Research on Robot Path Planning Based on Improved Adaptive Ant Colony Algorithm

Shao Xiaoqiang, Lv Zhichao, Zhao Xuan,Nie Xinchao

Xi'an University of Science and Technology, College of Electric and Control Engineering, Xi'an 710054
E-mail: 792305205@qq.com

Abstract: Aiming at the problem that ant colony algorithm is easy to fall into local optimal and slow convergence in robot path planning, a path planning method based on improved ant colony algorithm is proposed for static obstacle environment.This method improves the search efficiency of the algorithm by using the adaptive adjustment heuristic function; The attenuation coefficient is adjusted dynamically to accelerate the convergence speed of the algorithm based on ant colony rule, pheromone is updated and the maximum and minimum of pheromone concentration is limited.Simulation results show that compared with other algorithms in the same environment, the improved algorithm has a faster convergence rate when the path planning results are the same.The improved algorithm has obtained the optimal path in different complexity environments, which also shows the effectiveness and reliability of the algorithm.

Key Words: Dijkstra algorithm;Ant colony algorithm;Path planning

1 INTRODUCTION

The wide application of mobile robot has been paid attention to both at home and abroad.Path planning is a research hotspot in the field of mobile robot. The path planning problem has the characteristics of complexity, multi - constraint and multi-objective[1-2]. Traditional path planning algorithm includes Dijkstra, A* algorithm and so on.Dijkstra is a classical shortest path search algorithm, but it has high computational complexity and low efficiency. The A* algorithm determines the distance and search direction from the current point to the target point through the evaluation function. In a complex environment, an unsatisfactory estimation function is likely to lead to the unsearchable path or the unsatisfactory planning path effect.In the path planning method of mobile robots, domestic and foreign experts and scholars have proposed many bionic intelligent optimization algorithms, such as: genetic, particle swarm, neural network and ant colony algorithm, but these methods have their own limitations in different environments.

Ant colony algorithm is a kind of simulated evolutionary algorithm which has the advantages of self-organization, strong robustness, distributed computing, strong optimization ability and easy to be combined with other algorithms[3-4]. It is very suitable for the path planning of mobile robots. Ref.[5] has adopted maximum and minimum ant system (max-min) to limit the range of pheromone range and effectively improve the algorithm's local optimal solution. Ref.[6] improves the pheromone update rules of the algorithm and the efficiency of the algorithm. Ref.[7] proposed an adaptive ant colony algorithm, which can effectively avoid premature algorithm. At present, many algorithms have limitations in solving the global path problem of robots.This paper proposes a new way of using the improved ant colony algorithm to plan the path of mobile robot, and also put forward the dynamic adjustment of volatile coefficient and the adaptive adjustment of volatile coefficient ρ according to the number of iterations(NC), which improves the search rate of the algorithm and speeds up the convergence speed of the algorithm. The simulation experiment in Matlab software shows that the algorithm is effective and feasible.

This work is supported by National Nature Science Foundation under Grant NO.51804249

2 Two-dimensional path modeling and path initialization

Due to the workspace environment of the robot is complex and changeable, and the path search area is large, a simplified space model needs to be established before the path planning of the robot. The Dijkstra algorithm is used to plan an initial path from the starting point to the end point on the simplified space model.

2.1 Two-dimensio nal path environment modeling

This paper mainly studies the robot path planning in complex working environment, thus to realize the process of independent walking, therefore, to facilitate research, can be in do not break real cases, simplify the robot movement space model, the simplified model is limited as follows: first, the robot can be regarded as particle, and enlarge the obstacles margin for robot body width of half maximum;Secondly, the motion free space of the robot is limited to a two-dimensional finite space. Thirdly, it is stipulated that all obstacles in the free movement space are randomly distributed in the entire roadway space like polygons and are separated from the path by a certain distance.
After defining the simplified model of the robot, free link line should be used to construct the free space of the robot.At this point, the concept of free link line is introduced:

978-1-7281-0106-4/19/$31.00 ©2019 IEEE

the connection between the vertices of two randomly distributed obstacles or the connection between the vertices of obstacles and the points on the boundary of the working area is defined as free link line (hereinafter referred to as link line).It is stipulated that each free convex region is bounded by at least two link lines, each link line is the common edge of two adjacent convex regions, and each link line in free space does not intersect with any obstacles. Robot path planning work established by the map, this paper build Marlink graph model of path planning method to establish the two-dimensional space, usually simplified model selection of freedom as the weight, the length of link line Marlink method refers to no fellowship with the obstacles between the two obstacles of connections between vertices, and obstacles vertex and boundary intersection attachment, main effect is to generate two-dimensional space path planning of the initial feasible[8]. Figure 1 is a schematic diagram of Marlink.

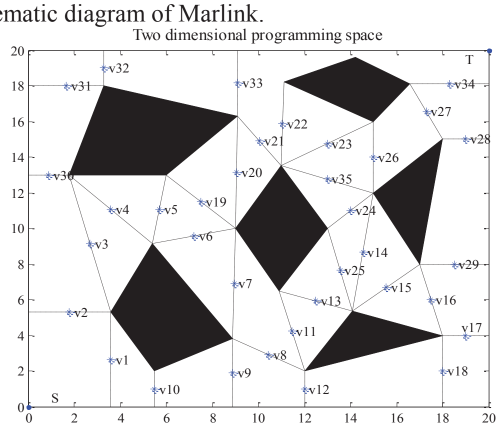

Fig 1 Marlink schematic diagram

The point line in the figure is the link line, and the black polygon is the obstacle[9].The midpoints of the line are $v_1, v_2, v_3, \ldots, v_i$, connecting these midpoints and the starting point S and the ending point T, which constitute the initial feasible space of two-dimensional path planning.

2.2 Dijkstra algorithm path initialization

Dijkstra algorithm is a method to generate shortest paths one by one according to the increasing order of path length. Unmarked nodes, temporary marked nodes and permanent marked nodes constitute the network nodes of Dijkstra algorithm.The basic implementation process is as follows: first, a weighted directed graph $G(V,E)$ is given, where V is the set of all nodes in the network topology, E is the set of all edges, and the weight of each edge is a non-negative real number[9].Its algorithm to realize the basic process is: the first algorithm is initialized, define all nodes in the grid to mark not node, and then search for nodes, update the connected to the nodes of the shortest path of nodes for temporary marking, finally to the temporary tag node selected from each iteration the node nearest distance from the origin to the destination node, at the same time, the conditions for the end of the defined decision algorithm find the target node or all nodes are marked as permanent tag node.

Since there are many paths in the initial feasible space of two-dimensional path planning, Dijkstra algorithm is adopted to plan an initial path from S to T in order to improve the efficiency of path search[10-12]. Dijkstra algorithm is a typical single-source shortest path algorithm in graph theory, which is used to calculate the shortest path from one node to all other nodes. Its basic idea is to divide the nodes into two groups, the first group includes nodes with determined shortest path, and the second group is nodes without determined shortest path. The Incrementally add nodes in group 2 to group 1 one by one until all nodes reachable from the source point are included in group 1.

Dijkstra algorithm flow is as follows:

(1) Initializes the node set V that does not determine the shortest path and the node set S that has determined the shortest path, and initializes the shortest path length by using the adjacency matrix $G(V,E)$.

(2) Select the minimum value $D(i)$ in D, $D(i)$ is the shortest path length from the source point to point i, take point i out of set V and put it into set E.

(3) Update the path length value corresponding to the source point in D to the node in set V according to node i.

(4) Repeat step (2) and (3) until you find the shortest path from the source point to all nodes.

This model ignores that the robot can walk along the boundary, so the path obtained above is only a collision avoidance sub-optimal path, which is not the most optimal solution of the whole path planning space, but this path can be used as the early model basis for improving classical particle swarm optimization algorithm and classical ant colony optimization algorithm

3 Improvement of ant colony algorithm

At present, great progress has been made in the path planning of mobile robots, but there is no planning method suitable for all kinds of environments and any system. For robots with different environments and performance, different planning methods have their own advantages and disadvantages.The fusion and improvement of many algorithms can often achieve the best planning effect.This paper adopts Dijkstra algorithm and improved ant colony algorithm fusion method.

3.1 Basic ant colony algorithm

Ant colony algorithm can be recognized as the ant species should start from a starting point, the process of unknown place in search of food, the ants will leave pheromone, the route to guide subsequent ants marched, determine an ant to two factors, namely the pheromone and the local heuristic information, pointing to the message of pheromone is equal to the group, the path pheromone, the more the more can guide the ant walking along the path, and the heuristic information is an ant according to their own self judgment of information environment, the combination of individual and group information to determine the next step how to transfer[14].The construction of pheromone model and heuristic function is the key to the merits of ant colony algorithm.How the ant chooses the next direction of travel is based on the transition probability, the formula is as follows

$$p_{ij}^{k}(t)=\begin{cases}\dfrac{\left[\tau_{ij}(t)\right]^{\alpha}\left[\eta_{ij}^{k}(t)\right]^{\beta}}{\sum\limits_{s\in J_k(i)}\left[\tau_{is}(t)\right]^{\alpha}\left[\eta_{ij}^{k}(t)\right]^{\beta}} & j\in J_k(i)\\ 0 & j\notin J_k(i)\end{cases} \tag{1}$$

$$\eta_{i,j}(t)=1/d(i,j) \tag{2}$$

In formula (1), k represents the ant number, i represents the current position label, j represents the next position label to be transferred, t represents the current iteration number, τ represents the pheromone, η represents the heuristic function, α , β respectively represents the relative importance of pheromone and heuristic factors, d represents the distance between the point i and j .

Pheromones are in the process of marching ants leave the guidance of subsequent chemical information of marching ants, ants marching, the shorter the path pheromone is thick, can lead the ants short path, as the growth of the number of iterations, pheromones are cumulative, will constantly volatile, therefore, to establish the pheromone update model, namely

$$\tau_{ij}(t+1)=(1-\rho)\tau_{ij}(t)+\Delta\tau_0 \tag{3}$$

$$\Delta\tau_{ij}^{m}(t)=\begin{cases}Q/L_m & \{i,j\}\subset visited_{t,q}^{m}\\ 0 & else\end{cases} \tag{4}$$

In formula (3) and (4), ρ is the volatile residue of pheromone, Q is the constant number of pheromones, both of which are assigned as required, L is the total length of the path traveled by the m ant in this cycle, and is the total number of ants.

3.2 Adaptive attenuation coefficient

The transition probability of traditional ant colony algorithm is composed of pheromone and local heuristic function, both of which are judged by distance length[15]. At early time of researching the algorithm, the difference of pheromone is small, the movement of ants may be very chaotic, thus affect the rate of convergence of the algorithm, the heuristic function is then played a key role, and in the middle, the algorithm is easy to fall into local optimum in the late algorithm to maintain the stability of the algorithm, in order to make the heuristic function and pheromone become better, in this paper, the following changes will be added into the heuristic function.

$$\eta_{ij}(t)=\begin{cases}\dfrac{1}{d(ij)+d(it)} & \mu NC_{\max}\le NC\le NC_{\max}\\ \dfrac{1}{d(ij)} & NC<\mu NC_{\max}\end{cases} \tag{5}$$

In formula (5) , d_{ij} is the Euclidean distance between the current node i and the feasible node j ; d_{it} is the Euclidean distance between the feasible node i and the destination node t .The reference of the destination node to the heuristic function strengthens the directivity of path search, reduces the search space of the algorithm, and effectively improves the search efficiency.However, directional heuristic information is introduced too early, which makes the initial search space too small and the algorithm easily falls into the local optimal solution.

The attenuation coefficient of pheromones ρ plays an important role in global path planning. When the environment is complex, a relatively large attenuation coefficient will increase the positive feedback of pheromones and reduce the search space so as to reduce the possibility of finding the optimal path. Even a smaller attenuation factor increases the search time[16]. With the increase of time and iteration times, traditional ant colony algorithm is prone to fall into the local optimal solution. In order to avoid this problem, reduce the algorithm search time and ensure to find the optimal path, the paper proposes to set the attenuation coefficient dynamically, expressed as

$$\rho(t+1)=\begin{cases}\sigma\rho_{\min}(t) & \sigma\rho(t)<\rho_{\max}\\ \rho_{\max} & else\end{cases} \tag{6}$$

$$\sigma=\frac{NC}{NC_{\max}} \tag{7}$$

In the formula, $NC_{\max}$ is the maximum iteration number; NC is the current iteration number; $\rho_{\min}$ is the initial attenuation coefficient; $\rho_{\max}$ is a constant of (0,1).

3.3 The threshold of a pheromone

After the improved information number updating strategy, the search efficiency of the algorithm and the quality of the optimal solution are improved to varying degrees, but the improved algorithm also has the disadvantage of premature convergence[17-19].In order to solve the problem of premature convergence of the algorithm mentioned above, the strategy of limiting pheromone threshold is introduced. Specifically, the upper and lower thresholds of the optimal path information number global update in each iteration are defined by formula (8) .

$$\tau_{ij}=\begin{cases}\tau_{\min}, \tau_{ij}\le\tau_{\min}\\ \tau_{ij}, \tau_{\min}<\tau_{ij}<\tau_{\max}\\ \tau_{\max}\ , \ \tau_{ij}\ge\tau_{\max}\end{cases} \tag{8}$$

In this paper, the ant colony algorithm is improved by defining the threshold value of pheromones to increase the global significance of the optimal solution and to disperse the distribution of pheromones in various sections of road by using the expansion of ant colony search range, so as to effectively avoid the algorithm falling into the local optimal solution and stagnating.

4 Algorithm simulation analysis

In order to verify the effectiveness and feasibility of the improved method in this paper, the traditional ant colony algorithm, the improved ant colony algorithm and the improved adaptive ant colony algorithm were respectively simulated on the Matlab software platform. The simulation parameters were shown in table 1. The simulation results were compared and analyzed.

Table 1 parameter setting

parameter	Traditional ACS	Modified ACS	Self-adapting ACS
m	50	50	50

α	1	1	1
β	2	2	2
q_0	0.8	0.8	0.8
ρ	0.1	0.1	0.1
τ_0	0.003	0.003	0.003
$NC_{\max}$	500	500	500

The optimized path is shown in figure 2, where the yellow line is the initialization path, the green line is the optimized path, and the optimized path is obviously better.FIG. 3, FIG. 4 and FIG.5 respectively show the evolution curves of traditional ant colony algorithm, improved ant colony algorithm and improved adaptive ant colony algorithm.

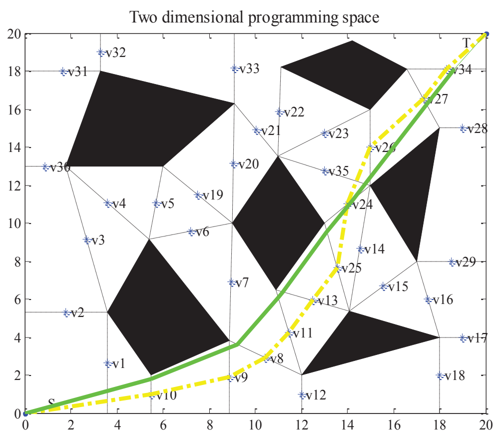

Fig 2.Path planning results

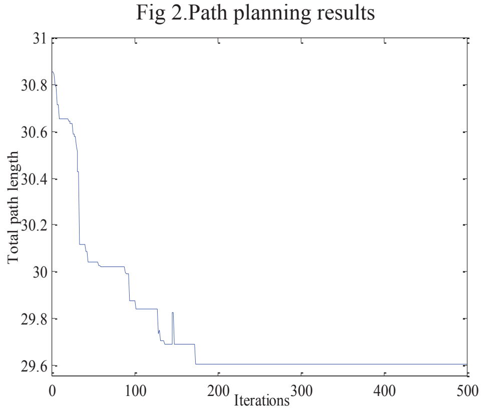

Fig 3.Evolution curve of traditional ant colony algorithm

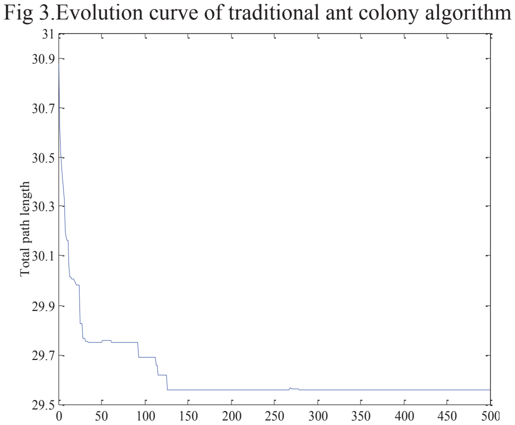

Fig 4.Improved ant colony algorithm evolution curve

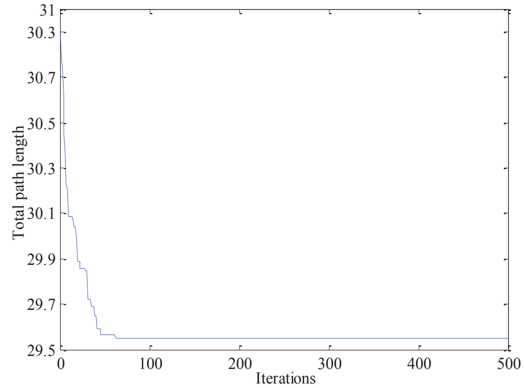

Fig 5.Adaptive ant colony algorithm evolution curve

Fig.2 is the result of path planning. Fig.3, Fig.4 and Fig. 5 are the evolution curves of traditional ant colony algorithm, improved ant colony algorithm and improved adaptive ant colony algorithm respectively.The simulation results show that the improved adaptive ant colony algorithm has better convergence speed and stability than the first two algorithms.

Table 2 algorithm comparison

	Traditional ACS	Improved ACS	Adapative ACS
Average path length	30.34	30.12	29.72
Optimal path length	28.45	27.94	27.58
Error/%	3.2	1.3	0
Iterations	89	182	75
Running time	6.4315	6.3922	6.4194

5 CONCLUSION

Traditional ant colony algorithm has longer search time in robot path planning, and is easy to fall into local optimal problems. To solve these problems, this paper proposes an adaptive path planning method, which dynamically limits the attenuation coefficient of pheromone according to the number of iterations, and defines the maximum and minimum attenuation coefficient.Experiments show that the improved algorithm improves the search efficiency, accelerates the convergence speed, and effectively avoids the problem of local optimal solution and stagnation.However, under special circumstances, there are still some deficiencies in the adaptive function of the limited attenuation coefficient, and its theoretical model will be studied and improved in the following work.

REFERENCES

[1] Liu Mingxia, You Xiaoming, Liu Sheng. Adaptive dynamic chaotic ant colony algorithm based on degree of aggregationComputer Engineering and Applications[J], Computer Engineerin and Applications,Vol 55, No.3,15-22,2019.

[2] Zhou lijuan. Path Planning of Agent Based on Adaptive Dynamic Programming and Ant Colony Algorithm[J], Journal of North University of China (Natural Science Edition), Vol 39,No.6,733-739,2018.

[3] Xu Yina,Wang Xuren,Su Hongli, Dynamic Path Planning Algorithm in Time lependent Road Networks [J]. Journal of Chinese Computer Systems, Vol.5, No.5, 1291-1298, 2018.

[4] Long Zhuoqun,Wu Chao,Lei Rixing. Intelligent planning method for mobile robot to avoidmultiple static obstacles path[J]. Automation & Instrumentation,Vol.1 No.10, 178-181+184,2018.

[5] Gu Junhua, Meng Huijie, Xia Hongmei,et al. Research on multi-robots path planning of robot basedon improved ant colony algorithm [J]. Journal of Hebei University of Technology, Vol.45, No.5, 103-119, 2016.

[6] Guo Ruiqin,Wang Xiaoyun. Research on mathematical model of downhole fire emergency rescue path planning based on laser guidance [J].Laser Journal, Vol.39, No.10, 101-110,2018.

[7] Du Yingfeng, Chen Wanmi, Fan Binbin. Research and application of swarm intelligence algorithm in path planning [J]. Electronic Measurement Technology, Vol.39, No.11, 65-70, 2016.

[8] Tan Yuxin,Yang Wei,Xu Zirui. Three-limensional path planning method for robot in underground local complex space[J]. Journal of China Coal Society,Vol.42, No.6, 1634-1642,2017.

[9] Tian Shuicheng, Yang Xingbo, Zhang Detao. Simulation Research on Optimum Escape Route in Mine Based on MATTAR[J]. Coal Technology, Vol.37, No.10,1634-1642, 2018.

[10] Zheng Yimin. Route Scheduling System of Garbage Truck Based on MMAS [J]. Instrumentation Technology, No.8, 33-35,2018.

[11] Zheng Yanbin, An Deyu, Li Na, et al.Three-limensional path planning method for robot in underground local complex space[J]. Journal of Shanxi University,Vol.40, No.4, 690-701,2017.

[12] Zhao Kaixin,Sun Xanlang,fang Dongshu,et al. Mobile Robot Path Planning with Improved Ant Colony Algorithm [J]. Bulletin of Science and Technologs,Vol.33,No.9,76-79, 2017.

[13] Wang Xiaoyan,Yang Le, Zhang Yu. Robot path planning based on improved ant colony algorithm withpotential field heuristic[J]. Control and Decision,Vol.33,No.10,1775-1781, 2018.

[14] Li Longshu,Yu Huan. Improved Ant Colony Algorithm in Complex Environments on the Robot Path Planning [J]. Journal of Chinese Computer Systems, Vol.38, No.9, 2067-2071,2017.

[15] Wang Jiejun, Liu Jiangkuan, Huang Xijun. Test path scheduling of digital microfluidic biochips based on combined genetic and ant colony algorithm [J]. Journal of . Electronic Measurement and Instrumentation, Vol.31, No.8, 1183-1191, 2017.

[16] Zhou Lingyun,Ding Lixin,Zou Zhenping. Ant Colony Optimization with Multi-Heuristic Information for Sampling Inspection Path Planning Problem [J]. J. Wuhan Univ, (Nat. Sci. Ed.), Vol.63, No.5, 439-447,2017.

[17] Pan Xin, Wu Xushen, Hou Xin. Global path planning based on geneti}ant hybrid algorithm for AUV [J]. J. Huazhong Univ, of Sci. & Tcch. (Natural Scicncc Edition), Vol.45, No.5, 45-49+76,2017.

[18] Liu Tao, Zhang Xin, Li Qinchuan. Indoor navigation path optimization algorithm considering visibility of landmarks [J]. Ucomatics and Information Scicncc of Wuhan University, Vol.42, No.1, 43-48,2017.

[19] Tan Yuxin,Yang Wei,Xu Zirui. Three-limensional path planning method for robot in underground local complex space [J]. Journal of China Coal Society, Vol.42, No.6, 1634-1642,2017.