Optimization Planning based on Improved Ant Colony Algorithm for Robot

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***Abstract*—As the ant colony algorithm has the defects in robot optimization path planning such as that low convergence cause local optimum, an improved ant colony algorithm is proposed to apply to the planning of path finding for robot. This algorithm uses the search way of exhumation ant to realize the complementation of advantages and accelerate the convergence of algorithm. The experimental result shows that the algorithm of this paper make the optimization planning of robot more reasonable.**

***Index Terms*—Optimization Rules; Core Area; Randomness; Comprehensive Assessment of Path**

I. Introduction

Robots will play an increasingly important role in the future space activities. Its wide range of applications includes satellite repair, structural construction of large space, track garbage, and so on, thus it gains more and more national attention. Spatial operation, different from the ground operation, requires robot to have the ability to work normally in unknown environment [1]. It not only relies on the vision, force, torque and tactile sensors, but also depends on advanced planning and decision-making capabilities

Mobile robot path planning is providing an optimal or suboptimal accessible path without collision from the beginning to the end in the work environment with obstacles according to planning time , the robot running time, path length and smoothness, energy consumption and other performance indicators. Mobile robot is a complex control system with a variety of technologies and path planning is one of the core technologies. Currently, the research on rescue and search robot research mainly focuses on the individual [2]. Most of them are the semi-autonomous systems and require manual operation and the research on autonomous intelligent robots and group robot is less, while using group robot can expand search range, improve work efficiency and improve the reliability and accuracy of information by robots collaboration.

In recent years, ant colony algorithm, simulated annealing algorithm, genetic algorithm, particle swarm algorithm and other intelligent optimization algorithms have been applied to path planning research of mobile robot. Dorigo M and others used artificial neural network model to describe the work environment of robot and used the genetic algorithm to optimize the path, in which the fitness function of genetic algorithm was built through the output of the neural network [3-5]; Feng Qi and Zhou Deyun used genetic algorithms for path planning under polar coordinates , reducing the search space, simplifying the encoding way, and refining the generated initial path to eliminate unnecessary inflection point, and got good results [6-9]. Sun Bo and others proposed the global path planning method of mobile robot based on particle swarm algorithm [10]. This method had the advantages such as simple model and low complexity, while it also had the disadvantages such as easily involving in local minimum, high dependence of parameter on search performance. A lot of improvements have been made at home and abroad for these defects. For example, Tao Xinmin and others divided the particle population into random subgroup and evolution subgroup [11]. Through coordinating the work of two subgroups, the defect of easily involving in local minimum was overcome and the convergence speed and stability was improved. Clerc proposed to introduce compression to control the convergence performance of particle swarm algorithm in velocity update formula of particle swarm algorithm [12]. The method could effectively search the different regions to get high-quality solutions. Li Qing and others used respectively special genetic algorithm and chaotic particle swarm algorithm to make mobile robot path planning and analyzed the advantages and disadvantages of these two algorithms through simulated comparison experiment [13-15].

Ant colony algorithm is initially used to solve TSP problem. It uses swarm intelligence algorithm of positive feedback. It has parallelism, strong robustness, global optimization and other advantages and can be used in path planning of many practical problems. For example, the literature [11] apply the ant colony algorithm to the route optimization of unmanned aerial vehicle so that unmanned aerial vehicle can efficiently avoid obstacles and radar; the literature [13] apply ant colony algorithm to local path planning of mine rescue and achieve good results. The ant colony algorithm is applied to path planning of intelligent search robot in this article and a viable plan is provided for group intelligence of search robot in algorithm.

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The path planning problem of search robot discussed in this article is that: in a grid map with static obstacles and unknown ending, the robot autonomously find an optimal path from the beginning to the trapped people according to a performance index or some indicators and there is no collision between robot and obstacles.

When ant colony algorithm is widely used in route planning, there are also slow convergence, easily involving in local optimum and other shortcomings. And most studies stop at the theoretical level and lack practical consideration of practical problems. This article improves the convergence speed, easily involving in local optimal solution and algorithm stagnation and other problems of ant colony algorithm and makes the algorithm find optimal path in the shortest time.

The expanded and innovative work of this article is mainly made in the following aspects:

(1) As for the path planning problem of search robot, the ant colony algorithm is improved and optimized in this article. Algorithm constructs a grid environment model and sets the taboo strategy to classify part of the raster grid as taboo grid to avoid path deadlock; reentrant ants are adopted and the forward and backward ants respectively apply different search tragedy to improve the convergence speed; the objective function of path comprehensive assessment is constructed to improve the ability to search the optimal path.

(2) In order to further validate the accuracy and validity of the improvement and optimization of the ant colony algorithm proposed in this paper, the simulated experiment compared with the ant colony algorithm. Compared with the ant colony algorithm, the convergence speed of this algorithm is accelerated obviously and global optimization ability is greatly improved. It can be seen from the comparison of convergence curve of amount of each evaluation that the amount of computation of computation and turning of optimal path found by the algorithm of this paper has a certain degree of reduction. To operate the planned optimal path in randomly generated 32 * 32 grid has strong ability to adaptation to complex maps. The simulation results show that: the algorithm proposed in this algorithm enables the robot quickly plan the optimal path in a complex environment by the optimization algorithm.

II. MODEL ESTABLISHMENT

A. Grid Modeling

Grid method was first proposed by the Howden. The method is simple and effective, adaptable in obstacles and can greatly reduce the complexity of modeling to facilitate computer storage and handling and can prevent the loss of part of feasible paths. It is currently the most widely used environmental modeling method. Therefore, the combination of serial number method and two-dimensional Cartesian coordinate is adopted to build grid modeling, in which the black grid is abstracted to be barrier grid and white grid to be free grid. Block (r,s) represents the information of (r_i, s_i) at node i. Let the starting node be s and the end point be g. In the grid, the corresponding relationship of grid number c and position coordinate (r,s) is:

$$\begin{cases} r = \mathrm{mod}(b/y) \\ s = 24 - \mathrm{int}(b/y) \end{cases} (0 \prec y \, and \, b \in V) \qquad (1)$$

In the formula, mod is complementation, int is rounding calculation, y is the number of grid of each line.

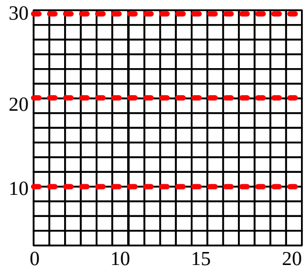

Figure 1. Environment modeling based on grid method

B. Problem Description

The target point of disaster scene is unknown. After the robot to find the target point, the grid map is build with the connection of the starting point to the target as diagonal to determine the searching range.

Search range of single robot is limited. It can only identify eight grids around itself and the size of grid is slightly larger than the volume of search robots. The robot can not be equivalent to particle, because of the stop of obstacle, and therefore can not move forward obliquely, only four running direction. Robots can choose the way to go forward in curve, shorten detour distance and extend the walking range.

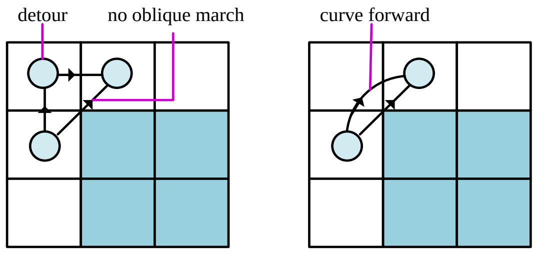

Figure 2. Schematic modeling of oblique and curved forward

III. ANT COLONY ALGORITHM

Ant colony algorithm was first proposed by the Italian scholar Dorigo M and others and ant colony system is raised to improve the ant colony algorithm. Also known as ant algorithm, it is a probability algorithm used to find the optimal path in the diagram. It was proposed by Marco Dorigo in his doctorial thesis in 1992, inspired by the behavior of ants of finding path during the process of searching for food.

Ant colony algorithm is a simulated evolutionary algorithm and preliminary studies show that the algorithm has many excellent properties. For the optimization problem of PID controller parameter, the result of ant colony algorithm design is compared with the result of genetic algorithm design. Numerical simulation result shows that ant colony algorithm has the validity and application value of a new kind of simulated evolutionary optimization method.

The characteristics of the ant colony algorithm 1) ant colony algorithm is a self-organizing algorithm. In system theory, self- organization and other-organization are the two basic categories of organization. The difference is that the organization or organizational order is derived from the internal system or from outside the system. The self-organization is from internal system and the other-organization is from external system. If there is no outside intervention in the process of system in getting structure of space, time or function, then the system is self-organized. In an abstract sense, self-organization is the process of increasing system entropy without outside interference (that is the process of the system changing from disorder to order). Ant colony algorithm exemplifies this process, taking ant colony optimization for the example. In the initial period of algorithm, single artificial ants find solution disorderly. After a period of evolution, artificial ants more and more spontaneously tend to find some solutions near the optimal solution through effect of pheromone. This is a process from disorder to order. 2) ant colony algorithm is an inherently parallel algorithms. Search process of each ant is independent of each other, only communicating by pheromones. So ant colony algorithm can be seen as a distributed multi- agent system. It starts independent search of solution in multipoint of problem space simultaneously, which not only increases the reliability of algorithm, but also makes the algorithm have strong global search capability.3) Ant colony algorithm is a positive feedback algorithm. It can be obviously seen from the foraging process of real ants that ants can finally find the shortest path is directly dependent on the accumulation of pheromone in the shortest path and the pheromone accumulation is a positive feedback process. For the ant colony algorithm, there are identical pheromones at the initial moment. They give a small perturbation to the system and make the track concentration in each edge different, so the solutions of ant structure have good and bad. The feedback way of algorithm is leaving more pheromone in the path that the optimal solution has passed and more pheromones attract more ants. The process of positive feedback constantly expands the initial difference and guides the whole system to develop towards the optimal solution. Therefore, the positive feedback is an important feature of ant algorithm. It makes the algorithm evolution proceed 4) ant colony algorithm has strong robustness. Compared with other algorithms, ant colony algorithm has low requirement for the initial route. That is, the solving result of ant colony algorithm is not dependent on the option of initial route and requires no manual adjustment in the search process. And, the number of parameter of ant colony algorithm is small and setting is simple, which make the ant colony algorithm easily applies to the solving of other combinatorial optimization problems.

Why the ant colony algorithm can attract the attention of researchers in related fields is because that the solving model can put the rapidity, global optimization feature and the reasonableness of answer within limited time of problem solving together. And, the rapidity of optimization is guaranteed by the transmission and accumulation of information of positive feedback. The premature convergence of algorithm is avoided by distributed computing features. Meanwhile, the ant colony system with the feature of greedy heuristic search can find acceptable answers to the questions in the early search process. This superior problem solving mode has been greatly improved and expanded based on the initial algorithm model after the attention and effort of researchers in related fields.

$$w_{xy}^{e}\left(q\right)\begin{cases}\dfrac{\vartheta_{xy}^{q}\left(q\right)\nu_{xy}^{j}\left(q\right)}{\sum\limits_{(r,s)\in allow}\vartheta_{xy}^{q}\left(q\right)\nu_{xy}^{j}\left(q\right)}, if\ x\in allow\\ 0, \qquad else\end{cases} \tag{2}$$

$w_{xy}^{e}\left(q\right)$ is the transition probability from point $i\left(r_i, s_i\right)$ to point $x\left(r_x, s_x\right)$ at t moment. ν_{xy}^{j} is the residual pheromone in node j at t moment. Is information heuristic factor, is desirable heuristic factor. $allowq$ is the nodes except for those just passed. ν_{xy}^{j} is the heuristic information from node i to node j at moment.

$$T=\begin{cases}\arg\max\in\vartheta_{xy}^{q}\left(q\right)\nu_{xy}^{j}\left(q\right), if\ r\le s\\ T, \qquad else\end{cases} \tag{3}$$

T is the state transition rules of improved ant colony system. r is uniformly distributed random numbers in interval [0,1], the size of r^0 determines the relative importance between the use of prior knowledge and the exploration of new paths.

$$\vartheta_{xy}^{q}\left(q\right)=\frac{1}{u_{ij}} \tag{4}$$

In the formula, u_{ij} is the distance between node i to j.

When the ant colony complete a cycle, the update of path pheromone is required:

$$\nu_{xy}^{j}\left(q\right)=\left(1-r\right)\nu_{xy}^{j}\left(q-1\right)+\Delta\nu_{xy}^{j} \tag{5}$$

$$\Delta\nu_{xy}^{j}\left(q\right)=\sum_{h=1}^{k}\Delta\nu_{xy}^{j}\left(q\right) \tag{6}$$

In the formula, $q\in\left(0,1\right)$ is a pheromone evaporation coefficient that represents the speed of pheromone disappearance, then $1-q$ is the residual factor of pheromone. $\Delta\nu_{xy}^{j}\left(q\right)$ is the pheromone increment from node i to j. $\Delta\nu_{xy}^{j}\left(q\right)$ is the pheromone of the m

ant remained in the path from i to j. For its value, Dorigo M presents three update strategy of pheromone, namely: Ant-cycle model, Ant-quantity model, Ant-density model. In order to improve the global search ability of ant colony, the Ant-cycle model is used in this paper:

$$\Delta \nu_{xy}^{j}(q)=\begin{cases}\frac{e}{l_m}, if\ m \text{ ant move from node i to j in this cycle} \\ 0, \quad else\end{cases} \quad (7)$$

Q is the newly added pheromone intensity factor, L k is the path length searched by the m ant.

IV. Path Optimization of Improved Ant Colony Algorithm

A. Taboo Grid Optimization Method

In the basic ant colony algorithm, ant it is easy to involve in the U-shaped obstacle and deadlock, resulting in the algorithm stagnation. Liu Xuxun proposed the ant fallback strategy, enhancing the robustness of the algorithm. But, when there are a lot of U-shaped obstacle, the ants need to repeatedly back and repeatedly determine whether they are in the U-shaped path, increasing the amount of computation. In this paper, it is optimized by setting taboo grid. When the ant enters the U-shaped path, push the entry node and do not use the transition probability formula to move to the next point but directly move forward by inertia, so the amount of calculation of path selection is simplified. If there is an exit, then the ant move on after passing through it; if there is no exit, then the ant goes back to the entry and defines the U-shaped grid as taboo grid, alerting other ants not to walk.

B. Update Strategy of Pheromone Based on Time and Space

In the traditional ant colony algorithm, pheromone evaporation factor s is constant. It may lead the algorithm fall into local optimal solution. Zhang Yudong presents an improved method of self-adaptation:

$$s(q)=\max\left[\eta s(q-1), s_{\min}\right] \quad (8)$$

In the formula, $s_{\min}$ is the minimum of ηs is the default attenuation constant, generally taken to be 0.98.

The formula is the function based on time. On this basis, the improved strategy based on the space is further proposed in this paper. Since the shortest path more concentrated in the vicinity of the connection from the starting to the end, thus the area near the diagonal is defined as important area; while the area near the starting and ending is particularly important, defined as the core region, and requires increasing search efforts; the probability of the appearance of the shortest path of the diagonal area opposite to the core area is minimal, defined as non-core areas. After the first ant searches the target point, the search range is established. The entire area is divided into the core area, the non-core area and key area, and the area search is realized by adjusting the value s:

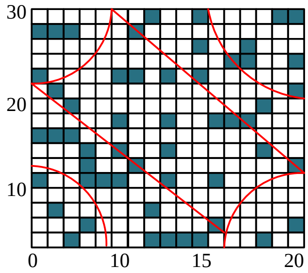

Figure 3. Diagram of corn area and non-diagram area

$$s(h)=\begin{cases}\eta|r_i-s_i|.\sqrt{(r_i-r_h)+\sqrt{(s_i-s_h)}}, if\ i \prec mid \\ \eta|r_i-s_i|.\sqrt{(r_i-r_h)+\sqrt{(s_i-s_h)}}, else\end{cases} \quad (9)$$

In the formula: r_i, s_i is the horizontal and vertical coordinates of node i, $s(h)$, s is the starting coordinate. r_h, s_h is the end coordinate, mid is the line of the intermediate partition, $s(h)$ is a constant that make $s(q)$ and $s(e)$ in the same level. Therefore, the update formula pheromone is changed to:

$$\nu_{xy}^{j}(q)=\max\left\{1-s(q)-s(h).\nu_{xy}^{j}(q-1)+\Delta\nu_{xy}^{j}(q), s_{\min}\right\} \quad (10)$$

After introducing $(q)1$, the value in non-corn area is large, which can accelerate the evaporation of the pheromone and reduce the probability that ants enter this area and search; In key area, the pheromone content is higher. But the value in corn area is minimum and the pheromone content is maximum, so ants prefer searching in this area. This can prevent ant from involving in the local optimization and shorten the search blindness and accelerate the convergence speed.

C. Exhumation Search Strategy of Ants

In practical application, when robots search and arrive at the target point, they should return to the starting point. To make better use of the search ability of individual ant, Wang Peidong and others proposed a iterative way with exhumation but this method will cause the positive pheromone's interference with reverse pheromone. A new improved strategy is proposed in this article: the individual ant moves from the beginning to the end, then the pheromone is updated; later, it returns to the beginning and updates the pheromone again, then another iteration of single ant is finished. This can reduce the waiting in the iteration of ant, increase the reuse of ant and improve search efficiency.

In the process of moving forward and backward exhumation, different transfer strategy is used:

Positive search strategy:

Heuristic information $\nu_{xy}^{j}(q)$ of formula (2) and pheromone factor are improved and the distance information is the main guide:

$$\nu_{xy}^{j}(q)=\frac{1}{u_{ih}}, u_{ih}=\sqrt{(s_i-s_h)^2+(x_i-z_h)^2} \quad (11)$$

In the formula: u_{ih} is the distance from node i to the target node h.

Using the distance from current node to the target node as heuristic information can greatly enhance the purpose of search of ants and accelerate the convergence speed of algorithm. To prevent that the search space is too small, the positive pheromone factor $\beta_y(\beta \succ 1)$ and the proportion of pheromone of selection of the next node need to increase. If $1 \le u_{ih}$, node j is defined to be close node; if $1 \succ u_{ih}$, node i is defined as remote node.

Transfer of ant generally uses roulette selection. When searching by distance factors, according to the above statement, there is no need to search remote node and only a few close node need to be calculated. Therefore, $allowq$ can be changed to all close nodes. Using this strategy can further reduce the amount of computation and accelerate the convergence speed of algorithm.

Reverse exhumation search strategy:

To reduce the influence of pheromone that positive search produced on the exhumation process and increase search randomness, the pheromone factor $\beta_x(\beta \prec 1)$ and the proportion of pheromone of the selection of the next node need to reduce. $u_{ih}(q)$ in formula（2）changes to :

$$v_{xy}^{j} = \frac{1}{u_{ih}}, u_{ih} = \sqrt{(s_i - s_h)^2 + (x_i - z_h)^2} \qquad (12)$$

u_{ih} is the distance from node i to node j. Using v_{xy}^{j} as the heuristic information can increase the randomness of search of ants and expand the search space properly.

Using exhumation search strategy can realize the advantage complementation between positive and exhumation ants, make up for the shortcoming of their search, improve the utilization and search efficiency and consider both the convergence speed and diversity of algorithm.

D. Objective Function of Assessment of Structural Path

In practical application, what the robot find is optimal path instead of the shortest path, so new indicators except for distance is introduced: the amount of calculation, the amount of transition, the objective function of structural comprehensive assessment. Robots often use embedded system in the application. The large amount of calculation in choosing nodes may result in short stagnation of robot, so the large amount of computation should be reduced and the objective function of computational assessment should be introduced:

$$Cal(l) = \sum_{i=1}^{m} r(l) \quad l = \{l_1, l_2, ..., l_m\}$$

When feasible node j of node i is obstacle grid or distant node, node j don't need to be substituted into the probability formula. Only when the node j is close node is the calculation needed, so the amount of calculation of each node is different.

$$r(l) = \frac{1}{7}\sum_{n=1}^{7}\begin{cases} 1, n \in \text{close grid} \\ 0, n \in \text{obstacle grid } or \text{ distant grid} \end{cases} \qquad (13)$$

When the robot takes a sharp turn, it will cause the loss of some energy, so a large amount of turn of robot should be avoided as soon as possible and the robot should move forward in the original direction. That is keeping a certain "inertia" to enhance the smoothness of the path and introduce subjective function of assessment of amount of turning:

$$Turn(l) = \sum_{i=1}^{m} t_k(l) \quad l = \{l_1, l_2, ...l_m\} \qquad (14)$$

Different corners have different impact on the movement, so penalty measure of corner is added: Because ants move in the grid, the corner can only be $45^0\ 90^0\ 135^0$. Three kinds of corner use different weighting coefficients to increase the punishment of the large corner.

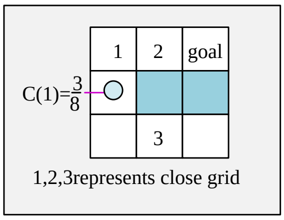

Figure 4. Diagram of the amount of calculation of node

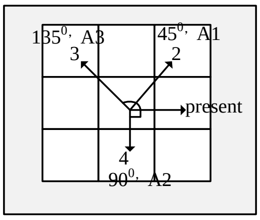

Figure 5. Diagram of corner penalty

$$t_i(l) = \gamma_1 t_{45^0} + \gamma_2 t_{90^0} + \gamma_3 t_{135^0} \qquad (15)$$

γ_1, γ_2, γ_3 is weight coefficient so function of comprehensive assessment is:

$$z_i = e_1 l_m + e_2 cal(l) + e_3 Turn(l) \qquad (16)$$

e_1, e_2, e_3 represents the size of different weight value, represents the weight of each parameter. The update strategy of pheromone changes to be $\Delta\eta_{km}^{m}(q) = p / z_i$. In this way, algorithm will consider both distance and the amount of calculation and turning when updating pheromone and select the optimal path.

E. Algorithm

Step1 improve the initialization of ant colony algorithm. Circulation time $r_s = 0$, time s = 0, group number of dispatched ant $r_{s\max}$. N ants are put on the Start position of a grid map . According to formula (8) to determine (l) and the concentration of pheromone of the distributed initial space $\eta_{km}^{m}(q)$;

Step 2 to launch m ants to search the optimal path according to positive search strategy. When ants find the target point, fill the taboo table and use formula(13)(15)to determine and record the amount of calculation $cal(q)$, the amount of turning Turn(l) and the comprehensive assessment function of this route z_i. For those ants that don't find the end, to make them die and make no update of pheromone. For those ants that find the end, the increment of pheromone is got from formula (6), the attenuation factor of current pheromone is determined according to formula (9) and the pheromone within the entire obstacle space is updated according to formula (13) .

Step 3 after updating pheromone, ants immediately reverse direction and search the starting point according to reverse search strategy. After finding the starting point, to calculate and record the value of $cal(1)$, $turn(1)$ according to the route that has been passed, determine the increment of pheromone and the attenuation factor of pheromone and update the pheromone within the entire obstacle space;

Step 4 after all the dispatched ants return to the starting point, to fill the taboo table and complete one cycle and find the shortest path. The time of circulation $r_s = r_s + 1$;

Step 5 if the time of circulation $r_s \prec r_{s\max}$, the taboo table is emptied and back to Step2; otherwise , comparing the value of $cal(1)$, $turn(1)$ of each ant in every circulation, then output the minimum and draw the optimal path.

V. Experimental Simulation and Analysis

A. Experimental Setting

To verify the performance of the algorithm, the Matlab is used to write the simulation program. CPU is the memory of Core i3, 2.13GHz, 2G.

The parameters in simulation are set as follows: the number of ant is 50; the initial concentration of pheromone $sr(q)=9$; the positive pheromone factor $\beta_k = 1.4$; the reverse pheromone factor $b = 0.9$; the intensity factor of new pheromone $p = 1$, the attenuation constant $r_1 = 0.98$, the evaporation factor of minimum pheromone $s_{\min} = 0.1$, the weight coefficient $r_1 = 1$, the weights value $e_1 : e_2 : e_3 = 6:3:1$, $s = 0.38$. Experiment is made in the grid map of 23×23.

B. Result Analysis

It can be seen from the table 1 that the algorithm in this paper find the same path with the basic ant colony algorithm by Liu Xuxun, but because of the introduction of comprehensive assessment function, the amount of calculation and turning is superior to other algorithms, therefore, the result of optimal path is better.

TABLE I. Comparison of the Algorithm of This Paper and Ant Colony Algorithm

norm of performance	ant colony algorithm	algorithm of this paper
optimal path of comprehensive assessment	183.4	180.7
optimal amount of turning	50	49
optimal amount of calculation	51	6
running time	20.0164	1.5023

The optimal path found by the improved algorithm of this paper is shown in figure 6:

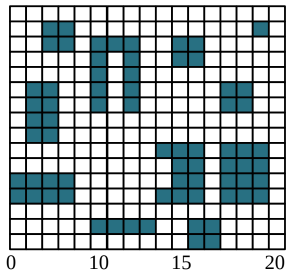

Figure 6. Optimal path

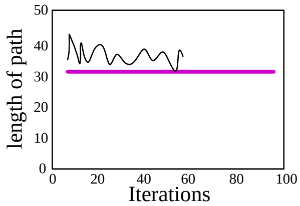

Figure 7. Convergence speed of the shortest path

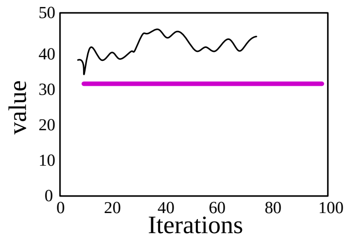

Figure 8. Convergence speed of the amount of turning

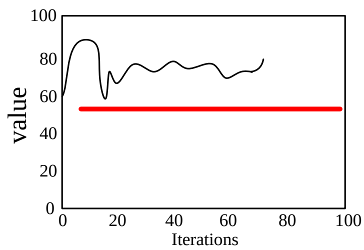

Figure 9. Convergence speed of amount of calculation

It can be seen from the result of simulation comparison that: compared with basic ant colony algorithm, the convergence speed of the algorithm of this paper is significantly faster and the ability of global optimization improves a lot. It can be seen from the comparison of convergence curve of each amount of assessment that the amount of calculation and turning of optimal path found by the algorithm of this paper has a certain degree of reduction.

The planned optimal path is run in the randomly generated grid of 30 * 30 as it shows in figure 10. A large number of simulation experiments show that this algorithm has strong ability to adapt to complex map. Even in a complex environment of obstacle, the algorithm can still work out the optimal path.

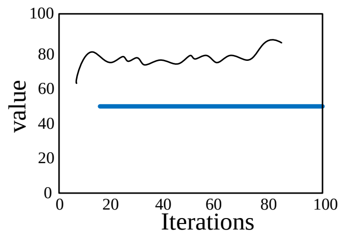

Figure 10. Convergence speed of comprehensive assessment

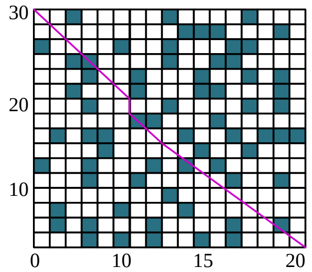

Figure 11. Optimal path

In practical application, in order to save cost, the number of robot can not be too large. Here, 3 robots is used to search in the grid environment of 16 * 16. The length of each grid is 18cm and the comparison of two algorithms is made.

It can be seen from the data in Table 2 that: because that the number of robot is too small, it is nearly impossible for basic ant colony algorithm to find the shortest path and it is easy to involve in local optimal solution. The algorithm of this paper still can search the optimal path at a very high efficiency. Therefore, it has a strong practical value.

TABLE II. THE COMPARISON OF ACTUAL OPERATING RESULT

norm of performance	ant colony algorithm	algorithm of this paper
average optimal path length	498.364	433.475
optimal amount of turning	50	3
optimal amount of calculation	78	5
running time	72	57

To further verify the feasibility of the algorithm, different number of grid is set and starting point, end and obstacle are generated. The number of grid in experimental environment is the square area of 80. This paper let $N_{\max}=200$, $n=10$, $\eta_0=1.6$, $\beta=1.2$, $r=1.3$, $o=0.2$, $Q=35$, $q_0=0.9$. The comparison of execution step and time of basic ant colony algorithm and improved algorithm in the same environment is made. The simulation result is shown as figure 13. Curve 1 represents the current optimal value of improved algorithm; curve 2 represents the current algorithm of basic ant colony algorithm. It can be seen from figure 13 that the improved tragedy has significant impact on the performance of algorithm after making comparison analysis of the execution step. The improved algorithm can converge to the optimal solution in about step 50 and basic algorithm in about step 80. Comparing these two algorithms, the improved algorithm uses the improved strategy and there are more ways to generate better path, so the number and speed of generation of good solution is higher than basic algorithm, then the optimization efficiency and convergence speed are accelerated.

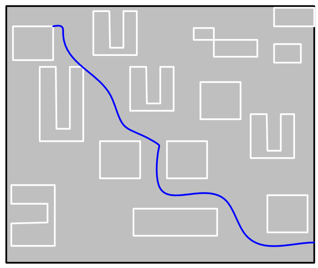

Figure 12. Operating result of hardware platform

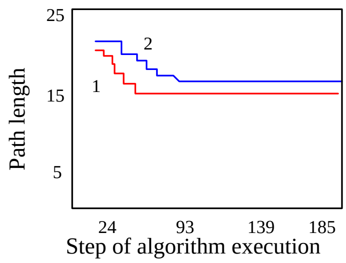

Figure 13. The comparison figure of algorithm optimization

VI. CONCLUSION

A certain improvement is made for the ant colony algorithm in this paper. The way to go forward in curve is used considering that the volume of robot avoid obstacles; taboo grid is set to avoid path deadlock in searching and accelerate the search speed; the search way of exhumation ant is used and the search strategy of the positive and reverse ant is different, which realizes the complementation of advantages and accelerates the convergence speed of algorithm; in the way of updating of pheromone, the updating strategy of pheromone based on time and space is used and the non-corn area is avoided, which make the algorithm converges more quickly. The construct of comprehensive assessment function of new path considers, except for the distance, the effect of the amount of calculation and turning on optimal path, which make the path optimization of algorithm more reasonable.

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