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MODIFICATION OF PARTICLE SWARM OPTIMIZATION BY REFORMING GLOBAL BEST TERM TO ACCELERATE THE SEARCHING OF ODOR SOURCES

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Abstract- ***Particle Swarm Optimization (PSO) has been widely utilized for Odor Source Localization (OSL)*** **purposes.*****There have been plenty of researches on this field. The latest research to modify original PSO were on the utilization of wind dynamics. In wind utilization research, the robot movement would be retarded if the robot movement direction is similar to the wind direction. Conform to the aforementioned method, this research proposed new modification on the global best term of PSO algorithm. There are two modifications proposed in this research, named Ignoring gBest 1 (IgB1) and Ignoring gBest 2 (IgB2).The basic concept of two proposed methods are identical by considering wind dynamic into global best term of PSO. The robot which in the original PSO will move to global best position would be deviated to the other point which is defined by deliberating wind direction. The main difference of both the method lies on the addition of new term in IgB1, whereas in IgB2 there is modification in social term without any additional term. The experiment was conducted on two PSO for***

OSL purposes algorithms i.e. Ranged Sub-Group PSO (RSPSO) and Ranged Multi Niche PSO (RMNPSO). The result on RMNPSO showed significant decrease in time consumption while employing both the proposed method. On the contrary in RSPSO the improvement is insignificant compared to the original algorithm.

Index Terms: Particle Swarm Optimization, odor Source Localization;wind dynamic, Ignore gBest 1, Ignore gBest 2, time consumption

I. INTRODUCTION

In robotics field there are two research area which are related to odor, i.e. odor olfaction and odor source localization (OSL).Odor olfaction concern on the odor type recognition. Where researches in [1-4] are research which concern to odor olfaction. While OSL focus on the searching of odor sources. The consecutive steps of OSL based upon research conducted by Hayes in [5,6] are: plume searching, plume transversal, and source declaration. Plume searching is the step of finding the plume itself. Afterwards, the plume would be traced in the second step. Finally, after the sources are found, there would be source declaration by robots.In Hayes research, only ingle robot was employed to find the odor location.

On the other hand, Particle Swarm Optimization (PSO) algorithm is a swarm intelligent algorithm which was first proposed by Eberhart and Kennedy in [7,8]. Some researches using PSO algorithm also conducted by Jatmiko et al. Some of them are detecting ellips which represent embryo in vitro process [9], tracking sperm was proposed by Aprinaldi in 2014 [10], and predicting the growth of algal cell by employed multilayer perceptron (MLP) which is optimized by Canonical PSO [11].

Research on OSL have profoundly been conducted by Jatmiko et. al[12]. In his research particle swarm optimization (PSO) was empowered to organize the robot swarm to search the odor location. In Jatmiko's research, each robot is represented as a single value in swarm of solution in PSO. Meanwhile, odor concentration and high odor concentration position as fitness value and global best respectively. In OSL case Jatmiko proposed two modifications on original PSO, i.e. wind utilization I and wind utilization II. In wind utilization I, the robot movement will be stopped in the predetermined forbidden area. Whereas in wind utilization II, while robot is entering the aforementioned forbidden area, the velocity constant will be reduced. The reduction follows certain equations.

In 2014, Hasrindra proposed Ranged Multi Niche PSO (RMNPSO) [13], which is the modification of Ranged Sub-Group PSO (RSPSO) [14]. RSPSO itself is the improvement of wind utilization by introducing niche concept which defined as the sub-swarm of the main swarm in PSO. Each niche is led by a main robot. Meanwhile, RMNPSO proposed the eradication of main robot to reduce the number of robot empowered in the odor searching. Due to the eradication of the main robot the time consumption was increasing. To tackle this drawback, new method is introduced in this research. The proposed method deliberates the dynamic of the wind and quantify it into mathematical operation.

II. RELATED WORK

This research employs three previous related research i.e. wind utilization, RSPSO, and RMNPSO. In this section those three related work would be briefly elaborated.

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) [15]

Before studying on wind-utilization, Jatmiko has studied the environmental conditions that contribute to improving komplektisitas in OSL, wind and molecule behavior research in [16] are some examples.

Jatmiko et al.[12] proposed the consideration of wind dynamic into the modification of original PSO. There are two proposed methods in this research, wind utilization I (WUI) and wind utilization II (WUII). In WUI, Jatmiko proposed forbidden area to restrict the movement of the robot. If the direction of robot's movement is similar to the wind direction, then the robot velocity will be set to zero.

The mechanism of WUI is by measuring the angle between the robot's velocity direction (v_t) and wind direction (w_t) as shown in equation (1).

$$\theta = \cos^{-1}\left(\frac{v_t . w_t}{\|v_t\| . \|w_t\|}\right) \tag{1}$$

Then the velocity update follows equation (2).

$$v_t = \begin{cases} 0 & if\ \theta < |\theta_{\text{forbidden}}| \\ \mathrm{v_t} & \text{otherwise} \end{cases} \tag{2}$$

Meanwhile, in WUII, the robot movement restriction employs parameter control function (χ_θ) as shown in equation (3), where $\chi_\theta(v_t, w_t)$ and v_i(t) can be determined using equation (4).

$$v_t = \chi_\theta . v_i(t) \tag{3}$$

$$\chi_\theta(v_i(t), w_t) = \frac{(1 - v_i(t).w_t)}{2}$$

$$v_i(t) = \chi(v_i(t-1) + c_1.r_1.(pbest - x_i(t-1)) + c_2.r_2(gbest - x_i(t-1))) \tag{4}$$

In addition of wind utilization, to solve OSL problem by using PSO Nugraha in [17] proposed spread phase for maintaining diversity. Spread phase is a method which modifies detect and response in [18]. Spread phase will make robots spread from the center point of the group, hence, increasing the possibility to detect undetected plumes. Besides sperad phase, Jatmiko in [12] proposed charged particle as well. The idea of using charged particles are based in [19,20] which proposed byBlackwell Charged particle is a particle which has electrical charge, which would make repulsion force between charged particle. The modified PSO algorithm by means of charged particle, can be explained as follow : Assumed there are three particles. They are an i-th particle (which has Q_i Coloumb of charged), $a_{1,2}$ and $a_{1,3}$ particles in position as illustrated in figure 1.

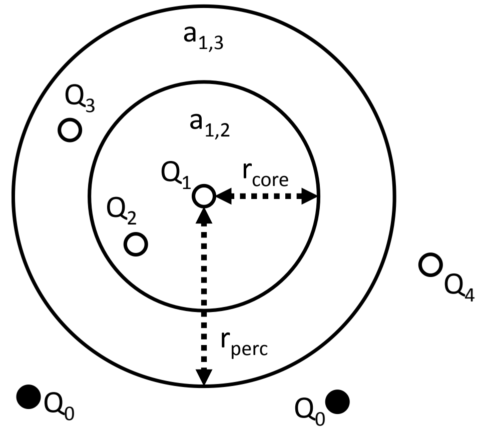

Figure 1. Charged Particle

Based illustration on figure 1, the repulsion forces of $a_{1,2}$ and $a_{1,3}$ can be determined using equation (5) and equation (6) respectively. Meanwhile equation (7) and equation (8) describe accumulations of repultion forces and determining particle velocity respectively.

$$a_{1,2} = \frac{Q_1.Q_2(x_1 - x_2)}{r_{core}^2.|x_1 - x_2|} \tag{5}$$

$$a_{1,3} = \frac{Q_1.Q_3(x_1 - x_3)}{|x_1 - x_3|^3} \tag{6}$$

$$a_i(t) = \sum_{for\ p=2to3} a_{1,p} \tag{7}$$

$$v_i(t) = \chi(v_i(t-1) + c_1.r_1.(pbest - x_i(t-1)) + c_2.r_2(gbest - x_i(t-1))) + a_i(t) \tag{8}$$

b. Ranged Sub-Group PSO (RSPSO)

Ranged Sub-Group PSO (RSPSO) is a PSO algorithm for Multi-Odor Source Localization (M-OSL) problem which based on locating multiple optima in [21]. In RSPSO main robot which represent the niche was introduced. Main robot is a robot which is located at the center of niche and has charged particle behavior only to another main robot. The purpose of this method was to assure the absence of double searching, i.e. 2 niche are looking for one odor source. Figure 2 delineates the aforementioned phenomena.

Due to the existence of this repulsion force, the possibility of double searching would be minimized. Nevertheless, the repulsion force does not affect another particle including charged particle. Figure 3 depicts the main robot, its R core and radius of force. Whereas the value of the force can be found in equation (13) in [14].

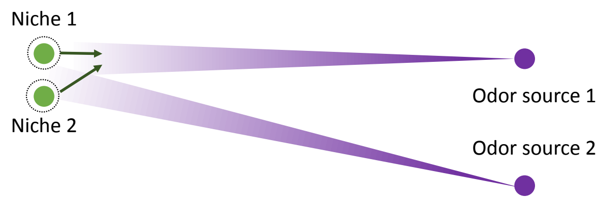

Figure 2. The Possibility of Two Niches Pursue Similar Source of Odor

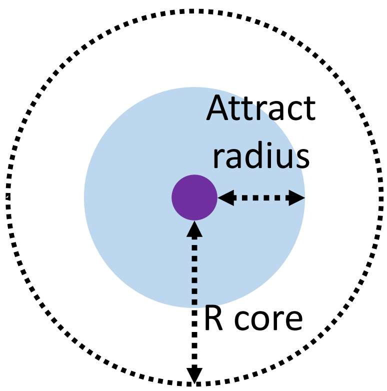

Figure 3. Main Robot and Its Accessories

Figure 4(a) illustrates the movement of two niches with insignificantly different destination. Figure 4(b) delineates the above-mentioned niches are aiming for the similar odor source. Due to the repulsion force of the main robot those two niche would be separated. Eventually both the niches will pursue different odor source which is depicted in Figure 4(c).

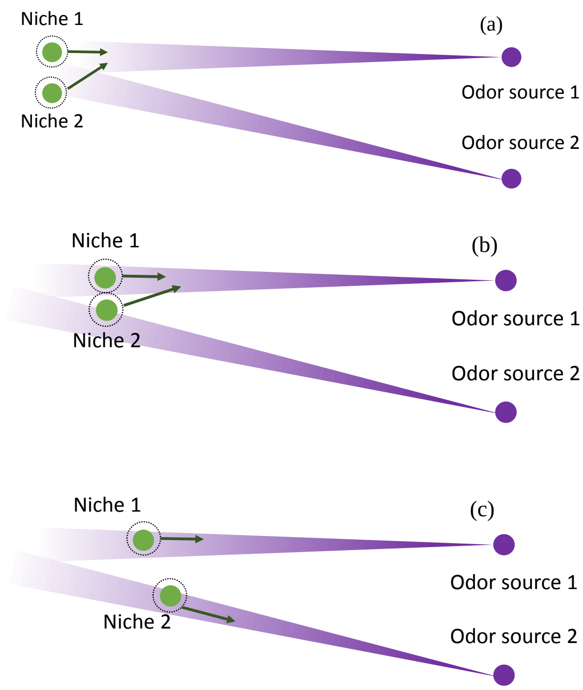

Figure 4. Main Robot Role Illustration

c. Ranged Multi Niche PSO (RMNPSO)

Range Multi Niche PSO (RMNPSO) [13] is modification of RSPSO which was proposed by Hasrindra. RMNPSO was proposed to tackle several drawbacks in RSPSO. First of all, in RSPSO there is possibility of niche that has no member due to the member exchange with another adjacent niche. Figure. 5 illustrates two adjacent niche in which one of charged robot from (c2) in niche 1 will possibly be attracted to niche 2. The initial member of both the niches are listed in table 1.

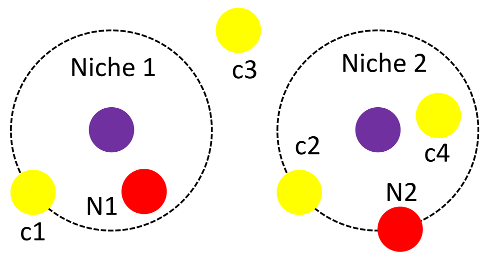

Figure 5. Robots position

Table 1: Robots Membership

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

If phenomena which is delineated in Figure. 5 continue, then all the robot member of niche 1 would likely to become member of niche 2. The niche which only has one robot member will have difficulty of exploring the area to detect and trace the plume. To overcome this problem, in RMNPSO restriction radius was introduced. If charged robot is outside the restriction radius, then that robot will be returned to the inside of restricted radius as illustrated in Figure. 6. Equation (9) shows the formula to restrict charged robot movement.

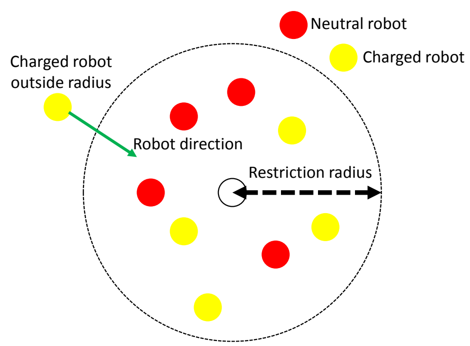

Figure 6. Robot Movement Restriction.

$$v'_{i,s}(t+1)=\begin{cases} c_s(t)-x_{is}(t) & if \ |c_s(t)-x_{is}(t)-v_{is}(t+1)| \le v_{restrict} \\ 0 & otherwise \end{cases} \quad (9)$$

Where:

$v'_{is}(t+1)$: velocity of i^{th} particle in s^{th} niche at t+1 iteration after restriction

$c_s(t)$: center position in s^{th} niche at t iteration

$x_{is}(t)$: position of i^{th} particle in s^{th} niche

$v_{is}(t+1)$:velocity of i^{th} particle in s^{th} niche at t+1 iteration before restriction

Second modification which was proposed by RMNPSO is the eradication of main robot in RSPSO. The center of the niche in RMNPSO was defined to be the center of neutral robots. The purpose of this modification was to reduce the usage of robot. Moreover, center of neutral robots represent the niche better. Figure 7 depicts the definition of niche center in RMNPSO. Meanwhile to calculate the repulsion force between each niche, equation (10) can be employed.

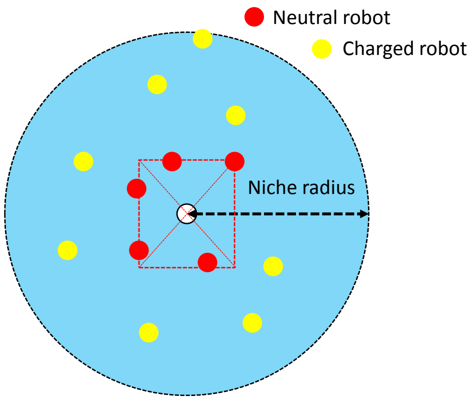

Figure 7. RMNPSO niche center modification.

$$a'_{sk}(t+1)=\begin{cases}\dfrac{Q_s.Q_k}{\left|c_s(t)-c_k(t)\right|^2}c_s(t)-c_k(t) & if\ \mathrm{r_{sk}}\le r_s+r_k\le \mathrm{gbest_k}(t)\\ 0 & otherwise\end{cases} \tag{10}$$

where:

$a_{sk}(t)$: repulsion force of niche s to niche k at t iteration after restriction

Q_s: charge of niche s

Q_k: charge of niche k

$c_s(t)$: vector position of center point of niche s at t iteration

$c_k(t)$: vector position of center point of niche k at t iteration

$r_{sk}(t)$: distance between center of niche s and niche k

$r_s(t)$: radius of niche s

$r_k(t)$: radius of niche k

III. PSO WITH GLOBAL BEST MODIFICATION

There are two principal differences between PSO for general optimization problem and PSO for OSL purposes. First of all, in general optimization problem, PSO function to find the optimum value for specific objective function. The indicator of the optimum value is the convergence of the global best value. Meanwhile, PSO for OSL case focus on the localizing the odor sources. Conform to Hayes research, the value of global best is unnecessary to be convergent to stop the operation. The indicator is the distance between the destination value and the global best value which must less than the prescribed value.Second difference lies on the global best assumption. In general optimization purpose PSO all direction in the vicinity of global best position has the similar probability to find the real global best. Whereas in PSO for OSL case, there is larger likelihood to find real global best in the direction against the wind direction (upwind).

This research propose method called Ignore gBest as the modification on global best term in PSO algorithm. The concept of the above mentioned method is depicted in Figure 8.

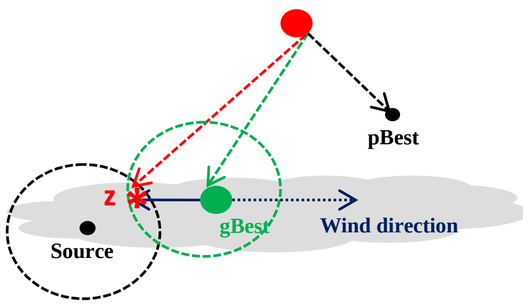

Figure 8. Ignore gBest Method

In the original PSO, the robot which is in Figure 1 delineated by red circle will move to global best point (green circle). In the proposed method, the global best is not defined as the destination for robot to move. Instead the adjacent point in certain area (red asterisk). The direction of the point is determined by the direction of upwind. The position of pint z (x_z) is defined in equation 11.

$$x_z = gbest + r_{found}\begin{pmatrix}\cos(\theta)\\ \sin(\theta)\end{pmatrix} \qquad (11)$$

Where:

x_z: new position of global best

r_{found}: radius of deviation from global best

θ: upwind angle

Due to the dynamic of the wind, the direction of the upwind at global best point and robot position might differ. Moreover at a certain time the position of global best may lose the plume. This discrepancy may lead to the ineffective of the proposed method. The possible direction difference between upwind ad global best and robot location is shown in Figure. 9.

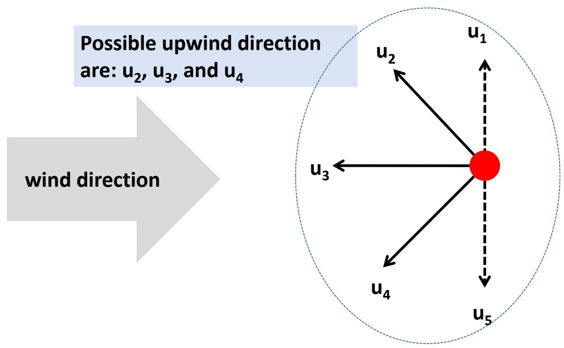

Figure 9. Possible Upwind Direction.

In this research, the angle between upwind at global best position and robot location assumed to be less than 90^o. This assumption valid due to the impossibility of the backflow since there is no obstacle in the odor searching area. The aforementioned phenomena might reduce the performance of the proposed method. Nevertheless, the hindrance can be overcome with these following elaboration.

Figure 10 shows the first case of the proposed method. As previously mentioned, there are three possibilities of upwind direction (u_s, u_l, and u_r). From the figure can be seen that the destination point (dashed green circle) is in front of the global best position (green circle). Therefore, the robot will ignore global best and move directly to the destination point which naturally have higher plume concentration. In the first upwind direction (u_s) the step required by robot to reach destination point is one. On the contrary, for u_l and u_r the robot need two. However, each upwind possibility will still cause the robot to reach dashed green circle which is the better position. Meanwhile, in the original PSO the minimum steps needed to reach the destination point (dashed green circle) is two. Therefore the worst performance of the proposed method is similar to the original PSO.

Figure 11 and Figure 12 show the secondand third case of the proposed method respectively. Both the figure represent the case in which the plume vanish from the global best position. However, the proposed method still show better performance. To illustrate this, as shown in the Figure 11, the destination point (dashed green circle) is located in the better position relative to odor source location. Even though the plume concentration at the destination point is close to zero, but the position is closer to the odor source. Moreover, there is possibility that the wind's direction would change and the destination point will acquire higher plume concentration. The similar explanation can be used for case 3 (Figure 12).

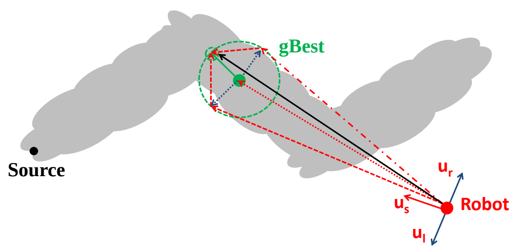

Figure 10. Case 1.

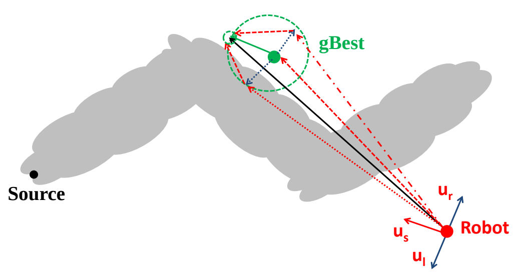

Figure 11. Case 2.

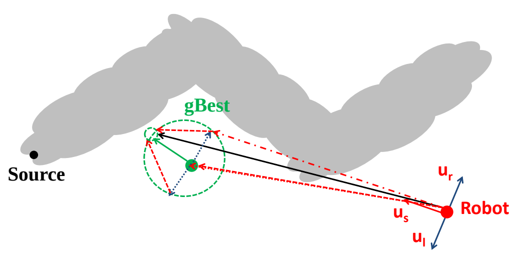

Figure 12. Case 3.

Based upon the previously explained method, this research proposed two modifications on original PSO. The modifications are named Ignore gBest 1 (IgB1) and Ignore gBest 2 (IgB2). The differences between IgB1 and IgB2 lie on the velocity formulation which are shown in equation (12) and equation (13) respectively.

$$v_i(t) = \chi\left(v_i(t-1) + c_1.r_1.(pbest - x_i(t-1)) + c_2.r_2\left(gbest - x_i(t-1)\right) + c_3.(1-r_1).(x_z - x_i(t-1))\right) \qquad (12)$$

$$v_i(t) = \chi\left(v_i(t-1) + c_1.r_1.(pbest - x_i(t-1)) + c_2.r_2\left(gbest + r_{found}.\begin{pmatrix}\cos(\theta)\\ \sin(\theta)\end{pmatrix} - x_i(t-1)\right)\right) \qquad (13)$$

where:

c_3: 3rd term constant

$(1-r_1)$: random number which will have the inverse behavior of r_1 random number

The $(1-r_1)$ random number is specified for 3rd term in order to preserve the inversion of its value with cognition term. Therefore, if the random value in cognition term is dominant, then the above-mentioned value is recessive and vice versa.

As shown in equation (12), IgB1 method proposes 3 terms, constituting initial velocity term, cognitive term, social term, and modification term. However, more term included, more distraction would be caused. Thus, the movement of the robot will be distracted by each term and the accuracy will possibly be decreased. To tackle the aforementioned issue, this paper also propose the improvement of IgB1 i.e. IgB2. In IgB2 method, as shown in equation (13), the 3rd term of IgB1 is included in the 2nd term of original PSO. The selection of social term instead of the other terms is based upon the realization that social term is predominant among the other terms.

Finally, the aforementioned global best modification would be employed on two existing PSO algorithm, i.e. Ranged Sub-Group PSO (RSPSO) and Ranged Multi-Niche PSO (RMNPSO). The selection of RSPSO is based upon the latest method utilized in PSO for OSL purposes. Meanwhile, the selection of RMNPSO is based upon the undergoing research on the adaptive niche PSO in which the niche is formed depend on the amount of odor source.

IV. EXPERIMENTAL SETUP

In this research, the simulations were undertaken by empowering Microsoft Visual Studio 2008 and using C++ as the programming language.The parameter while conducting the experiment are listed in table 2. Meanwhile, the scenario undertaken in this research are:

- Original RSPSO
- RSPSO with IgB1
- RSPSO with IgB2
- Original RMNPSO
- RMNPSO with IgB1
- RMNPSO with IgB2

Table 2: Parameter Setup Used in Experiment

Parameters	Explanation
Plumes Model	Filament-Based [22]
Area (L)	10 × 10 m2
	12.5 × 12.5 m2
	15×15 m^2
Number of Sources	2, 3, 4, 7 , 9, and 11 sources
Robot per Niches	4 Charged, 3 Neutral
Charged (Columb)	1
Iteration Time Out	1000sec
Velocity Clamping	1m/s
Constriction Factor (χ)	0.729843788
$c_1 = c_2$	2.05
Niche Radius	0.1L

In this experiment, we defined area (L) to be 10 × 10, 12.5 × 12.5, and 15 × 15 m^2. This selection was based upon the assumption that this area is large enough. Therefore, the odor searching would be longer than the smaller area, and hence the significance of the proposed method can be seen.The number of odor sources were determined to be 2, 3, 4, 7, 9, and 11. Whereas the number of niche was predetermined to be similar to the number of the odor source. In each niche the number of charged robot was defined to be 4 robots and the number of neutral robot was determined to be 3 robots. The charge of robot was prescribed to be 1 Coulomb and the iteration time out was 1000 second.

Velocity clamping was prescribed to be 1 m/s and required to restrict the velocity of the robot, thus the robot would not out of predetermined range. The constriction factor was 0.729843788, with constant $c_1 = c_2 = 2.05$. Finally, the niche radius was defined to be 0.1 L which conforms to [13].

V. RESULT AND DISCUSSION

In this experiment, we measure time consumption (TC) of algorithm to locate all sources. The small TC values mean that the algorithm locates all sources quickly, and vice versa for great TC values.

The first measurement is TC measurements for RSPSO and RMNPSO algorithms in area 10 × 10 m^2. TC measurements for RSPSO and RMNPSO are done for original and improved algorithm using IgB1 and IgB2. Table 3 descibes that the improved algorithm using IgB1 and IgB2 for RSPSO and RMNPSO can reduce TC values in area 10×10.

Table 3: Time Consumption of each Algorithm (10 × 10)

Algorithm	Odor Sources					
	2	3	4	7	9	11
RSPSO	92,5	113,7	119,4	123,2	129,8	139,8
RSPSOIgB1	88	112,9	104,1	122,7	126,1	137,7
RSPSOIgB2	86,8	92,3	101,5	120,2	124,4	126,7
RMNPSO	71,3	91,2	150,9	301,6	344,3	337,5
RMNPSOIgB1	64,7	90,9	109,6	194,4	191	207,9
RMNPSOIgB2	47,9	69,4	99,7	184,1	175,8	199,6

Figure 13 illustrates that for RSPSO, the improvement using IgB1 is the better results than RSPSO without improvement (in original version), and the improvement using IgB2 has the best result of IgB1 improvement and RSPSO in original. The same as figure 13 is in figure 14 illistrates that the improvement using IgB1 and IgB2 for RMNPSO have the same result as RSPSO. It mean that IgB2 really can reduce time consumption for RSPSO and RMNPSO.

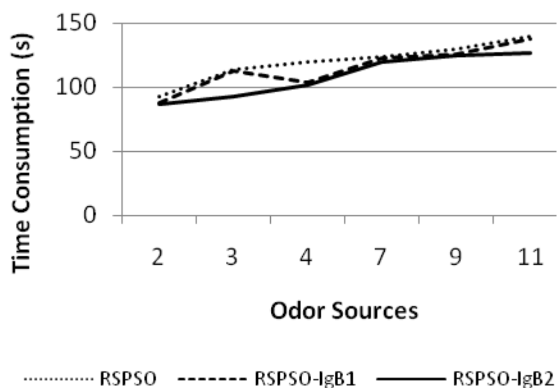

Figure 13. Result in RSPSO (10 × 10).

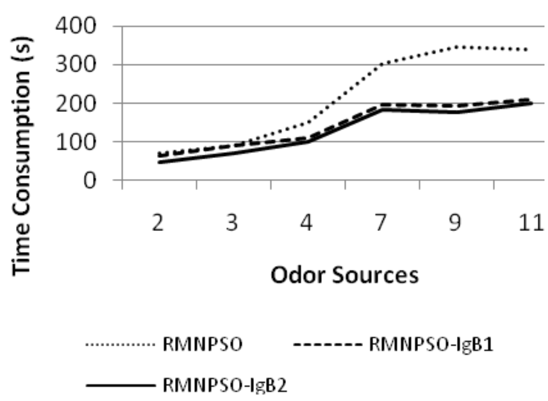

Figure 14. Result in RMNPSO (10 × 10).

In area 12.5 × 12.5, TC measurement for RSPSO, RMNPSO, and their improvement were describes in table 4. For odor sources less than 9 sources, improvement RSPSO using IgB2 seems as the best improvement of IgB1 and unimproved RSPSO. But for 9 and 11 sources, improvement using IgB1 and IgB2 seem insignificant. Those results are illustrated in figure 15 RSPSO improvement. For RMNPSO, figure 16 illustrates that the improvement using IgB2 has the best results mainly for odor sources greater than 3 sources. For odor sources less than or equal to 3 sources, the IgB2 improvement seems insignificant when is compared to IgB1 improvement.

Table 4: Time Consumption of each Algorithm (12.5 × 12.5)

Algorithm	Odor Sources					
	2	3	4	7	9	11
RSPSO	138,8	142,5	149,2	162,3	176,9	172,7
RSPSOIgB1	112,2	136,2	143,2	147	155,6	168,7
RSPSOIgB2	100,1	121,1	131,6	139,8	155,3	164,5
RMNPSO	137,8	330,8	529,9	778,8	726	668,7
RMNPSOIgB1	99,7	162,1	289	366,4	413,6	374,7
RMNPSOIgB2	94,9	152,3	137	235,8	348,4	306,2

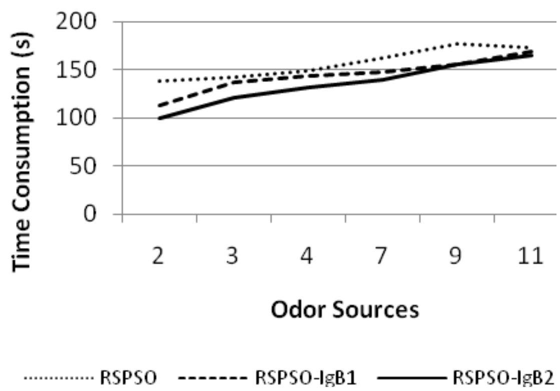

Figure 15. Result in RS-PSO (12.5 × 12.5).

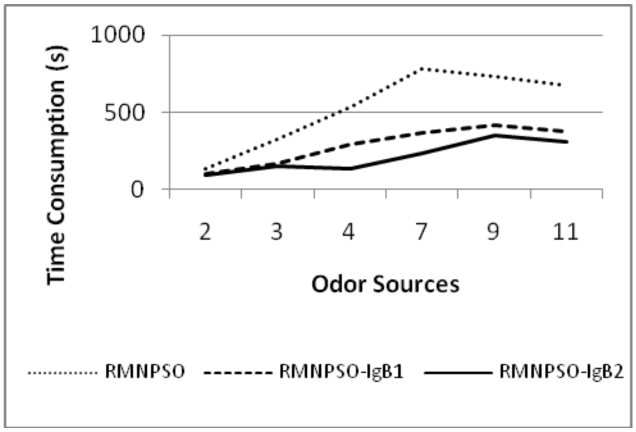

Figure 16. Result in RMNPSO (12.5 × 12.5).

Table 5: Time Consumption of each Algorithm (15 × 15)

Algorithm	Odor Sources					
	2	3	4	7	9	11
RSPSO	142.8	252.6	183.1	172.6	195.8	210.8
RSPSOIgB1	108.4	152.1	167	182.4	202.3	166.3
RSPSOIgB2	127.6	155.4	184.5	162.5	226.8	190.6
RMNPSO	112.1	271.1	329.7	638.1	703	855.6
RMNPSOIgB1	79.9	286.2	288.1	530.8	507.4	637.3
RMNPSOIgB2	112.1	156.6	283.4	399.7	443.5	477.7

Figure 17 and Figure 18 delineate the experiment of the addition of both IgB1 and IgB2 in RSPSO and RMNPSO respectively in area 15×15. In RSPSO (as shown in figure 17) the improvement of the time consumption is insignificant. The significance of the improvement occurred only in the odor source of 2 and 3 sources. Afterwards, the time consumption of all the method were quite similar. On the contrary, in RMNPSO (as shown in figure 14) the performance improvement were significant. In each odor source the time consumption of the modified PSO were lower than the original. Moreover, the IgB2 showed better performance than IgB1. The exact value of the time consumption are listed in table 5.

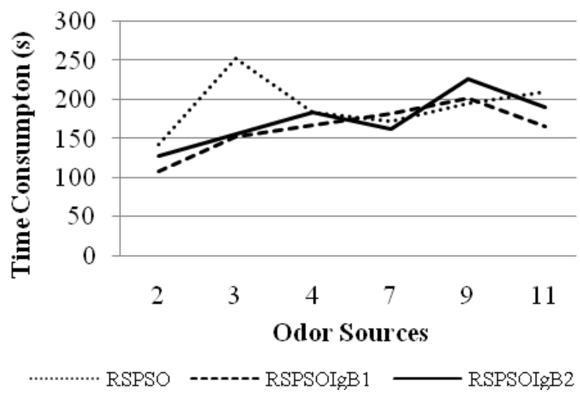

Figure 17. Result in RS-PSO (15 × 15).

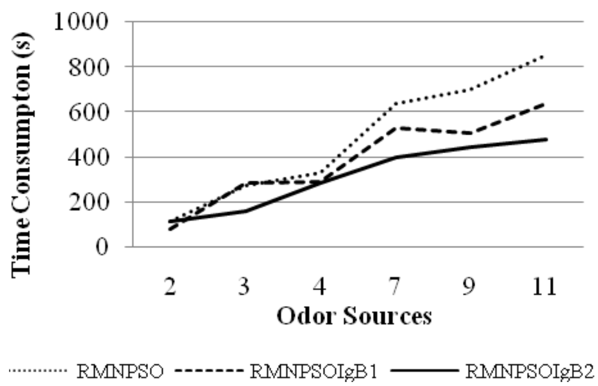

Figure 18. Result in RMNPSO (15 × 15).

In RSPSO the addition of both IgB1 and IgB2 didn't increase the performance of the original PSO due to the fact that in RSPSO main robot is used. In main robot the main term is social term and it caused the swarm would not be distracted by the addition term too much. Meanwhile in RMNPSO, with the inexistence of main robot, caused the significant improvement in original PSO. In accordance with the comparison of both the proposed methods IgB2 showed better performance than IgB1 due to the smaller distraction of IgB2 method. Finally, from the Figure 7 can be seen that greater the number of odor source the larger the gap is. This phenomena due to the accumulative time consumption difference which made the greater odor source number is the larger the cumulative time different.

VI. CONCLUSION

The modification of global best term have been undertaken. The modification showed better performance than the original PSO. There were two proposed modification, and both the modification decreased the time consumption of the odor searching. Even though the improvement in RSPSO algorithm was insignificant, the improvement in RMNPSO was substantial. Compared with each other IgB2 showed better performance than IgB1. To conclude, ignore global best method could increase the performance of the original PSO, especially in RMNPSO which would be developed for adaptive niching PSO in the undergoing research.

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