

Improved Ant Colony Optimization Algorithm and Its Application on Path Planning of Mobile Robot

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Abstract—This paper uses the grid method with coding tactic based on effective vertexes of barriers (EVB-CT-GM) as the method of environment modeling and ant colony optimization algorithm with two-way parallel searching strategy (TWSS-ACOA) is adopted to accelerate searching speed. In view of that the TWSS-ACOA has the defects of losing some feasible paths and even optimal paths because of its ants meeting judgment strategy (AMJS), so a new AMJS is proposed. Then a new method to rationally distribute initial pheromone is given to accelerate convergence speed of initial stages of ACO algorithm. Later, in order to avoid running into local optima and to speed up optimization process, a new path selecting method and a new global pheromone updating technique are put forward. Finally simulation researches of path planning of mobile robot based on improved TWSS-ACOA are made under different two-dimension environments and simulation results show the improved algorithm can find safe paths at higher convergence speed even in complex environment.

Index Terms—ant colony optimization, path planning, mobile robot, two-way parallel searching, meeting judgment, initial pheromone distributing, global pheromone updating

I. INTRODUCTION

Nowadays, robotics is an essential part in manufacturing processes automatization. Concerning mobile robots, autonomous navigation entails a great challenge. A mobile robot can be very useful in different situations where humans could be in danger or when they are not able to reach certain targets because of terrain conditions^[1]. Then mobile robotics field is an interesting and challenging subject for science and engineering^[2]. Hence, robot should have those required characteristics to avoid an obstacle that lies in his path^[3], and path planning becomes an important task in mobile robotics to enable

the robot navigation system to identify a safe path (without colliding with obstacles) to goal^[4].

Many scholars make lots of researches on path planning and put forward some methods, such as artificial potential field approach^[5,6], the free space method^[7,8], neural networks^[9,10], genetic algorithm^[11,12], simulated annealing algorithm^[13,14], fuzzy Logic^[15,16] and so on, but generally, these methods were shown to lack of computational complexity, local minimum, adaption and non-robust behavior^[17].

The ant colony optimization (ACO) algorithm is a meta-heuristic approach inspired by the behavior of the biological ants in real world and proposed by Dorigo M.. The algorithm is a kind of random optimization approach and has the many advantages, such as good robustness, distributed computing, easy combined with other methods^[18]. It is also one of the most successful examples of swarm intelligent systems and has been applied to solve many different types of problems^[19], such as quadratic assignment problem^[20,21], job shop scheduling problem^[22-24], vehicle routing problem^[25-27], network routing selecting problem^[28,29] and robot path planning problem^[30,31], and so on.

This work presents a new proposal to solve the problem of path planning for mobile robots; it is based on TWSS-ACOA to find the best route according to certain cost function. There are two core steps about path planning methods: environment modeling and planning algorithm. So we firstly build the environment model of robot by EVB-CT-GM^[32], since this method was certified to be an effective method to overcome environment traps problem, and then TWSS-ACOA proposed in [33] is used to adequately develop mutual cooperation ability between ants. But in view of that the TWSS-ACOA has the defects of losing some feasible paths and even optimal paths, a new ants meeting judgment method that can judge if ants meet according to the kind of pheromones is proposed. And then a new method, which rationally distributes initial pheromone of ants, is given to speed up the convergence velocity of initial stages of ACO algorithm, since equivalent

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distributing of initial pheromone in ant colony optimization algorithm results in longer searching time. Further, a new path selecting method and a new global pheromone updating technique are introduced to avoid running into local optima. Simulation results under two-dimension environment indicate that improved algorithm can plan a safe and optimal path quickly.

The rest of the paper is organized as follows. In the next section, we introduce the problem of environment problem. Section III is devoted to the algorithm improvements and the program flow chart of improved algorithm is given in Section IV. Simulation is shown in Section V. Conclusions are addressed in Section IV.

II. ENVIRONMENT MODELING

The Grid method proposed by W. E. Howden in 1968 is the most widely-used and well-developed environment modeling algorithm. It is brief and effective, has better adaptability to barriers, can readily store and calculate for computer and is applied to many mature algorithms and techniques successfully. So the work space of mobile robots is still divided by grid method in this paper. Although using conventional grid method to establish environment model of robot workspace can avoid complex calculation when barriers boundaries are disposed, it is also easy to run into environment traps. Therefore EVB-CT-GM^[32] is used to avoid environment traps problem in this paper. The detailed process is as follows.

Firstly, appropriate distension treatment is made for barriers according to volume radius of practical robot in order to ensure the security of robot movement until physical robot can be regarded as a particle at last, as Fig.1 shown, and then the robot workspace is divided by grids method. Next, grids are identified by serial numbers as shown in Fig.2 and Fig.3. So the serial number is used as a parameter of coding of robot path planning to shorten the length of coding.

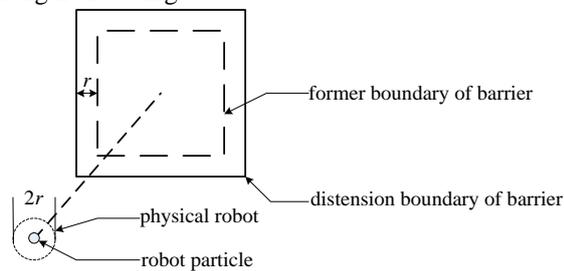


Figure 1. Extrusion processing of the obstacles.

1	2	3	4	5	6
7	8	9	10	11	12
13	14	15	16	17	18
19	20	21	22	23	24
25	26	27	28	29	30
31	32	33	34	35	36

Figure 2. Coding of grids

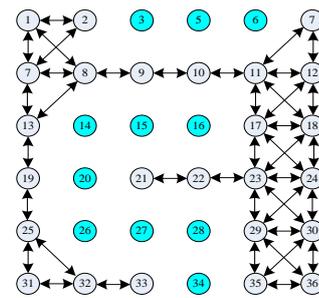


Figure 3. Figure structure of the grid environment

Finally, effective vertexes of barriers are constructed. They should satisfy two conditions: (1) The crossover point between barriers grids are not on the edge of environment map since robots don't pass through them. (2) There is only one barrier grid in four grids centered on a barrier vertex.

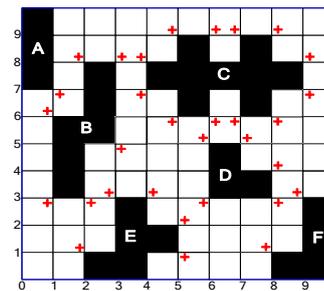


Figure 4. Sketch map of ants meeting identification

So there are thirty-one effective vertexes in Fig.4 that can be used to code path and practical coordinate of every vertex can be handily fixed according to grids coordinate. Robot path planning based on it can avoid difficulties due to coordinate transformation and is more suitable for computer realization, so the generality of algorithm is enhanced.

Now, the path planning is the problem to find a sequence of free grid nodes from the start position to the target position in grids environment shown as Fig.4.

III. ALGORITHM IMPROVEMENTS

A. Rational Distributing of Initial Pheromone

Since the differences of the initial pheromones between paths are not clear, ants walk to each feasible direction nearly in the same probability when original ant colony is created. In the other words, it takes long time until the pheromone superiority of better paths is obvious, so it is need long time to search initial feasible solutions for ACO algorithm and most of the time is used to construct solutions. So it seriously affects the quality of ACO algorithm searching for the best solutions.

In order to accelerate convergence speed of initial stages of ACO algorithm, heuristic information is augmented to distribute initial pheromones reasonably. Namely, initial pheromone is distributed according to local information of relative length of path of current city, and chaos information is added to tiny adjust to avoid running into local optima.

Now, the expression of pheromone distributing is

$$\tau_{ij}(t_0) = \left(\frac{d_i^{\min} + d_j^{\min}}{2d_{ij}} + q\Delta\lambda \right) \times \tau_0 \quad (1)$$

Where, d_i^{\min} is the city distance nearest to city i , d_j^{\min} is the city distance nearest to city j , d_{ij} denotes the distance from city i to city j , τ_0 is a pheromone constant. $q \in [0,1]$ shows the intensity of chaos and $\Delta\lambda$ denotes the chaos.

Applying typical Logistic obtains^[34]

$$\begin{aligned} \Delta\lambda(t+1) &= \mu \times \Delta\lambda(t) \times (1 - \Delta\lambda(t)) \\ \Delta\lambda(t) &\in [0,1], \quad \mu \in [3.56, 4] \end{aligned} \quad (2)$$

B. Two-way Parallel Searching Tactic

In conventional ACO algorithm, a new path L_{new} creates when an ant reaches a goal from a start point, so the efficiency and convergence speed of ACO algorithm are relatively slow since it doesn't make good use of interoperability between ants. TWPSS-ACOA is designed in [33] to increase the efficiency of ACO algorithm and bring interoperability between ants into full play. In other words, whole ants are divided into the same two groups, and ants simultaneously search feasible paths respectively from two different directions. A feasible path is produced if an ant walks from a start point to a end point by itself or two ants from different directions meet during searching process.

The searching strategy not only improves constructed efficiency of initial feasible solutions, but also keeps searching diversity, so the searching strategy is used in this paper.

C. New Meeting Judgment Strategy between Ants

Two ants from different directions can meet during TWPSS process, ants separately carry their searching information, and a new feasible path can be obtained by linking the paths meeting ants walked. Then how to determine whether ants encounter becomes a focal problem.

In most literatures ants are to be affirmed encountering by the distance between two grids on which two ants are at the moment. Namely, ants k_i , k_j ($flag_{k_i} \neq flag_{k_j}$) are on grids g_i and g_j at the same time t during executing process of algorithm, if $|d(g_i, g_j)| \leq \sqrt{2}$ and there is logical connecting line between the two grids, then ants k_i , k_j will be called encountering. But this judgment method is easy to lose some feasible paths, as in Fig.5. It even loses optimal path and makes algorithm can't find global optima.

In Fig.5 g_i is the location of ant k_i coming from the start point and g_j is the position of ant k_j coming from end point at moment t during executing process of ACO

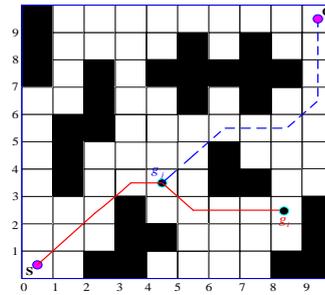


Figure 5. Sketch map of ants meeting identification.

algorithm. The red real line is the path ant k_i has passed by and the blue dotted line is the path ant k_j went through. From Fig.5 it follows that ants k_i and k_j both passed through node g_j , but at same moment t the distance between them $|d(g_i, g_j)| > \sqrt{2}$. According to the former AMJS, the two ants will be regarded as no-encountering, so there is not feasible path between them. Factually, there is a feasible path between them as shown in Fig.5. We are now confident that the AMJS of [33] loses some feasible paths, reduces optimization range artificially and even makes algorithm can't find global optima, so an effective AMJS is needed.

For convenience, some definitions are given firstly, as follows.

Definition I: Let $\tau 0_{(i,j)}(0)$ be the pheromone released by ants coming from the start point and $\tau 1_{(i,j)}(0)$ the pheromone released by ants coming from the end point.

Definition II: if a grid both has the pheromone $\tau 0_{(i,j)}(0)$ and the pheromone $\tau 1_{(i,j)}(0)$ at same moment during algorithm executing process, then there are at least two ants passing by the grid. So the ants are known as meeting.

A new path is obtained by connecting the records in taboo tables of the two meeting ants during algorithm executing process.

The path ants met can be described as follows:

$$P_{new} = P(ant_tabu_{k_i}) \cap P(ant_tabu_{k_j}) \quad (3)$$

Where, P_{new} is a new path obtained by meeting, and $P(ant_tabu_{k_i})$ and $P(ant_tabu_{k_j})$ are the paths individually obtained from taboo tables of ants k_i and k_j when ants k_i and k_j met.

For example, grid forty-five has both the pheromone $\tau 0_{(i,j)}(0)$ and the pheromone $\tau 1_{(i,j)}(0)$ in Fig.5, and then the ants k_i and k_j can be said meeting. The grids the two ants passed by are found, and the records of $ant_tabu_{k_i}$ is $\{Start, 12, 23, 33, 44, 45, 35, 26, 17\}$, the records of $ant_tabu_{k_j}$ is $\{Goal, 90, 80, 70, 59, 58, 57, 46, 45\}$. The new path is obtained, $\{Start, 12, 23, 33, 44, 45, 46, 57, 58, 59, 70, 80, 90, Goal\}$, by connecting $ant_tabu_{k_1}$ and $ant_tabu_{k_2}$.

D. New Path Selecting Strategy

The transference probability only depends on the historical information τ_{ij} and the current information η_{ij} in conventional ACO algorithm, so the transference probability lacks the leading of the future information and it makes algorithm easily running into local optima^[17]. Therefore a new path selecting strategy is proposed in this paper.

Definition III: activity degree of city j : denotes the branching extent of city connection established by ant colony in city j during an iteration, described by $liveness_j$.

$$liveness_j = \frac{node_branch_j}{n} \tag{4}$$

Where, $node_branch_j$ is the branching number of city j .

Then the expression of transference probability with activity degree of city is

$$p_{ij}^k(t) = \begin{cases} \frac{liveness_j [\tau_{ij}(t)]^\alpha [\eta_{ij}(t)]^\beta}{\sum_{s \in ant_window_k^i} liveness_s [\tau_{is}(t)]^\alpha [\eta_{is}(t)]^\beta} & j \in ant_window_k^i \\ 0 & otherwise \end{cases} \tag{5}$$

Where, α is a pheromone heuristic factor, which reflects the function of the accumulated pheromone on ants' movement, and β is a desired heuristic divisor, shows the important degree of heuristic information on the path selecting of ants. $\tau_{ij}(t)$ is the information quantity on the path (i, j) at moment t , $\eta_{ij}(t)$ is a heuristic function which denotes the expected degree for ant moving from city i to city j , and which is usually equal to the inverse of the distant from city i to city j for ACO algorithm, namely:

$$\eta_{ij}(t) = \frac{1}{d_{ij}} \tag{6}$$

Where, d_{ij} is the distant between two neighbor cities i and j . So the less d_{ij} is, the bigger $\eta_{ij}(t)$ is and the larger $p_{ij}^k(t)$ is.

As shown, heuristic information τ_{ij} and η_{ij} is used as future information to guide probability updating and city activity degree is added in transference probability formula. Form the definition of city activity degree, it is shown that the less city branches are, the lower city activity degree is, but the more city branches are, the higher city activity degree is. Namely, if choosing a city with low city activity, candidate cities are fewer and the diversity of ant colony reduces, so cities with higher city activity degree must be selected to prevent getting into local optima. On the other hand, the invalid paths are

reduced since the paths with lower city activity degree aren't selected when paths are selected according to city activity degree, so it decreases the computation by ant meeting judgment and quickens the speed of ACO algorithm.

E. New Method for Global Pheromone Updating

All ants update their pheromones after ant colony completed an iteration in conventional ACO algorithm. But it doesn't adequately reveal guidance function of optimal solutions; at the same time the information of bad solutions also disturbs colony iteration of next generation. But if only optimal ants update their pheromones, there are also some problems. More specifically, if only global optimal ants update their pheromones, then the convergence speed is quicker at initial phase of ACO algorithm, but the possibility of running into local optima will increase. On the contrary, if current optimal ants are updated, the diversity of ACO algorithm appeared well maintained, but the convergence speed isn't perfect. So this paper applies itself to find preferable updating strategy and replace former two kinds of updating strategies in order to improve performance of algorithm.

Colony iteration is divided into two stages: the stage that ACO algorithm does not reach stagnancy and stagnation phase. In the first stage, the updating probability of global optimal ants should be great, whereas the updating probability of current optimal ants should be increase step by step in order to insure the diversity of ACO algorithm when it enters stagnancy stage. This is a kind of alternant tactic of probability type and two different updating strategies both are work at every stage.

Let alternation probability be:

$$q_{now} = \begin{cases} q_0 + \min\left(\frac{Plateau - N_{plateau}}{N_{plateau}}, 1 - q_0\right) & Plateau > N_{plateau} \\ q_0 & Plateau \leq N_{plateau} \end{cases} \tag{7}$$

Where, q_{now} is the probability that current optimal ants update their pheromones and $q_0 \in [0,1]$ is a constant.

$Plateau$ denotes the accumulation of generations after appearing successive stagnation, $N_{plateau}$ shows the start time when the successive stagnation arises. This expression means that current optimal ants update their pheromones with fixed probability q_0 before stagnation stage but the updating probabilities of current optimal ants increase step by step after achieving stagnation stage in order to obtain better diversity of ACO algorithm.

Current optimal ants are confirmed as formula (8) shown.

$$Ant_{best} = \begin{cases} Ant_{best}^{Now} & q \leq q_{now} \\ Ant_{best}^G & q > q_{now} \end{cases} \tag{8}$$

Where, Ant_{best} is the optimal ants used currently, namely the ants selected to update their pheromones,

Ant_{best}^{Now} denotes current optimal ants and Ant_{best}^G shows global optimal ants.

Lastly, the pheromones of selected ants are updated, as shown follows.

The expression of pheromone iteration is

$$\tau_{ij}(t+1) = (1-\rho)\tau_{ij}(t) + \Delta\tau_{ij}^{best} \quad (9)$$

The incremental formula is

$$\Delta\tau_{ij}^{best} = \begin{cases} \frac{Q}{L_{best}} & \text{tour}(i, j) \in \text{tour}_{best} \\ 0 & \text{otherwise} \end{cases} \quad (10)$$

Where Q is the pheromone intensity, L_{best} is the overall length of the path that Ant_{best} , the currently used ant, takes across in this circulation.

IV. THE FLOWCHART OF IMPROVED ALGORITHM

The flowchart of improved TWPSACO algorithm is shown as Fig.6.

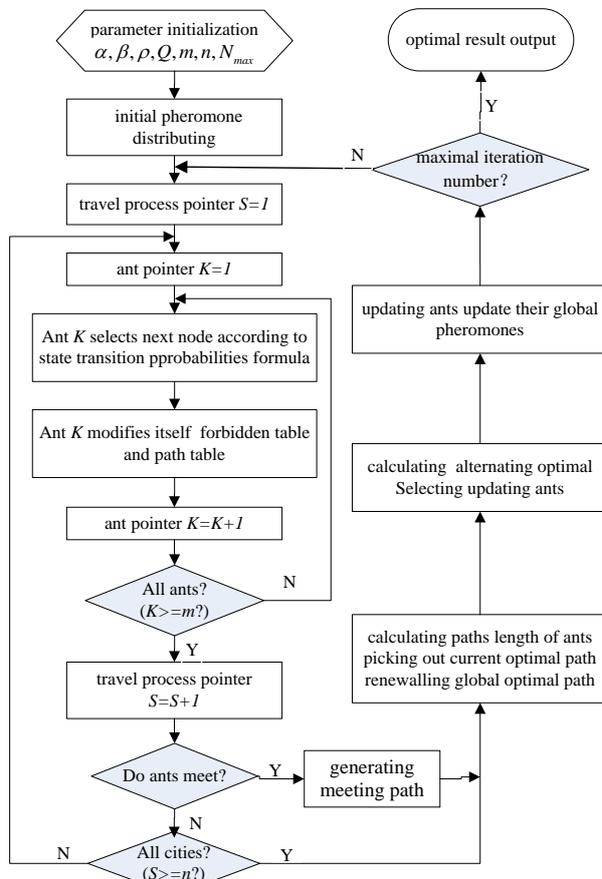
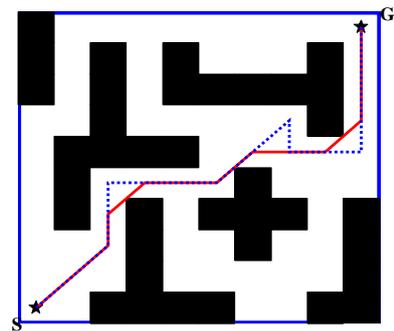


Figure 6. Flowchart of improved algorithm.

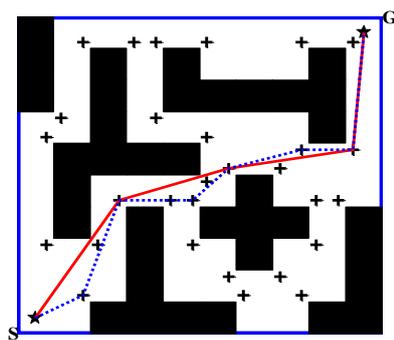
IV. SIMULATION RESEARCHES

Simulation researches are made in two-dimension environment. Because ant-cycle model is used in this paper, basic parameters are set as follows: $\alpha = 1$, $\beta = 5$, $\rho_1 = 0.5$, $\rho_2 = 0.5$ referring to the conclusions obtained by DUAN Hai-bin in [35]. Other parameters are taken as $m_1 = m_2 = 30$, $N_{max} = 100$, $Q_1 = 2$, $Q_2 = 1$, $Q_3 = 0.5$,

$\eta = 0.05$, the starting point is (0.5, 0.5), and the finishing point is (29.5, 29.5). Simulation results are shown as follows.

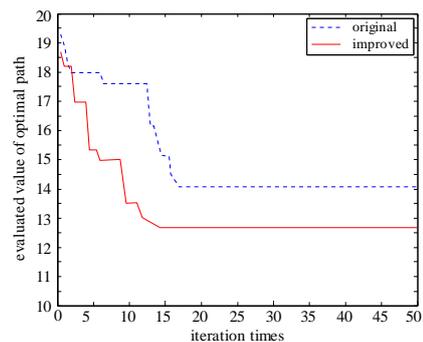


(a). Path planning figure based on common grids method.

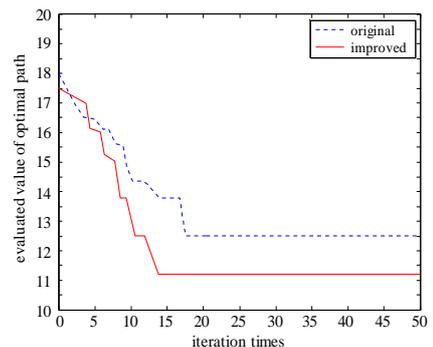


(b). Path planning figure based on EVB-CT-GM.

Figure 7. Path planning figures in map 1

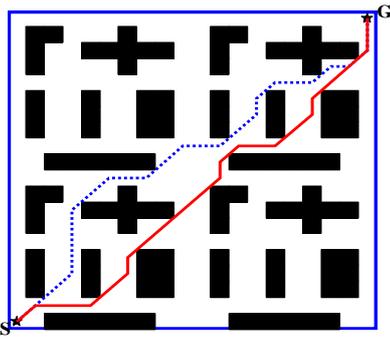


(a). Convergence curve of optimal path based on common grids method.

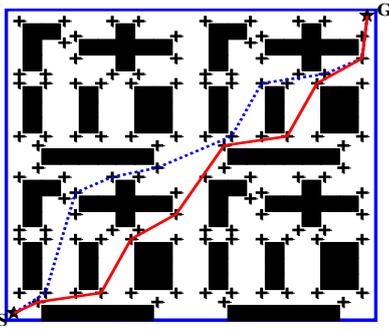


(b). Convergence curve of optimal path based on EVB-CT-GM

Figure 8. Convergence curves of optimal path in map 1

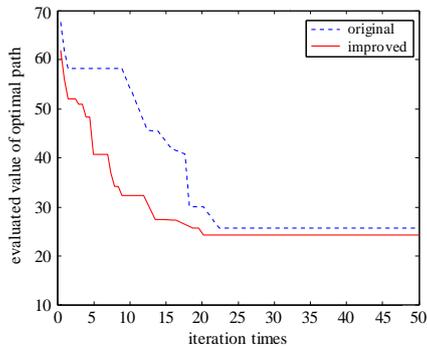


(a). Path planning figure based on common grids method.

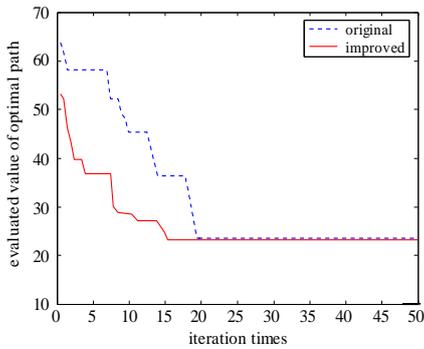


(b). Path planning figure based on EVB-CT-GM.

Figure 9. Path planning figures in map 2

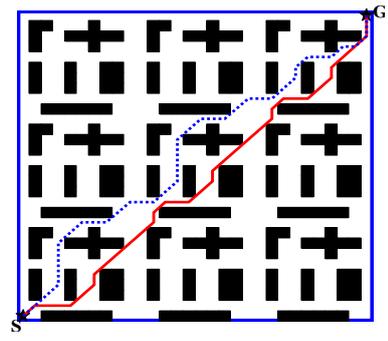


(a). Convergence curve of optimal path based on common grids method.

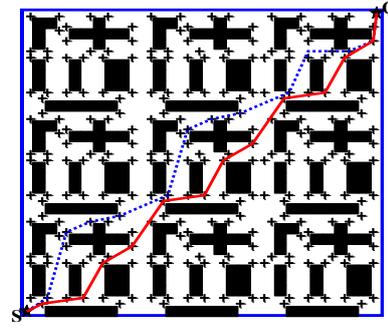


(b). Convergence curve of optimal path based on EVB-CT-GM.

Figure 10. Convergence curves of optimal path in map 2

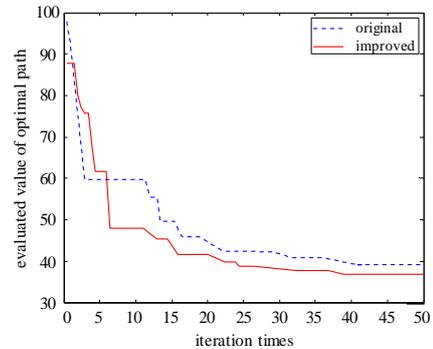


(a). Path planning figure based on common grids method.

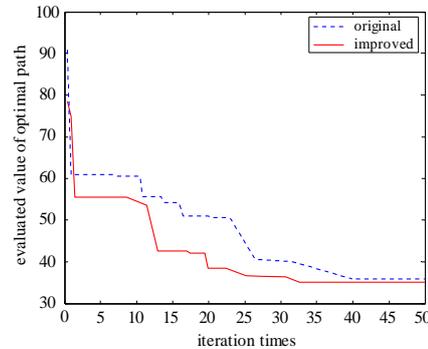


(b). Path planning figure based on EVB-CT-GM.

Figure 11. Path planning figures in map 3



(a). Convergence curve of optimal path based on common grids method.



(b). Convergence curve of optimal path based on EVB-CT-GM.

Figure 12. Convergence curves of optimal path in map 2

TABLE I.
STATISTICS RESULTS OF THE ALGORITHMS IN THE MAP 1, 2 AND 3

environment map	performance index	Based on common grids method		Based on EVB-CS-GM	
		former algorithm	improved algorithm	former algorithm	improved algorithm
Map 1	optimal path length	17.0711	15.0711	15.2532	14.6836
	path inflexion number	7	7	6	3
	running time	0.43214	0.42365	0.36378	0.30276
	iteration times	17	15	17	14
	optimal evaluating value	14.0498	12.6498	12.4772	11.1785
Map 2	optimal path length	30.9706	29.7990	30.0820	29.4931
	path inflexion number	13	11	8	8
	running time	0.8063	0.7625	0.75337	0.69763
	iteration times	22	20	20	16
	optimal evaluating value	25.5794	24.1593	23.4574	23.0452
Map 3	optimal path length	47.4558	45.1127	45.8610	44.6985
	path inflexion number	19	17	12	12
	running time	1.6656	1.5906	1.5806	1.5294
	iteration times	43	39	40	33
	optimal evaluating value	38.9191	36.6789	35.7027	34.8890

Simulation results show that the improved algorithm can find paths at higher convergence speed. In other words, global optimizing ability and search speed of improved algorithm are both enhanced obviously.

IV. CONCLUSIONS

ACO Algorithm is a colonial intelligence-optimized algorithm which is successfully applied to many problems, and applying it to path planning of mobile robot reflects the autonomy and intelligent of path planning of mobile robot. Primary TWPSS-ACOA is improved to overcome its defects and then the improved algorithm is used to path planning of mobile robot in this paper. Simulation results indicate that improved method has stronger robustness, better efficiency, and the optimal path can be obtained safely and rapidly even in complex environment.

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