*

The more detailed interaction of robot with PSO algorithm is described as follows. Suppose that a population of robots is initialized with certain positions and velocities; let $X_i(t)$and $V_i(t)$denote the position and the velocity vector of the i-th robot at the iteration time t (t=1,2...). Also $P_i$and $P_g$are defined as the local best and the global best respectively, where a plume distribution is evaluated using the position of the robot. The position and the velocity are updated so as to improve the fitness function at each time step. When a robot discovers a pattern that is better than any previously found, the positional coordinates are stored in the vector P_i, the best position found by robot i so far. The difference between P_i and the current position $X_i(t)$ is stochastically added to the current velocity $V_i(t)$. This would cause a fluctuation to the trajectory around the position. The stochastically weighted difference between the population's best position P_g and the individual's current position X_i is also appended to the velocity, in order to adjust for the next time step. These adjustments to the robot behavior lead to the search around two best positions.

The values of elements in P_g(concentration of the gas and position of the robot) are determined by comparing the best performances of all the members of the population, defined by indexes of other population members and assigning the best performer's indices to the variable g. Thus, P_g represents the best position found by all population members. An ad-hoc wireless network and global positioning system (GPS) are assumed to be equipped on all robots. Through the ad-hoc network, each robot can collect the information of the gas concentration and choose the best one. Then the position of the robot can be determined by GPS.

4.1.1) Standard PSO: The concept of standard PSO is described in eq. (1) and (2).

$$\begin{aligned} V_i(t) &= x(V_i(t-1) + c_1 rand()(P_i(t-1) - X_i(t-1)) \\ &\quad + c_2 Rand()(P_g(t-1) - X_i(t-1))) \end{aligned} \tag{1}$$

$$X_i(t) = X_i(t-1) + V_i(t) \tag{2}$$

After finding the two best values, the particle updates its velocity and position with eq.(1) and (2). The functions Rand() and rand() are random functions returning a value between (0,1). Coefficient is a constriction factor, which is supposed to be less than 1, the coefficient c_1 and $c_2$are learning parameters, which are supposed to be $c_1 = c_2 = 2$.

4.1.2) Detection and responding PSO: The standard PSO cannot solve the problems in the dynamic environment [5, 6]. To deal with a dynamic problem, PSO should be improved by incorporating the change detection and the responding mechanism [7,8]. The change detection function is used for monitoring the global best information P_g. If P_g has not been changed for certain number of iterations, it implies that another optimum solution might exist. After the detection of environmental changes, there must be a strategy for effectively responding to a wide variety of changes. However, if the whole population of robots has already converged to a small area, it might be difficult to cope with extreme changes. Therefore, a diversity extension mechanism of the spatial distribution is investigated when a change is detected. For simplicity, all robots are assumed to spread at a certain step to cope with the changes. Figure 3 shows the logic diagram of detection and responding PSO.

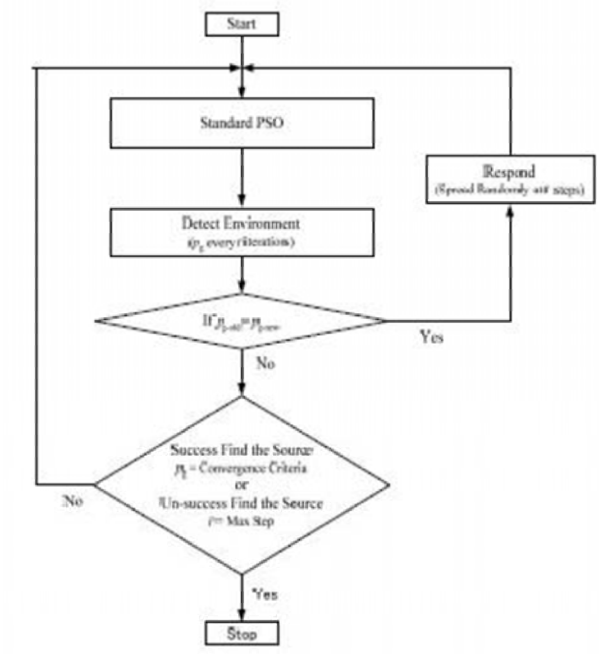

Fig. 3. Logic diagrams of the detection and responding PSO

4.1.3) CPSO: Applying the notion of Coulomb's law, a charged swarm robot is introduced in order to maintain diversity of the spatial distribution of robots and to prevent from being trapped in a local maximum. This is expected to enhance adaptability to extreme changes of the environment. Figure 4 shows the repulsion function for charged swarm robots. Suppose that robot i can observe the present position of the other robots ($X_P \neq X_i$)and has a constant charge $Q_i$in order to keep the mutual distance away and maintain the positional diversity. In this paper, however, two types of swarm robots are defined; neutral and charged robots, where neutral robot takes always $Q_i = 0$, hence, no repulsive force is applied to the neutral robots. For charged robots, the mutual repulsive force between robots i and p is defined according to the relative distance, $|X_i - X_p|$as follows.

$$a_ip = \begin{cases} \frac{Q_iQ_p(X_i-X_p)}{(r_{core}^2|X_i-X_p|} & |X_i - X_p| < r_{core} \\ \frac{Q_iQ_p}{|X_i-X_p|)^3}(X_iX_p) & r_{core} < |X_i - X_p| < r_{perc} \\ 0 & r_{perc} < |X_i - X_p| \end{cases} \quad (3)$$

where,($i \neq p$) ,r_{core} denotes the diameter inside which the constant strong repulsion force is applied, and r_{perc} denotes the recognition range of robot; hence, if the mutual distance is beyond r_{perc}, there exists 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:

$$a_i(t) = \sum_{p \neq i}^{N} a_{ip} \quad (4)$$

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

$$\begin{aligned} V_i(t) &= x(V_i(t-1) + c_1rand()(p_i(t-1) - X_i(t-1)) \\ &\quad + c_2Rand()(P_g(t-1) - X_i(t-1))) + a_i(t) \quad (5) \end{aligned}$$

$$X_i(t) = X_i(t-1) + V_i(t) \quad (6)$$

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

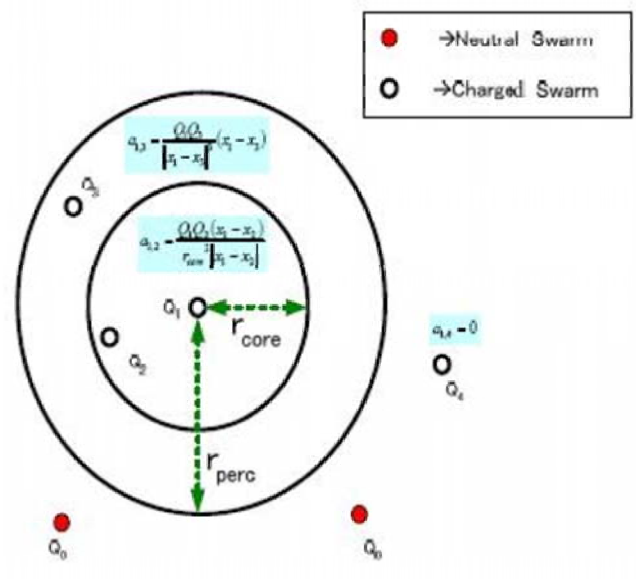

Fig. 4. Charged swarm robot interaction

4.2. Algorithm Implementation

4.2.1) Environment: As an odor source distribution model, Odor Gaussian Distribution model has been adopted in the previous work [22] and shown in Fig. 5. In this paper, we adopted the extended Advection-Diffusion odor model by Farrell et al. [25]; because of its efficiency, instantaneous and represent the time-averaged results for measurement of the actual plume, including chemical diffusion and advective transportation. In addition, Advection-Diffusion odor model has a key complicating factor to plume tracing that is sinuous (or meandering) nature of the plume.

The Advection-Diffusion model is composed of a large number of advected and dispersed filament. Given a large number of filaments, the overall instantaneous concentration at $X_0 = (x, y)$ is the sum of the concentrations at that location contributed by each filament:

$$C(X_0, t_0) = \sum_{t=1}^{M} C_i(X_0, t_0) \tag{7}$$

where C is the concentration of the plume (molecules/cm3), t_0 is the number of iteration and M is the number of filaments currently being simulated. The Advection-Diffusion gas concentration at the location due t_0 the i-th filaments is expressed by:

$$C_i(X_0, t_0) = \frac{q}{\sqrt{8\pi^3}} \exp\left[\frac{-r_i^2(t_0)}{R_i^2(t_0)}\right] \tag{8}$$

$$r_i(t_0) = |X_0 - P_i(t_0)| \tag{9}$$

where q is the amount of odor released, R_i is the parameter controlling the size of the i-th filament and P_i is changing positions of the i-th filament. For further explanation on this model, see [25], section two and three.

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

4.2.2) 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. Particle Swarm concept will be applied to following the cues determined from the sensed gas distribution toward the source. The last task is the source declaration based on the certainty that the gas source has been found. If a robot senses the gas density that is beyond a certain threshold value, it means that the gas source location is specified, and hence the searching behavior is terminated. Moreover, the search isterminated if the swarm robots fail to localize the odor source by the maximum iteration time step.

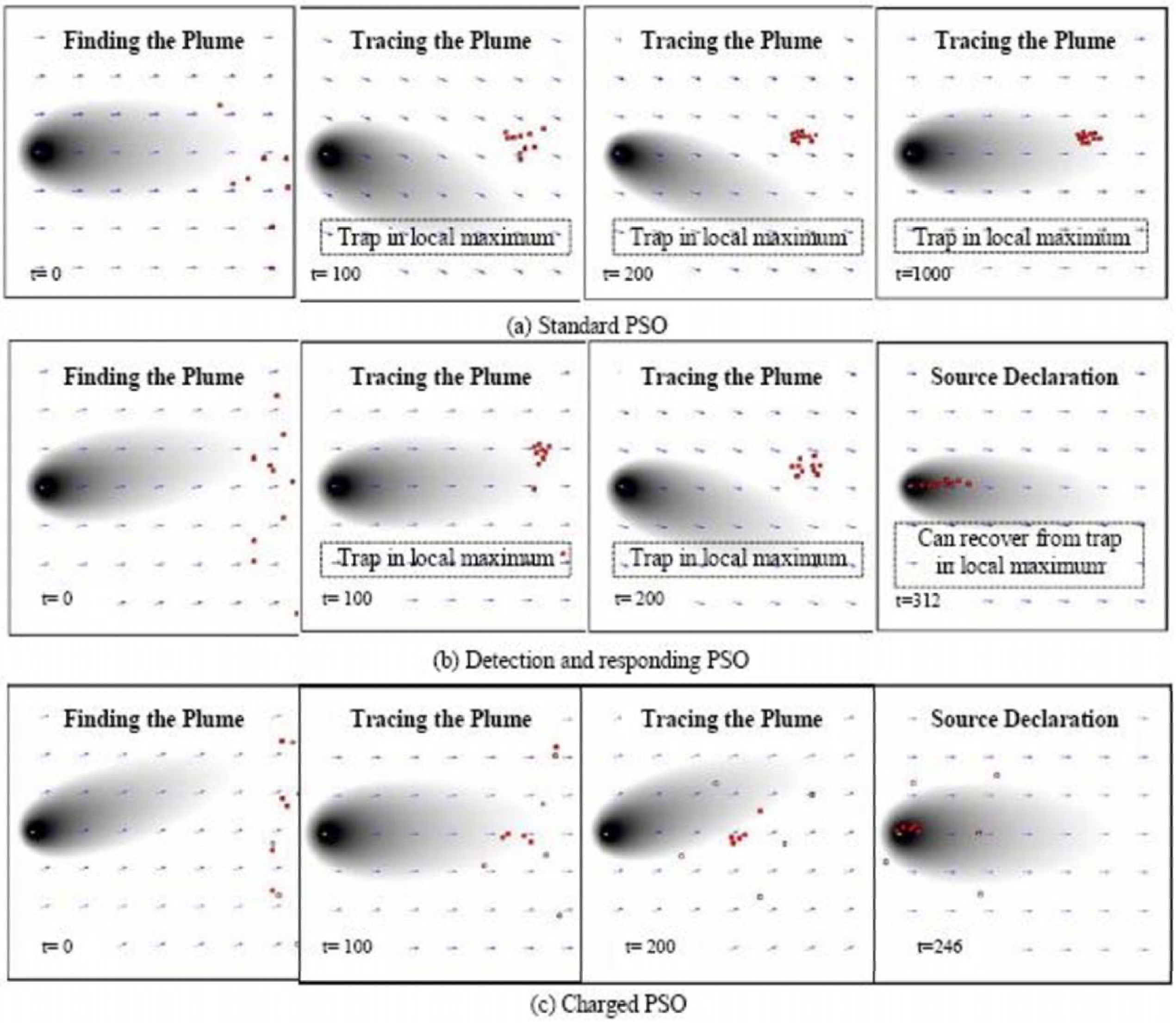

Fig. 5. Visualization of proposed approaches for odor source localization in Gaussian odor model

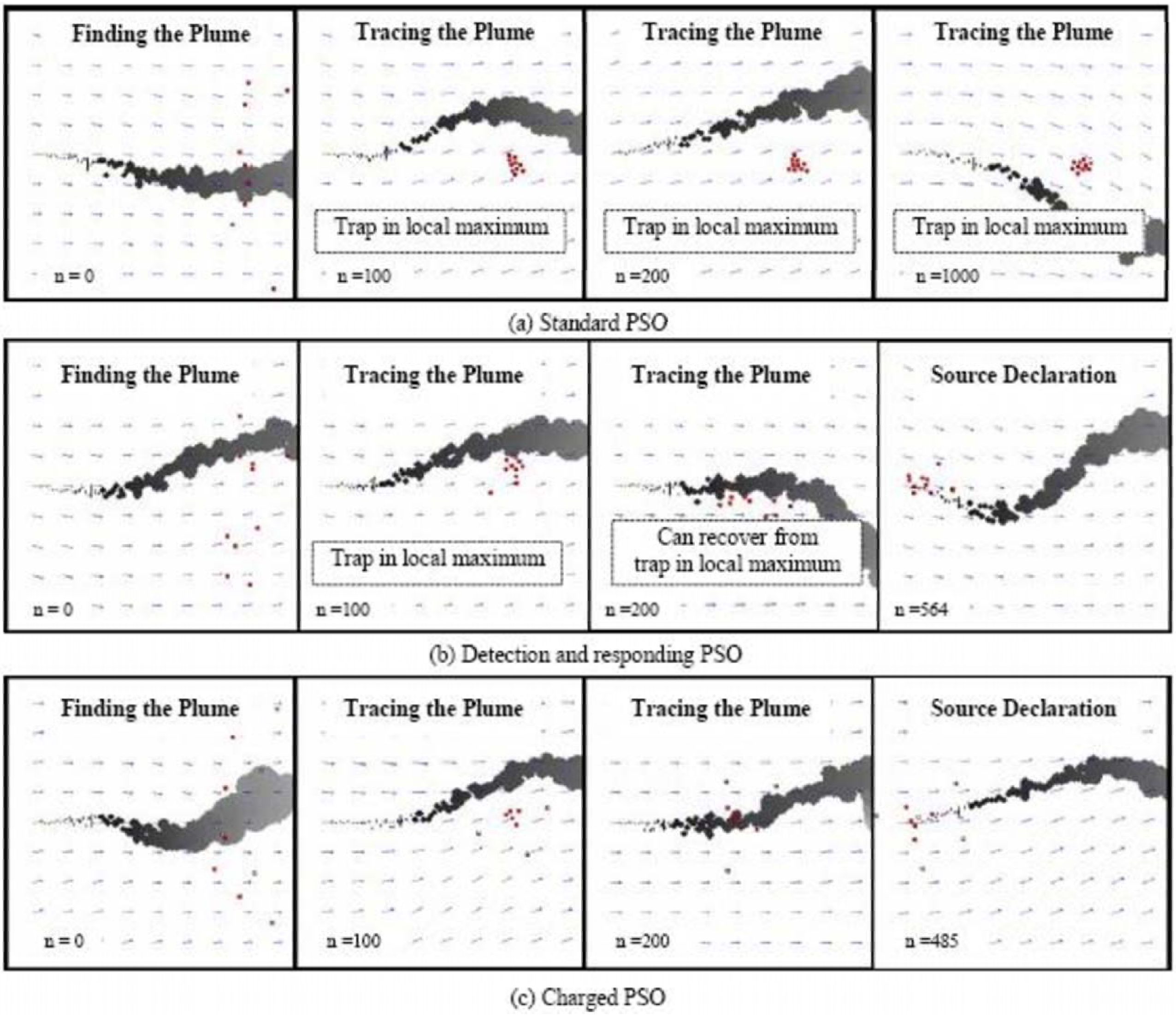

Fig. 6. Visualization of proposed approaches for odor source localization in Advection-Diffusion odor model

To ensure that the performance of proposed strategies is applicable to the hardware experiments, the simulation must contain the key features of the hardware setup. Firstly, the real robot has the maximum velocity to move, hence, the value of velocity vector can be restricted to the range [-Vmax, Vmax]; in this simulation, the maximum velocity is set to 0.05 (m/s), by following definition:

$$V_i(t) = min(V_i(t), V_{max}) \tag{10}$$

Secondly, in order to incorporate a collision avoidance mechanism, which is not considered in the standard PSO algorithm, we assume that the infra red sensors are equipped with each robot.

Then the parameters of sensor noise and threshold value are added to model sensor responses. We assume that iteration time t of the robot in eq. (1) to (6) and iteration time t_0 in eq. (7) to (9) have different time step resolution. Time correlation between time step t and time step t_0 is explained as follows. Time scale of t has higher resolution than that of time step t_0 and count up is represented as:

$$t_0 + 1 = t_0 + \Delta t \tag{11}$$

t is the interval time step t_0 interms of time step t. Hence; t_0 is represented with t by:

$$t_0 = \left[\frac{t}{\Delta t}\right] \tag{12}$$

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

$$S(t) = \begin{cases} C\left(\left[\frac{t}{\Delta t}\right]\right) + e(t) & IfC > \tau \\ 0 & Otherwie \end{cases} \tag{13}$$

where S is the sensor's response, C is the gas concentration, e is the random sensor noise with $e << C$, and τ is sensor threshold.

Finally, the basic concept of PSO algorithm uses a common assumption that all robots have accurate GPS that give the robot its global location and no error model is used for the position. These errors should be modeled as well to reveal more realistic situation. From that reason, the random position error sensor was added as defined by:

$$X_(t) = (X_i(t-1) + V_i(t)) + D_{error} \tag{14}$$

$$D_{error} = \begin{bmatrix} x_{error} \\ y_{error} \end{bmatrix} \tag{15}$$

$$x_{error} = ((\frac{rand()}{RAND\_MAX}) \times 100) - RE \tag{16}$$

$$y_{error} = ((\frac{rand()}{RAND\_MAX}) \times 100) - RE \tag{17}$$

where RE is range of error, and $x_{error} \neq y_{error}$is an error position.

TABLE I
PSO PARAMETERS USED FOR EXPERIMENTS

Parameters	Values
c_1, c_2	2
x	0.5
Derection function	20 iteration
Responding Function	5 steps
Robots	10
r_{core}	1m
r_{limit}	2m
Q	1 coulomb
Time-step(Δt)	10 steps
Convergence Value	50 ppm
Max. Iterations	1000 steps

5. SIMULATION EXPERIMENT

5.1. Experiment Results in Dynamic Environment

The parameter setting for changing the plume is adopted at the values in [25]. The parameter settings for the PSO algorithms are defined in table 1. Two types of modified PSO are used to solve the odor source localization in dynamic problem; (1) PSO incorporating change detection and responding mechanisms and (2) CPSO. And also standard PSO is used for compare the swarm behaviors visually.

Figure 6 shows the visualization for odor source localization in Advection-Diffusion odor model. The standard PSO cannot solve the problem in dynamic environment as shown in figure 6(a). The robots were trapped in local maximum area due to the loss of diversity of the spatial distribution of the robots.

Experimental result of detection and responding PSO are shown in figure 6(b). The change detection function is used for monitoring the global best information P_g . If P_g is not changed for 20 iterations, there is a possible optimum change and the value of the global best will be reinitialized to zero (global best=0). Therefore, the random spread mechanism of spatial distribution is applied when a change is detected. All robots will spread for 5 steps to cope with the changes, and then robots can recover from the local maximum.

The effect of re-initialization of the global best and spreading implies loss of information gathered during the search so far. As an alternative adaptation, CPSO approach is introduced. Experimental results of CPSO are shown in figure 6(c). Because the robots maintain the diversity of spatial distribution, they expected to escape from being trap in local maximum.

Figure 7 shows the compared results of plotting averages of convergence time among PSO algorithms modified for solving odor source localization in dynamic advection-diffusion environments. To demonstrate the scalability of our approach we increased the number of the robots. Figure 8 shows that increasing the number of the robots increase the performance.

5.2. Statistical Analysis

It is important to analyze the results from several repeated runs by statistical methods in order to obtain empirical evidence of the capabilities of the proposed method. The efficiency of the proposed method, which expressed as the number of iterations required to find the solution should be analyzed. The performance is measured by statistical mean.

For example, for n observations of a stochastic variable, the sample mean (average) value is defined by:

$$\bar{\mu} = \bar{t} = \frac{1}{n}\sum_{i=1}^{n} t_i \tag{18}$$

Where, t is the number of iterations for the robots to find the source.

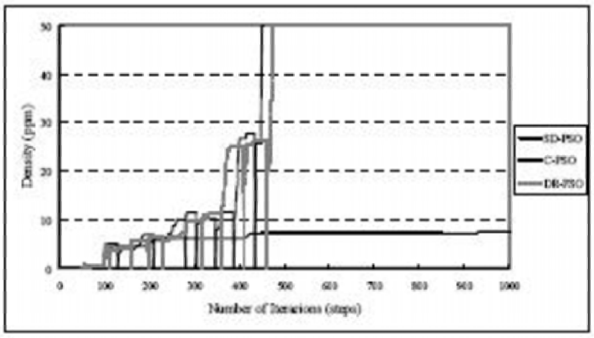

Fig. 7. Time development of global best coping with dynamical change of environment with various PSO algorithms. (Repeated 50 times)

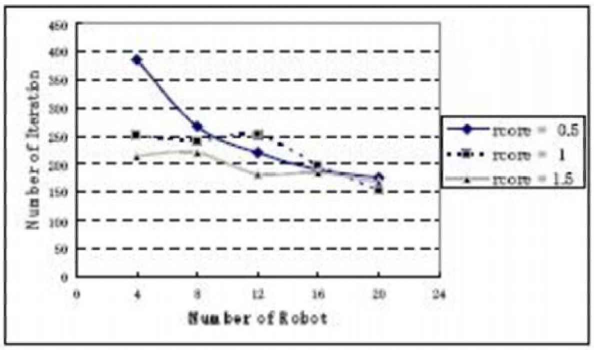

Fig. 8. Average of convergence time when number of the robot became increase used CPSO. (Repeated 50 times)

And the standard deviation and confidence analysis of measurement are also used. The sample standard deviation is defined by:

$$\sigma = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(t_i - \bar{t})^2} \tag{19}$$

The sample of confidence interval (CI) of measurement is defined by:

$$CI = \bar{t} \pm \sigma \tag{20}$$

Previous experiment has been done with odor sensor and position sensor errors were not employed. For further analysis the effect of odor sensor and position sensor error were investigated as shown in table 2. Then with mean, standard deviation and confidence interval the statistic performance are measured.

Table 2 shows time development of global best coping with small meander dynamic changes of environment using CPSO algorithm with uncertain sensor parameters and various odor sensor and position errors. Adding position error, e.g., 25 (cm) and 50 (cm), will slightly decrease the performance. The position errors, 25 (cm) and 50 (cm) are within realistic range in comparison with the dimension of robot (10 cm). It can be concluded that the proposed approach is theoretically sound. Even though when the position error became very large, e.g., 100 (cm), all robots fail to find the odor source location.

TABLE II

AN INFINITE VALUE MEANS THAT AT LEAST HALF THE EXPERIMENTS WERE UNSUCCESSFUL. (REPEATED 50 TIMES)

Odor Sensor Error(ppm) / Position Error(cm)	0.1	0.2	0.5
0	507 ± 208	550 ± 161	448 ± 167
25	754 ± 161	725 ± 187	797± 178
50	816 ± 196	941 ± 94	∞
100	∞	∞	∞

6. CONCLUSIONS

In this paper, we have presented two types of particle swarm optimization (PSO) modification approaches to control autonomous vehicle robots to search for odor source in dynamic environments. The detection and responding PSO can solve the odor source localization problems, however the drawback is with the arbitrary nature of the detection and response algorithms. The charged particle swarm optimization (CPSO) need no further adaptation to cope with dynamic scenario due to the extended swarm shape. Modified PSO, especially CPSO, is theoretically sound. These proposed approaches can solve such dynamic environment problems in both Gaussian and Advance turbulence model.

But in practical, for real natural environment, the robot will find variety of situations which require multi-disciplinary research from biology, physic-chemistry, engineering and robotics. Unresolved problems still exist in implementation phase. Most of those could be grouped into one of the following categories.

1) Environment:
   The real environment has various obstacles. As a result, the odor distribution will have more than one optimal solution and thus the problem becomes more complicated.
2) Algorithm optimization:
   The common problem using PSO lies in the parameter tuning to find the optimal solution. Most of the researchers use the cross validation or try and error methods to tune parameters. Further algorithm development in simulation will include online learning, which system can learn parameters from environment.

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