Robot Path Planning Based on Improved Ant Colony Optimization

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***Abstract*—Aiming at the problem of global path planning of robots under static and complicated environment, firstly, the working environment of the robot is modeled by the grid method, and then the ant colony optimization is introduced. After analyzing the basic principle of the algorithm, this paper proposes a robot path planning scheme. Finally, the simulation experiment and analysis verify the validity and practicability of the improved algorithm.**

Keywords-Path Planning; Grid Method; Ant Colony Optimization; Optimize

I. INTRODUCTION

Path planning is one of the important techniques in robotics. The robot path planning[1] is to optimize the optimal path that covers the entire region without collision in the working scene according to some optimization objective. The path planning is an important symbol of intelligent robot intelligence, and also an important guarantee for the robot to complete tasks safely.

At present, many scholars at home and abroad have made many outstanding achievements in robot path planning technology. In the 1980s, artificial potential field method, grid method, visual method and free space method were proposed. In the 21st century, ant colony optimization[2], particle swarm optimization[3] and other intelligent optimization algorithms began to be widely used in robot path planning. However, the basic ant colony optimization is easy to fall into the local optimal, and search time is long. In this paper, the ant colony optimization is improved, and the global path planning of the robot is carried out on the basis of the known two-dimensional environment map.

II. ESTABLISHMENT OF ENVIRONMENTAL MAP

A. Grid Method

Global path planning is based on known environment maps. In the global path planning, the establishment of environmental maps are mainly grid method, topology method, geometric information method. Among them, the grid method[4] is a method of creating an environmental map by using 0 or 1 to represent an obstacle or a road in a plane two-dimensional coordinate. Grid model is shown in Figure 1. The traditional grid method is convenient and rapid to maintain and modify. However, the granularity of the grid is smaller, the more accurate the obstacle representation is, but at the same time it takes up a lot of storage space and prolongs the planning time. The search scope of the algorithm will increase exponentially; when the grid granularity is too large, the planned path will be inaccurate.

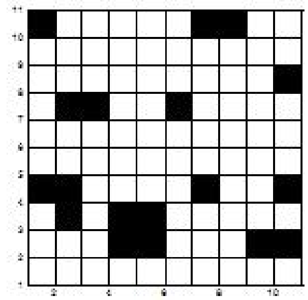

Figure 1. The grid method model

B. Improvement Of Grid Method

This paper will use an improved grid method to model, the robot model is reduced to a small particle, the actual size of the robot converted into the area of obstacles, according to the actual size of the robot to expand the boundary of the obstacle to the outside. If there is an obstacle in a grid, the black grid is defined as a barrier grid, which is represented as 1; whereas the white is a free grid, which means 0. A plurality of grids are used to represent obstacles in different shapes, and the free grids are merged into an accessible area of the robot, and the size of the grid is based on the accuracy of the obstacle representation.

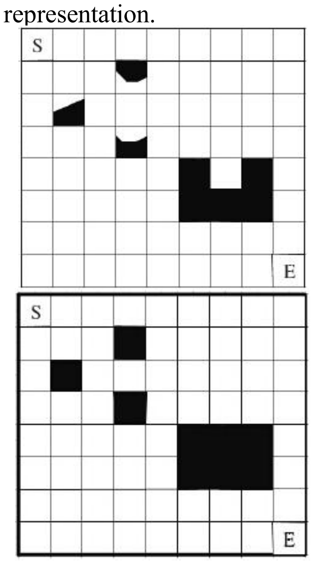

Figure 2. The obstacle shape before and after treatment

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Therefore, when modeling a space, the obstacles in the space are treated as follows: 1) a grid when dissatisfied with one grid; 2) the hollow part of the obstacle and this obstacle count as a whole obstacle, to avoid the emergence of a partial deadlock, called the merger of obstacles; 3) the boundaries of the map as an obstacle to deal with. The shape of the obstacle before and after the treatment are shown in Figure 2.

III. THE ANT COLONY OPTIMIZATION PRINCIPLE

Ant colony optimization is proposed to simulate the collective behavior of real ants scavenging in nature, which belongs to a random search algorithm. In the process of scavenging, ants communicate with each other through a biological medium called pheromone. Ants in athletic process, on the one hand to follow the former pheromones and more trails left by the ants, but also in the path of their own left pheromones, so after a period of time, more and more ants tend to move in the pheromone path, eventually finding an effective path from ant to food.

The basic principle of ant colony optimization[5]: Let *m* be the number of ants in ant, which means the amount of information hormone remaining on *ij* edge at time *t*. The pheromone of each edge is the same constant at the initial time. During the movement of ants *k*, The amount of information left on the path determines the way forward. *P (t)* represents the probability of ants moving from position *i* to position j at time *t*, which is expressed as:

$$P_{ij}^{k} = \begin{cases} \dfrac{[\tau_{ij}(t)]^{\alpha}[\eta_{ij}(t)]^{\beta}}{\sum\limits_{S \in allowed_k}[\tau_{is}(t)]^{\alpha}[\eta_{is}(t)]^{\beta}}, & if \quad j \in allowed_k \\ 0, & else \end{cases} \quad (1)$$

In the formula, $allowed_k = \{0,1,\cdots,n-1\}$ $tabu_k$ represents the city that ant *k* can choose next. $tabu_k(k = 1,2,\cdots,m)$ is a collection of tabu tables, it is used to record the city that ant *k* passes through now and avoid repeated selection. α and β respectively represent the information and heuristic factors that the ant accumulates during the exercise. η represents the degree of expectation of transfer between cities, which are determined by the algorithm under specific conditions.

IV. ROBOT PATH PLANNING BASED ON ANT COLONY OPTIMIZATION

Ant colony optimization has been able to solve TSP, maze and other issues, while many scholars apply it to the robot path planning. To solve the problem of global path planning by ant colony optimization itself, it has the disadvantage of being easy to converge to the local optimal solution and solving the inefficiency of the large-scale symmetric environment. An improved ant colony optimization [6] is proposed.

A. The Algorithm Improvement

1) Pseudo-random proportional path selection

For the *k-th* ant in the *i-th* city, when choosing the *j-th* city it wants to go at time *t*, the probability formula of the ant selection path is as follows:

$$\begin{cases} j = \arg\max_{y \in allow()}\{\tau_{iy}(t)\eta_{iy}^{\beta}\}, q \le q_o \\ p_{ij}^{k} = \dfrac{\tau_{ij}(t)\eta_{ij}^{\beta}}{\sum\limits_{y \in allow()}\tau_{iy}\eta_{iy}^{\beta}}, else \end{cases} \quad (2)$$

Where $\tau_{ij}(t)$ is the concentration of pheromone on path (i, j) at time *t*, η_{ij} is the heuristic information, $allow()$ is the candidate city that ants can go to, β is the weight coefficient representing the importance of heuristic information, *q* is the random number of $[0,1)$, q_o is the set gate value.

Formula (2) can make ants move to a city with a relatively large product of $\tau_{ij}(t)$ and η_{ij} with a relatively large probability q_o, while randomly selecting cities with a small probability of $(1-q_o)$ to ensure the diversity of search.

2) Pheromone update method

In the process of pheromone updating, the ant colony optimization is easy to fall into the local optimal solution. At the same time, when the new optimal path appears, the concentration of pheromone on the local optimal path is too strong, which leads to the algorithm is low efficient when it jumps to the optimal path. In order to overcome the above shortcomings, the combination of local and global pheromone updating is adopted.

Partial pheromone update:

When ants pass through the path *(i, j)*, the pheromone concentration on the path *(i, j)* is updated by the following formula to reduce the probability that other ants will choose this path and increase the probability that other ants will choose other paths.

$$\tau_{ij}(t+1) = (1-\varepsilon)\tau_{ij}(t) + \varepsilon\tau_0 \quad (3)$$

Where ε is the pheromone local evaporation coefficient and τ_0 is the initial pheromone concentration.

Global pheromone update:

After a cycle is completed, the pheromone update is performed on the current optimal path by using the following formula, and the optimal path discovered by this cycle can be retained in the next cycle through pheromone feedback.

$$\tau_{ij}(t+1) = (1-\rho)\tau_{ij}(t) + \rho\Delta\tau_{ij} \quad (4)$$

$$\Delta\tau_{ij} = \frac{L_1 - L_g}{L_g} \quad (5)$$

Where ρ is the pheromone global evaporation coefficient, $\Delta\tau_{ij}$ is the pheromone global update increment, L_l is the optimal path length of this cycle, L_g is the current optimal path length.

3) Local optimal search strategy

Ant colony optimization is prone to precocity and stagnation. Local optimal search strategy is introduced here.

That is, local optimal solution can be improved through the exchange of edges and adjustment in the field of solution until the solution can not be improved in the neighborhood. The existing local optimal strategies are 2-opt, 3-opt, 4-opt, greedy algorithm and genetic algorithm. In this paper, the 4-opt strategy is used to delete 4 edges from the path and add 4 edges to keep the path intact, reducing the time required for the algorithm to converge.

B. The Algorithm Implementation

The improved ant colony optimization implementation process is shown in Figure 3.

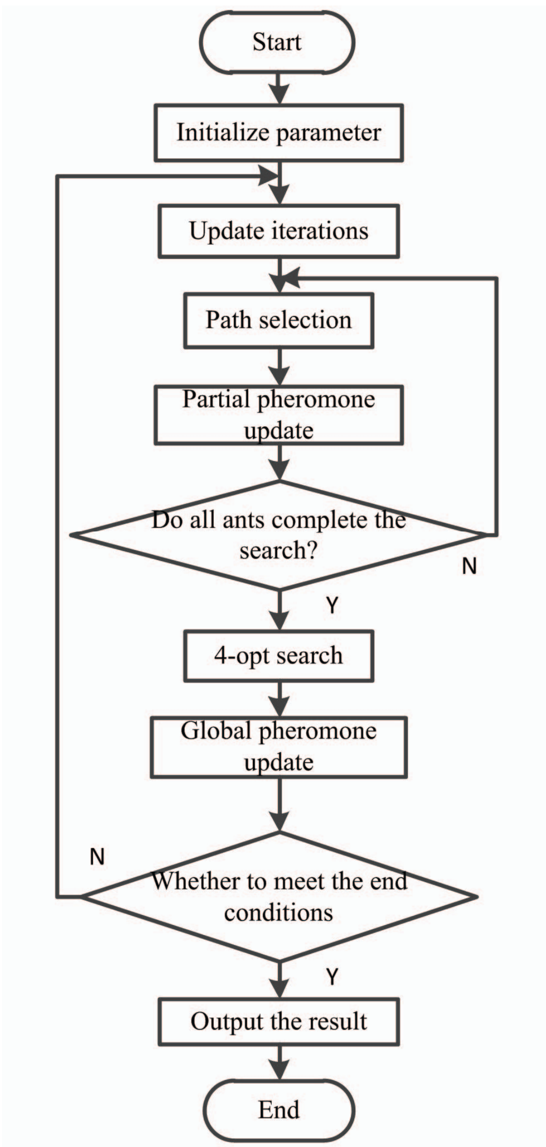


Figure 3. The improved ACO algorithm flow chart

V. THE SIMULATION EXPERIMENT AND ANALYSIS

This paper use Matlab7.0 software to simulate the robot path planning, to improve four important parameters ρ , ε , β , m of the ant colony optimization by choosing Oliver30. TSP data set as a test case, the results are shown in Table 1. β is the influence factor of the heuristic information in the path selection formula, which affects the choice of the ant to the path. When it increases, the algorithm is apt to fall into the local optimal solution. ε is the local evaporation coefficient of pheromone, and when it increases, the ant will give up the current optimal path because of the low pheromone, and slow down the convergence rate of the algorithm, but avoid getting into local optimal. ρ is the global pheromone evaporation coefficient, and when it increases, the ant will not choose the current optimal path because of the low pheromone, which will reduce the efficiency of the algorithm, but increase the search span. m is the number of ants. When it increases, the algorithm consumes a lot of time, but the search ability is stronger, and the optimal solution is more likely to be found.

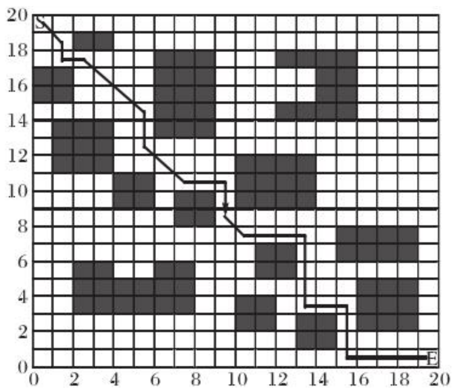
Table1. The optimal solution and number of cycles corresponding to different parameter values (time:/s)

β	The optimal solution	The average time spent	ε	The optimal solution	The average time spent
2	424.71	1.677	0.1	423.98	1.05
3	427.05	1.58	0.3	423.73	1.54
4	422.71	1.26	0.5	427.13	1.95
ρ	The optimal solution	The average time spent	m	The optimal solution	The average time spent
0.1	425.23	1.1	10	427.02	1.66
0.3	425.26	2.21	20	428.12	1.98
0.5	426.68	2.42	30	423.74	2.34

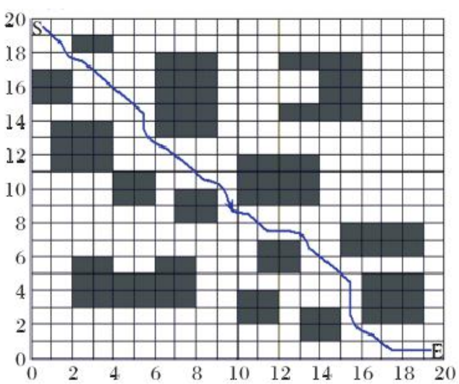
Table2. The comparison between improved ant colony optimization and general ant colony optimization (time:/s)

The algorithm	The average shortest path	The average conver gence time	The average coverage	The average repetiti on rate
The ACO	405.4	905.5	100%	20.9%
The improved ACO	400.6	126.5	100%	5.6%

During the test, we choose the following parameters: $\varepsilon = 0.1$, $\beta = 2.5$, $m = 30$, $\rho = 0.15$,and it has iterated 50 times. The improved ant colony optimization and the general ant colony optimization are compared, the contrast data as shown in Table 2. After comparison, the repetition rate after the improved algorithm has been greatly improved, and the algorithm is more efficient. The robot path planning simulation of ant colony optimization and improved ant colony optimization are shown in Figure 4.



(a) The ACO path planning diagram



(b) The improved ACO path planning diagram

Figure 4. The simulation diagrams of two algorithms on robot path planning

VI. CONCLUSIONS

In this paper, the ant colony optimization is applied to the global path planning of robots, which shows that the improved ant colony optimization has a good search function. Based on the previous researches, a global path planning method for robots adapted to grid maps is proposed. Through the simulation experiment, the influence of the corresponding parameters on the planning problem is analyzed, the feasibility of the algorithm is verified, and the research of the global path planning technology is deepened.

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