An Evaluation of Swarm Robotic Cooperative Target Search

Shijie Lu and Yingguang Hao
School of Information and Communication Engineering, Dalian University of Technology, Dalian, MyTown, China
lushijie@mail.dlut.edu.cn

Keywords: Swarm Robotics, Particle swarm optimization, Auxiliary orientation, Roaming algorithm.

Abstract: To search for multiple targets with swarm robots, those robots should be divided into some sub-swarm by job allocation, so that each sub-swarm can cooperatively work focusing on its desired target. Each sub-swarm searches for its target by evolutionary algorithm. In order to improve the cooperative search ability of sub-swarm, a new particle swarm algorithm based on auxiliary orientation improvement is proposed to enhance the efficiency and accuracy of the search. In the simulation, the general roaming algorithm consumes a longer time to find the target, and reduces the overall efficiency of the system. In order to solve this problem, a spiral roaming method based on artificial potential field is introduced to improve the global search capability. The simulation results show that the search efficiency is improved significantly by using this method.

1 INTRODUCTION

Swarm robotic (SR) research is inspired by the group behaviors of bees, birds and other groups. A single robot is thought to be unintelligent, but it can achieve the desired goal through group behaviors and demonstrate intelligence. The concept of swarm robotics was first proposed by G. Beni et.al. Swarm intelligence studies are devoted to simulating swarm intelligence of natural organisms, which is to enable individuals with simple perception to emerge swarm intelligence through local communication. The characteristics of swarm robotics: (1) the robot has independent perception and communication ability. (2) the robot has simple ability and low cost. (3) the robot is independent of each other, and the structure is distributed. (4) the self-organization ability based on local communication (Şahin, E. 2004; Balch, T. 2004; Xue, S.,2008; Zeng, 2010; Zhuang, 2013)

Target search is one of the benchmark problems in swarm robotics. Robots can perform tasks that humans can't accomplish or are extremely dangerous at low cost and price with the application of swarm intelligence. For example, exploration, mine sweeping, battlefield search, search and rescue in hazardous areas, etc. In view of the fact that particle swarm optimization uses individual effective information and local communication to influence the neighborhood individuals moving toward local optimum, Doctor. s et.al. (2004) introduce Particle Swarm Optimization (PSO) algorithm into multi robot search system. Aiming at the characteristics of dynamic neighborhood and limited communication range in multi robot search, Pugh et.al. (2006) improved the problem model and formed a classical swarm robotic target search model. Anh-Quy H et.al. (Zhang, 2014) analyzed and compared the effects of two improved particle swarm algorithms in the exploration of unknown environments. The paper mainly improved the missing and collision problems. Based on the model of swarm robotic search problem proposed by Doctor. S et.al. (2004) and Pugh et.al. (2006), Zhang et.al. (2014) proposed a model that robots search targets cooperatively in the unknown environment. In this model, the distributed robot has a single perception ability, and has the ability of self-localization and local information interaction. This model fits the characteristics of swarm intelligence and is representative. However, the search efficiency of swarm robotics in the random search stage is not achieved, especially when the target location is remote, which slows down the overall search process.

The improved particle swarm optimization with artificial potential field has achieved good results in solving the problem of loss and collision (Hoang, 2016). In order to solve the problem that the exploration range is too concentrated and the remote area is easy to miss when the robot performs the unknown environment exploration task. In this paper, the artificial potential field improved spiral search method is used to drive other roaming robots to other unexplored regions. Through this improvement, the

Lu, S. and Hao, Y.
An Evaluation of Swarm Robotic Cooperative Target Search.
In *3rd International Conference on Electromechanical Control Technology and Transportation (ICECTT 2018)*, pages 476-486
ISBN: 978-989-758-312-4

target in the unknown position can get the attention of the search robot earlier. Thus, the robot can detect unknown targets as soon as possible. Simulation results show that the search time of roaming stage is reduced.

The cooperative search of swarm robotics can be divided into three steps. The first step is roaming search. The second step is to obtain local search information through neighborhood communication, and then determine their respective targets to search. The third step is that robots with the same goal form search alliances, and then search their targets precisely by particle swarm optimization. The traditional particle swarm optimization algorithm guides the robots to the position of the local optimal positions and their optimal positions. Inspired by localization technology, directional technology is introduced into particle swarm optimization. The directional results are used to guide the robots to approach the most likely positions of the targets. Based on the proposed roaming strategy, a particle swarm optimization algorithm based on auxiliary orientation technology is proposed. Simulation results show that the algorithm improves the efficiency of swarm robotic search.

2 PROBLEM DESCRIPTION

2.1 Description of environment and system

The robot starts from a random location of the search environment to search for the task target in the environment space. It is assumed that the robot can locate itself (Pugh, 2006) in a certain positioning mechanism and obtain its own position relative to the environment. Only based on these can the robot acquire and update its best position and share the best position with other robots in the neighborhood. Then, the local optimal location in neighborhood is obtained by comparison. Finally, the particle swarm algorithm is used to approach and locate the target.

Four tuple <R, E, T, S> can be used to describe the multi objective search problem of swarm robots (Kennedy, 2002):

a. Search agents (R): R=<U, B, C>;

R refers to a single robot. U is a collection of objects directly detected by the robot and indirectly obtained by interacting with the robots in the neighborhood. B is the autonomous decision-making behavior of the robot, that is, according to its own perception of the environment and information indirectly obtained, the robot autonomously determines its own search mode; C represents the cooperation of robots on the basis of neighborhood communication;

b. Targets (T): T = $\{T_i$, i = 1 ... M$\}$, m > 1;

T are the targets of swarm robots, that is, the task set to be searched. Each target has its own signal frequency, which is used to distinguish different targets. M is the number of targets in a task.

c. Swarm robot (S): S = $\{R_j$, j=1 ... n$\}$ n> >m;

S is a collection of all robots participating in the search task. N is the total number of robots.

d. search environment (E): two-dimensional space in closed space

2.2 Robot

N autonomous robots, as search subjects, constitute swarm robots, which are robots with limited detection distance, positioning accuracy, communication range and so on (Zhang, 2015). The detector configured by the robot can detect the signal emitted by the target and obtain the intensity information. However, the detection radius of the robot detector is relatively small compared with the environmental dimension.

Based on the detected target intensity information and neighborhood information, each robot switches between three working modes: roaming mode, particle swarm search mode, and capturing target mode (Liu, 2010). When the robot does not obtain the target information directly or indirectly, the roaming mode is adopted. When the robot senses the target directly or indirectly, and decides to take part in the local search, the particle swarm search model is adopted. Moreover, the robot continuously exchanges the latest position and intensity information with other robots in the communication neighborhood. When the signal intensity directly detected by the robot reaches the standard, the robot enters the capturing target mode and announces the target to be searched through neighborhood communication. Then the robot continues to participate in the search for the remaining target until all the targets are searched.

2.3 Communication neighborhood and distributed control

In the standard particle swarm optimization algorithm, the neighborhood of the particle is the whole search space. The particle can exchange information with particles at any position in the search space. In the swarm robotic system, considering the communication distance and ability of a single robot is bound to be limited, the communication distance must be greater than the detection distance, but it should be smaller than the environmental size. Otherwise, the robot will have global communication capability. In our model, the neighborhood of each robot is defined as the region within its maximum communication distance. The neighborhood is dynamic with time, because the robot is moving continuously (Pugh, 2007). The robot exchanges its own position and detected signal intensity with other robots in the neighborhood. Distributed control requires less communication distance and capability, and does not require a robot with central processor function. Full distributed control is an important feature of swarm robotics.

2.4 Signal intensity

In particle swarm optimization, the local optimum positions and the optimal locations of individuals are determined by the intensity of the perceived signals. Suppose each robot is equipped with a signal detector, which can detect the intensity of different frequency signals emitted by different targets. Xue et.al. (2008) made a detailed analysis of the signal. The signal intensity model of this paper is Eq.1 (Pugh, 2007):

$$I_i = P / d_i^2 + \eta() \tag{1}$$

P is the power of the signal source. d is the Euclidean distance between the robot and the signal source. η is a random disturbance. Assuming that the detection threshold is I_m, then $I_m = I(R_{\max})$. If the distance between the robot and the target exceeds the maximum detection radius of $R_{\max}$, the target signal cannot be detected.

2.5 Collision problem and speed limit

Particles are assumed to be infinitely small in particle swarm algorithms, so they cannot conflict with each other. But in the robot cooperative search system, both the robot and the target have their own geometric dimensions, so the collision problem needs to be considered. Pugh et.al. (2007) adopts the Braitenberg obstacle avoidance method, which is that the robot will continue to select the previous motion speed after changing direction. The obstacle avoidance method proposed by Liu et.al. (2012) requires the current state of motion of each robot and the speed at the next moment. It is difficult to apply for robot with limited detection ability and accuracy. Anh et.al. applies the artificial potential field method to particle swarm optimization to solve the problems of disconnection and collision in multi-robot target search (Hoang, 2016). This paper uses the same method to solve the obstacle avoidance problem in particle swarm optimization.

The particles in the basic particle swarm optimization algorithm have no acceleration and speed constraints, but the speed of the robot is limited in reality. If the speed of the robot obtained by particle swarm algorithm exceeds the maximum, the speed will be set to the maximum value. Only in this way can the collision problem be handled at each step and the robot can avoid crossing each other. Furthermore, in order to make each step of the robot not seem to be done in a flash. The moving distance of the robot in each loop is divided into several segments to make its moving trajectory smoother.

2.6 Division of tasks

One of the most commonly used methods of task assignment is market based strategy (Dias, 2006). It is not suitable to adopt the market based strategy in swarm robotic system. The decomposition of the tasks is accomplished by the robots autonomously in the framework of swarm robotic system (Liu, L., 2012). The global division of tasks is completed after each robot decides its own goal. Therefore, the most commonly used method of division in swarm robot system is the method based on threshold (Zhang, 2014). This paper adopts the method based on threshold to divide the tasks.

2.7 Adjustment of division

The target detected first will take the attention of much more robots. It is possible all the robots that have detected the target will take the target as their goals, if we do not introduce the adjustment of task selection. Which will cause local crowding and waste the resources of system. Furthermore, it will reduce the efficiency of global search.

Based on the intensities of the objective signal detected by the robots. We rank the robots those choose to search the same target. Zhang et.al. (2014) point out that the ideal search efficiency can be achieved by setting the maximum number of robots to six in an alliance. The alliance is composed of the robots with the same target to search. Only the top six robots can join in the alliance, while there are more than six robots choose the same target. The other robots should convert to roaming mode. On the other hand, while there are less than six robots choose the same target, all these robots can join in the alliance.

Furthermore, we adopt the mechanisms of exit and punishment (Zhang, 2014).

3 APE IMPROVED SPIRAL ROAMING STRATEGY

3.1 APE

Proposed by Khatib.O in 1986 for single robot path planning (Kennedy, 2002), APF is now widely used in works on multi-robot system. APF generates around each robot a virtual potential field containing a repulsive field and an attractive field. The attractive field directs each robot towards other robots in the system while the repulsive field keeps them far away from other robots or obstacles. The magnitude of potential forces exerted on each robot are continuously updated based on the information it gets from the immediate surrounding environment, or from other robots via connection network (Hoang, 2016).

3.2 Spiral roaming strategy

The size of the space to be explored is much larger than the maximum detection distance of the detector configured by the robot. When the search begins, the robot first enters the random wandering state to find the target signal (Xue, 2009). In order to cover as much space as possible in the shortest time, we can adopt the spiral roaming strategy mentioned by AT Hayes (2002), and the explosion dispersing roaming strategy proposed by Meng et.al. (2008). In view of the fact that the explosive dispersion roaming strategy may be too dispersed in the long distance, and then the blind zone appears, the spiral roaming strategy is adopted in this paper. The spiral can be realized by Eq.2.

$$\begin{cases} x = v \cdot t \cdot \cos(\pi / 4 + w \cdot t) \\ y = v \cdot t \cdot \sin(\pi / 4 + w \cdot t) \end{cases} \quad (2)$$

Where, x and y are the coordinates of the points on the spiral, t is the time variable, v is the linear velocity, w is angular velocity, $\pi / 4$ is the initial angle. The divergence of the spiral can be controlled by controlling those parameters.

3.3 APE-Spiral Roam

In the simulation of (Liu, 2010; Xue, 2009) or in this paper, in the original spiral roaming state, the robot search paths are close to each other, and do not play the proper efficiency of multiple robots. The efficiency of swarm robotic search has been greatly affected. At this point, the machines appear to be unintelligent, and on the contrary, when people cooperate to find the target, they will inform the people within the scope of communication "there is no target here.

It is not a new idea to applying APF to multi-robot system. However, in previous works, they are only used for formation control and path planning (Hoang, 2016; Pugh, 2006; Liu, 2012). Furthermore, Anh-Quy H et.al. (2016) use APE for the task of space exploration. To solve the problem mentioned above, we use artificial potential field to simulate human communication, that is to tell the surrounding robot, search elsewhere. Thus, the original spiral roaming strategy is improved.

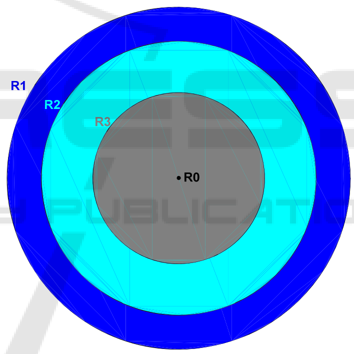

Figure 1: Potential field.

The potential field of each robot is shown in Fig.1, with the center of the position of each robot as the center of the circle, and three circular regions with radius of R_1 , R_2 and R_3 are established respectively.

In the figure, R_0 is the center of the robot. R_1 is the radius of attractive field. The robots are attracted by the robot at R_0 when they are between R_1 and R_2 . Between R_2 and R_3, the robots are not affected by the robots at R_0 in this area. R_3 is the radius of the repulsive field, and the robots are repulsed by the robot at R_0 when they are in the repulsive field. Under the combined action of attractive field and repulsive field. It avoids the gaps between the robots become the blind area of the detection, and also prevents the robot from penetrating into the detection area of other robots. After introducing the concept mentioned above. We let the roaming robot adopt the spiral roaming strategy. This is called the Ape-Spiral Roam method. To illustrate this method, the following Eq.3 is introduced:

$$F_{APE12} = \frac{G m_1 m_2 \mathbf{r_{12}}}{r_{12}^3}[\mathrm{u}(\mathrm{r}_{12}) - \mathrm{u}(\mathrm{r}_{12} - \mathrm{r}_1) - \mathrm{k}\,\mathrm{u}(\mathrm{r}_{12} - \mathrm{r}_2) + \mathrm{k}\,\mathrm{u}(\mathrm{r}_{12} - \mathrm{r}_3)] \tag{3}$$

$$u(t) = \begin{cases} 1, & t > 0 \\ 0, & t \le 0 \end{cases} \tag{4}$$

G is the gravitational constant in the formula, and k is the adjustment factor. m_1 and m_2 represent the reliability values of robots. R_{12} is the distance vector from robot 1 to robot 2. F_{12} is the force of robot 1 acting on robot 2. The combinative force of other robots under robot j is calculated by Eq.5:

$$F_{APEj} = \sum_{i=1}^{N} F_{APEij} \tag{5}$$

The combinative force gives an additional acceleration component to each robot. The velocity of each robot is calculated by Eq.6:

$$v_i(t+1) = v_i(t) + v_{APEi}(t) \tag{6}$$

4 AO IMPROVED PSO

4.1 Premature convergence of PSO

PSO algorithm shows good performance in multi-target search. But in the traditional particle swarm algorithm, in the later stage of the search process, after several cycles, the particles are likely to follow the local optimal particles to fly. Thus, the ability of individual exploration decreases and premature convergence occurs.

Similarly, the location of the local optimal robot is not the location of the target in multi-target search system. Premature convergence is also easy to happen. It is better to direct robots to the potential target position than to direct robots to the optimal position in the neighborhood.

4.2 Auxiliary orientation technology

Inspired by localization technology, directional technology is introduced into particle swarm optimization. Before the premature convergence occurs, the position of the target is estimated by using the robot which satisfies the distance between each other by local communication. The estimated position is introduced into particle swarm optimization to improve the searching ability of PSO.

The signal intensity perceived by the optimal robot is directly related to the distance between the robot and the signal source. The signal intensity can be used to estimate the distance between the signal source and the local optimal robot by Eq.7. Where i is the number of the robot. It can be inferred that the signal source is in a circular orbit around the local optimum robot, whose radius is the estimated distance.

$$\mathrm{d}_i = |\sqrt{P / \mathrm{I}_i}| \tag{7}$$

If there is another robot directly detects the same source. We can find the distance between the second robot and the signal source in the same way. The signal source is also in a circular orbit around the robot, whose radius is the estimated distance. Suppose the coordinates of two robots are (x_1, y_1) and (x_2, y_2). Then two intersection points can be obtained by solving the system of Eq.8 formed by two circles.

$$\begin{cases} (x - x_1)^2 + (y - y_1)^2 = {d_1}^2 \\ (x - x_2)^2 + (y - y_2)^2 = {d_2}^2 \end{cases} \tag{8}$$

Suppose the coordinates of two intersection points are (s_1, z_1) and (s_2, z_2). The coordinates of the third robot are (x_3, y_3). And d_3 is the distance between the third robot and the signal source. Find the distances between third robot relative to the two intersections by Eq.9.

$$d_{3i} = \sqrt{(x_3 - s_i)^2 + (y_3 - z_i)^2} \tag{9}$$

As the follow Eq.10. If the two distances are not equal. The distance which is closer to d_3 is used to inferred the position of the signal source. And h is the adjustable constant to avoid the mistake choice. In this paper we select h=10.

$$x_{s,z}=\begin{cases}(s_i,z_i),|d_{3i}-d_3|<h<|d_{3j}-d_3|\\(s_j,z_j),|d_{3j}-d_3|<h<|d_{3i}-d_3|\end{cases} \quad (10)$$

Where $x_{s,z}$ is the estimation position of the signal source. Which is introduced into particle swarm optimization by Eq.11.

$$v_{i,j}(t+1)=\begin{cases}w\times v_{i,j}(t)+w_p\times rand()\times(x^*_{i,j}-x_{i,j})+w_n\times u(L-d_{fs})(x^*_{i',j}-x_{i,j})+w_n\times\varepsilon(d_{fs}-L)\times(x_{s,z}-x_{i,j}) & N_d\geq 3\\ w\times v_{i,j}(t)+w_p\times rand()\times(x^*_{i,j}-x_{i,j})+w_n\times rand()\times(x^*_{i',j}-x_{i,j}) & N_d<3\end{cases} \quad (11)$$

$$\varepsilon(t)=\begin{cases}1, & t\geq 0\\0, & t<0\end{cases} \quad (12)$$

Where d_{fs} is the distance from the first robot to the second robot that detect the same target. L is the adjustable factor to avoid the second robot being too close to the first robot. In this paper we select L=20. N_d represent the number of robots that detect the same target directly. ε(t) is the unit step function, $x^*_{i,j}$ is the best position of the individual robot, $x^*_{i',j}$ is the best position of the sub-swarm robots. w is the weight of inertia, w_p is the weight of the best position of the individual, w_n is the weight of local best position.

$$x_{i,j}(t+1)=x_{i,j}(t)+v_{i,j}(t) \quad (13)$$

The position of every robots is calculated by Eq.13. This algorithm is called auxiliary orientation technology improved Particle swarm optimization algorithm (AO-PSO).

4.3 Extension of Directional technology

In the early stage of particle swarm algorithm, there is only one robot that detects the target directly. Inspired by the characteristics of directional Yagi antenna. The position information and the target intensity information of the robot which uniquely detects the target are stored. The early position of the target is estimated by the position information and intensity information of a single robot in the scattered position. Using the estimated location information to direct other robots to detect the target as early as possible.

5 SIMULATION AND RESULTS

In order to evaluate the effectiveness of the algorithm, visual simulation was performed under Matlab. Two groups of experiments were carried out under two conditions. According to the different experimental purposes, various parameters were changed and repeated experiments were carried out. The experimental results are analyzed and compared with the existing methods, and the statistical results are obtained.

5.1 Parameters and conditions

The main parameters of the simulation include subject, object, environment, etc. The parameters are shown in Table 1.

The initial position of each robot is randomly generated in the range of 20 to 120 from the starting point. The initial velocity of the robot is randomly generated between 1 and 5, and the direction is random. The target is generated at a random location at a certain distance from the starting point.

Table 1: Parameter settings for simulation.

Symbol	Meaning	Value
Nrob	Number of robots	6-100
D	Number of targets	1-12
E	Size of environment	1000*1000-2000*2000
Rmax	Detection distance	100-200
Rcom	Communication radius	300
P	The power of the signal emitted by the target	1000
λ	gain	10
Nmax	Upper limit of alliance size	6
T	Maximum time	2000
Vmax	Maximum speed	5

5.2 Experiment 1

In the first set of experiments. In order to facilitate the comparison, the swarm robotic search method in paper (Liu, 2010) is called algorithm 1, and the method after using the improved roaming strategy of APE in this paper is algorithm M1.

In order to highlight the difference of search efficiency between two algorithms in roaming stage, the algorithm stops when the roaming algorithm gets the initial position of the target. What enhances the alignment of the experiment and highlights the effect of the improved roaming algorithm.

The starting point of robot is fixed near the coordinate origin, and the position of target is changed continuously. This enhances the adaptability of the model and is more suitable for the search model in unknown environments. The number of robots is adjusted to 6 and 12, and the number of targets is adjusted to 1. Environment size, maximum detection distance, and other parameters are shown in Table 2.

Table 2: Parameter settings for Experiment 1.

Symbol	Meaning	Value
Nrob	Number of robots	6-12
D	Number of targets	1
E	Size of environment	1000*1000-2000*2000
Rmax	Detection distance	100-150
R1	Radius of attraction force	300
R2	Radius of stable region	280
R3	Radius of repulsive force	180
P	The power of the signal emitted by the target	1000
λ	gain	10
T	Maximum time	2000
Vmax	Maximum speed	5

Performance criteria: the probability of completing tasks, the average steps required to complete the task, the average path length, the scalability of the system scale, the adaptability of the environmental scale, and the adaptability of the detection range.

In each case, we have done 120 repetitions. Then the average of the results is calculated. The probability of the two algorithms to complete the task is one hundred percent. The comparison of other data is shown in Fig.2 to Fig.5.

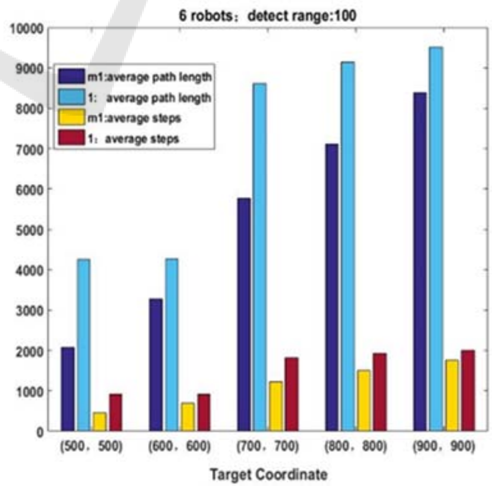

Figure 2: For 6 robots with the detect range of 100.

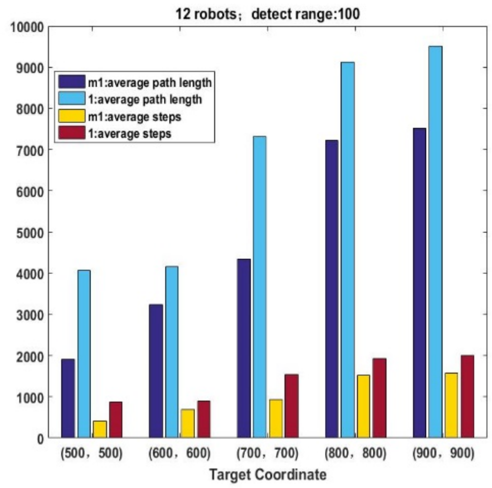

Figure 3: For 12 robots with the detect range of 100.

We can see from Fig.2 and Fig.3 In aspect of system size, the number of robots in the system increased from 6 to 12. In aspect of environmental scale adaptation, the position of the target varies from (500,500) to (900,900). Compared with the algorithm 1, the algorithm M1 has significant improvement in two aspects: the average steps required to complete the task and the average length of the path to complete the task.

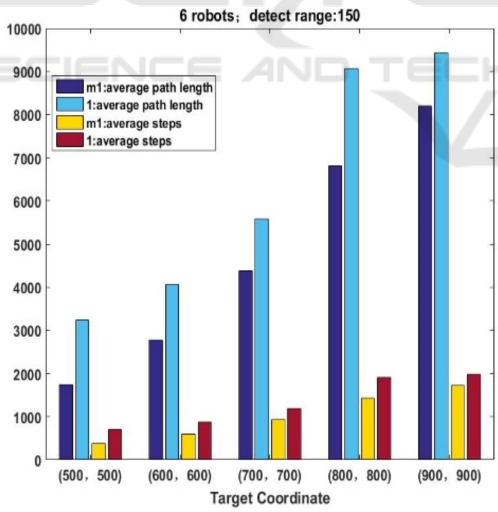

Figure 4: For 6 robots with the detect range of 150.

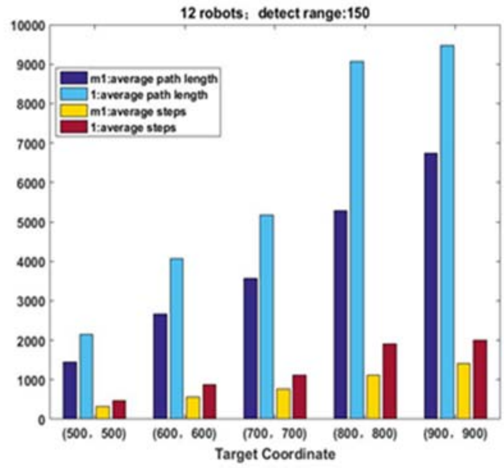

Figure 5: For 12 robots with the detect range of 150.

Compared with Fig.2 and Fig.3, the detection distances in Fig.4 and Fig.5 are increased from 100 to 150. Compared with algorithm 1, the algorithm M1 still has significant improvement in two aspects: the average steps required to complete the task and the average length of the path to complete the task. Thus, the advantages of the algorithm M1 are verified in the detection range adaptation.

In summary, the APE improved roaming strategy proposed in this paper has obvious effect in improving the search efficiency of roaming stage.

5.3 Experiment 2

In the second experiment, the particle swarm optimization algorithm in the literature (Zhang, 2014) is called algorithm 2, and the AO-PSO algorithm is called algorithm M2.

In order to emphasize the difference between the two algorithms in the particle swarm search stage, the roaming stage is not improved. In order to compare the efficiency of particle swarm optimization after the improvement of AO-PSO, and enhance the contrast effect, the maximum detection distance is expanded to 250. Other parameters such as the size of the environment, the number of robots, the number of targets, etc. are shown in Table 3.

Table 3: Parameter settings for Experiment 2.

Symbol	Meaning	Value
Nrob	Number of robots	12-18
D	Number of targets	1
E	Size of environment	1000*1000-2000*2000
Rmax	Detection distance	150-250
P	The power of the signal emitted by the target	1000
λ	gain	10
T	Maximum time	2000
Vmax	Maximum speed	5

Performance criteria: the probability of completing tasks, the average steps required to complete the task, the average path length, the scalability of the system scale, the adaptability of the environmental scale, and the adaptability of the detection range.

In each case, we have done 120 repetitions. Then the average of the results is calculated. The probability of the two algorithms to complete the task is one hundred percent. The comparison of other data is shown in Fig.6 to Fig.9.

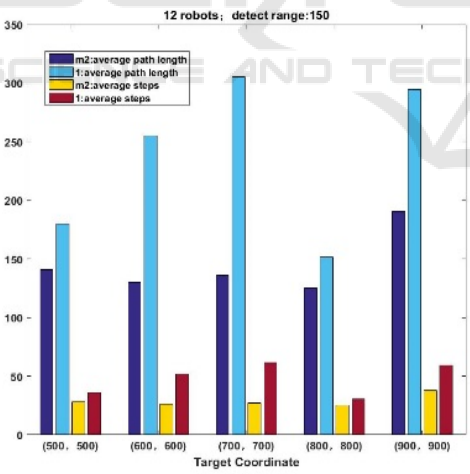

Figure 6: For 12 robots with the detect range of 150.

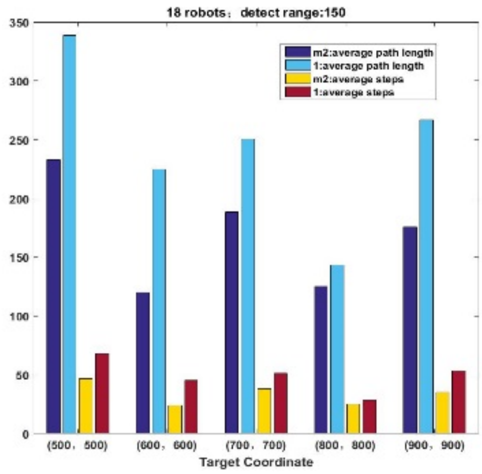

Figure 7: For 18 robots with the detect range of 150.

We can see from Fig.6 and Fig.7. In the aspect of system size, the number of robots in the system increased from 12 to 18. In the aspect of environmental scale adaptation, the target position varies from (500,500) to (900,900). Compared with the algorithm 2, the algorithm M2 has significant improvement in two aspects: the average steps required to complete the task and the average length of the path to complete the task.

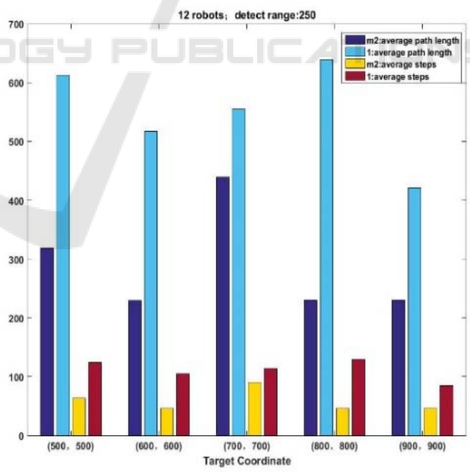

Figure 8: For 12 robots with the detect range of 250.

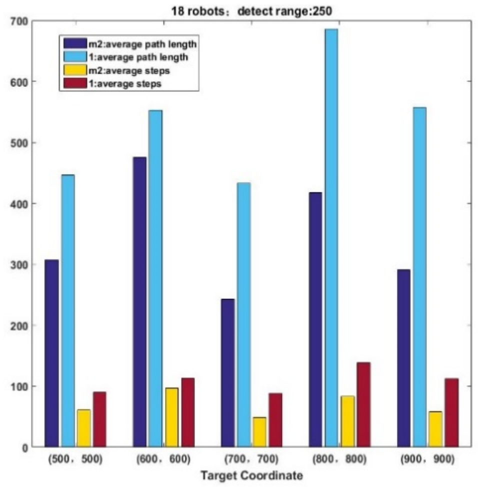

Figure 9: For 18 robots with the detect range of 250.

Compared with Fig.6 and Fig.7, the detection distances in Fig.8 and Fig.9 are increased from 150 to 250. Compared with algorithm 2, the algorithm M2 still has significant improvement in two aspects: the average steps required to complete the task and the average length of the path to complete the task. Thus, the advantage of the algorithm M2 has the adaptability of detection range.

In summary, the AO-PSO algorithm proposed in this paper has obvious effect in improving the efficiency of particle swarm optimization search stage.

6 CONCLUSIONS

In this paper, we propose algorithm M1 and algorithm M2. Two algorithms are used to solve the problem of comprehensive efficiency in swarm robotic search. The simulation results show that the algorithm M1 and the algorithm M2 maintain good environment, system scale, and detection distance fitness. In the case of the same completion rate, the two improved algorithms have greatly improved the search efficiency compared with the original method. Compared with the algorithm 1, through the improvement of the M1 algorithm, the time and the average path to find the approximate location of the target in the roaming phase are reduced. It effectively improves the search efficiency of the roaming phase in swarm robotic search. Compared with the algorithm 2, the improvement of M2 algorithm reduces the time consuming and average path of collaborative search stage, and improves the search efficiency in the collaborative search phase.

REFERENCES

Şahin, E. (2004). Swarm Robotics: From Sources of Inspiration to Domains of Application. International Conference on Swarm Robotics (Vol.3342, pp.10-20). Springer-Verlag.

Balch, T. (2004). Communication, Diversity and Learning: Cornerstones of Swarm Behavior. International Conference on Swarm Robotics (Vol.3342, pp.21-30). Springer-Verlag.

Xue, S., & Zeng, J. (2008). Swarm Robotics: A Survey. PR & AI, 21(2), 177-185.

Zeng, J, & Xue, S. (2010). Modeling and Simulation Approaches to Swarm Robotic Systems. Journal of System Simulation, 22(6), 1327-1330.

Zhuang, Q. (2013). Prototype system design for coordinated control research of swarm robotics. (Doctoral dissertation, Taiyuan University of Science and Technology).

Doctor, S., Venayagamoorthy, G. K., & Gudise, V. G. (2004). Optimal PSO for collective robotic search applications. Evolutionary Computation, 2004. CEC2004. Congress on (Vol.2, pp.1390-1395 Vol.2). IEEE.

Pugh, J., & Martinoli, A. (2006). Applying aspects of multi-robot search to particle swarm optimization. International Workshop on Ant Colony Optimization and Swarm Intelligence (Vol.4150, pp.506-507). Springer Berlin Heidelberg.

Zhang, Y., Xue, S., & Zeng, J. (2014). Dynamic Task Allocation with Closed-Loop Adjusting in Swarm Robotic Search for Multiple Targets. Robot, 36(1), 57-68.

Hoang, A. Q., & Pham, M. T. (2016). Comparing modified pso algorithms for mrs in unknown environment exploration.

Pugh, J., & Martinoli, A. (2006). Relative localization and communication module for small-scale multi-robot systems. IEEE International Conference on Robotics and Automation (pp.188-193). IEEE.

Kennedy, J., & Eberhart, R. (2002). Particle swarm optimization. IEEE International Conference on Neural Networks, 1995. Proceedings (Vol.4, pp.1942-1948 vol.4). IEEE.

Zhang, Y., Xue, S., & Zeng, J. (2015). Cooperative and Competitive Coordination in Swarm Robotic Search for Multiple Targets. Robot, 37(2), 142-151.

Liu, Z., Xue, S., Zeng, J., Jing, Z., & Zhang, G. (2010). An evaluation of PSO-type swarm robotic search: Modeling method and controlling properties. International Conference on Networking, Sensing and Control (pp.360-365). IEEE.

Pugh, J., & Martinoli, A. (2007). Inspiring and Modeling Multi-Robot Search with Particle Swarm Optimization.

Swarm Intelligence Symposium, 2007. Sis (Vol.51, pp.332-339). IEEE.
Xue, S. D., & Zeng, J. C. (2008). Control over swarm robots search with swarm intelligence principles. Journal of System Simulation, 20(13), 3449-3454.
Liu, F., Narayanan, A., & Bai, Q. (2012). Effective methods for generating collision free paths for multiple robots based on collision type (demonstration). International Conference on Autonomous Agents and Multiagent Systems (pp.1459-1460). International Foundation for Autonomous Agents and Multiagent Systems.
Dias, M. B., Zlot, R., Kalra, N., & Stentz, A. (2006). Market-based multirobot coordination: a survey and analysis. Proceedings of the IEEE, 94(7), 1257-1270.
Liu, L., & Shell, D. A. (2012). Large-scale multi-robot task allocation via dynamic partitioning and distribution. Autonomous Robots, 33(3), 291-307.
Zhang, G., & Zeng, J. (2011). Area Coverage Algorithm in Swarm Robotics Based on Wasp Swarm Algorithm. PR & Al, 24(3), 431-437.
Xue, S. D. (2009). Swarm Robotic Search for Target: Cooperative Control Techniques, Strategies, and Simulations. (Doctoral dissertation, Lanzhou University of Technology).
Hayes, A. T. (2002). Self-organized robotic system design and autonomous odor localization. California Institute of Technology.
Meng, Q., Li, F., Zhang, M., Zeng, M., & Wei, X. (2008). Study on Realization Method of Multi-Robot Active Olfaction in Turbulent Plume Environments. ACTA AUTOMATICA SINCA, 34(10), 1281-1290.