Research on Static Path Planning for Mobile Robot Based on Improved Ant Colony Algorithm

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Abstract. This paper proposes enhancements to the traditional ant colony optimization (ACO) algorithm for path planning. Firstly, it improves the heuristic function by combining current step size ε and the Euclidean distance of the endpoint μ, strengthening path directionality. Secondly, it updates pheromone volatilization dynamically, enhancing convergence. Compared to the classical ACO, the improved algorithm increases the likelihood of ants choosing optimal paths, avoids local optima, and enhances convergence speed and global search ability.

Keywords: Mobile Robot; Path Planning; Ant Colony Algorithm; Heuristic Function;

1 INTRODUCTION

Mobile robot path planning is an important part of the research field of robotics[1]，It is widely used in unmanned vehicles, navigation systems, warehousing and logistics and other fields. Scholars at home and abroad have done a lot of research on robot path planning algorithms, and the commonly used algorithms include A* algorithm[2]、particle swarm algorithm[3]、ACO algorithm[4]。Among them, the ant colony algorithm has the characteristics of robustness and parallelism, which has been favored by a large number of scholars. With the deepening of the research, it is found that the ant colony algorithm also has the shortcomings of slow convergence, low search efficiency and easy to fall into the local optimum, inspired by the above studies, this paper adopts the following improvement strategies for the classical ACO algorithm, which is generally easy to fall into local optimization and prone to stagnation and other shortcomings.

Firstly, the heuristic function is improved by combining the current step length and the Euclidean distance of the end point, and the directionality of the search path is strengthened by referring to the front position factor ε and the end position factor μ. Secondly, the pheromone volatilization degree is changed to a dynamic updating method, which makes the algorithm possess better convergence[5].

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2 MODELING OF ROBOTIC WORKING ENVIRONMENTS

Path planning is crucial for mobile robots, involving finding a safe, collision-free path from start to end in complex environments. Global path planning does this in static environments with known global information, while local path planning adapts to dynamic environments, updating based on sensor data when environment knowledge is limited or absent[6]. Robot path planning is complex and multi-constraint. Environment representation methods include raster maps, feature maps, direct representation, and topological maps[7]. Among them, the raster map method of modeling has the characteristics of simplicity, ease of implementation, and intuitiveness, so the raster map method is chosen for environment modeling in this chapter[8]. The raster map method assigns 0 to obstacle-free areas and 1 to areas with obstacles, simplifying the physical environment into a binary matrix. See Figure 1 for an example.

Raster decomposition of the x, y coordinate axes and general coordinate axes in the same order of increasing. There are i rows and m columns in the raster decomposition diagram, and the length of a single raster is 1. The center coordinate of each raster can be expressed as shown in equation (1).

$$\begin{cases} x_i = 1 * (bomd(i,m) - 0.5) \\ y_i = 1 * \left(m + 0.5 - ceil(i/m)\right) \end{cases} \tag{1}$$

In equation (1), xi and yi represent the horizontal and vertical coordinates of the center of the point; mod(*) represents the remainder of the division; and ceil(*) represents the closest number of each element rounded up to a number greater than or equal to this element.

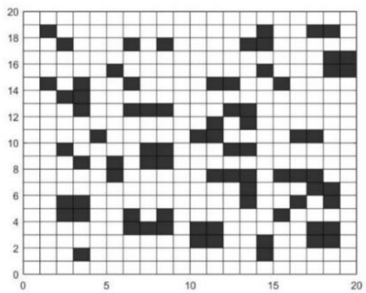


Fig. 1. Mobile robot environment model

In addition, in general, when the robot moves within the range of the grid, its trajectory direction can be simplified and equated to 8 directions, as shown in Fig.2.

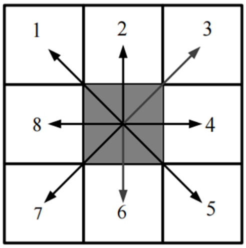


Fig. 2. Robot movement direction diagram

3 CLASSICAL ANT COLONY ALGORITHM (ACO)

3.1 Algorithmic Principle

The ant colony algorithm mimics the behavior of ants when searching for food, and achieves path search by releasing and sensing pheromones. The algorithm uses a positive feedback mechanism to make paths with high pheromone concentration more preferred by ants, while the pheromone evaporates over time to avoid falling into a local optimum. In the algorithm, ants select paths according to the pheromone concentration and heuristic information, and keep searching iteratively until the stopping condition is satisfied. This algorithm is suitable for solving problems such as combinatorial optimization and path planning, and shows good results when dealing with complex search spaces.

3.2 Algorithm Formula

According to the operation process of the ant colony algorithm, there are a total of M ants, and the ants k (k = 1, 2, ..., M) will be influenced by the pheromone concentration to choose the next path to visit, p_{ik}^{k} (t) denotes the probability that ant k moves from grid i to grid j at time t. Its calculation formula is shown in equation (2) and (3).

$$p_{ik}^{k} = \begin{cases} \frac{[\tau_{ij}(t)]^{\alpha} \cdot [\eta_{ij}(t)]^{\beta}}{\sum_{s \in allowed_k} [\tau_{ij}(t)]^{\alpha} \cdot [\eta_{ij}(t)]^{\beta}}, s \in allowed_k \\ 0, s \notin allowed_k \end{cases} \tag{2}$$

$$\eta_{ij} = 1/d_{ij} \tag{3}$$

In equation (2), $\tau_{ij}(t)$ denotes the pheromone concentration on i to j at time t; and $\eta_{ij}(t)$ is the heuristic function, denotes the expectation level of the ants from i to j; allow denotes a map point that belongs to the one that can be traveled; and α denotes the pheromone importance factor; the β denotes the heuristic function important factor. While the ant colony will leave the pheromone after passing through a certain path, the original pheromone concentration will slowly decrease, and the set parameter ρ(0 < ρ < 1) denotes the volatilization degree of the pheromone. Therefore, after cycling once, the pheromone concentration on each path that has been traveled will change, and its formula is shown in equation (4).

$$\begin{cases} \tau_{ij}(t+1) = (1-\rho) * \tau_{ij}(t) + \Delta\tau_{ij} \\ \Delta\tau_{ij} = \sum_{k=1}^{n} \Delta\tau_{ij}^{k} \end{cases}, 0< \rho < 1 \tag{4}$$

In equation (4). $\Delta\tau_{ij}^{k}$ denotes the pheromone left by the kth ant when i passes through the j-path. $\Delta\tau_{ij}$ denotes the sum of pheromone concentrations left behind by the ants that have passed through i to j.

4 IMPROVEMENT OF ANT COLONY ALGORITHM

4.1 Improvement of the Heuristic Function

The heuristic function in the ant colony algorithm usually considers only the Euclidean distance to the endpoint, which is too simplistic and prone to local optima. By incorporating the distance from the current position to the next selectable position into the formula, the path search directionality is improved. Adding position factors allows flexible adjustment of distance weights. See equation for details. (5).

$$\eta_{ij} = \frac{1}{(\varepsilon * d_{is} + \mu * d_{jE})^{\frac{3}{2}}} \tag{5}$$

In equation (5), d_{is} denotes the Euclidean distance from the current node and the next node to be selected; d_{jE} denotes the Euclidean distance from the next to-be-selected node to the endpoint of E; ε denotes the current position factor; μ denotes the end position factor.

4.2 Improvement of Pheromone Volatilization

Through pheromone release and volatilization, the ant colony gradually converges to better solutions while exploring the solution space extensively to find the global optimum. Dynamically updating pheromone volatilization enhances path exploration, with decreasing volatilization leading ants toward paths with higher pheromone concentration, boosting convergence speed. See equation for details(6).

$$\rho(t+1) = \frac{t}{T} \times \frac{1}{e^{|1-\rho(t)|}} \tag{6}$$

In equation (6), T represents the total number of iterations; t represents the current number of iterations.

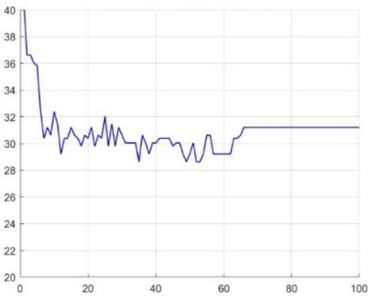
5 SIMULATION EXPERIMENT VERIFICATION AND ANALYSIS

5.1 Simulation Experiment Parameters

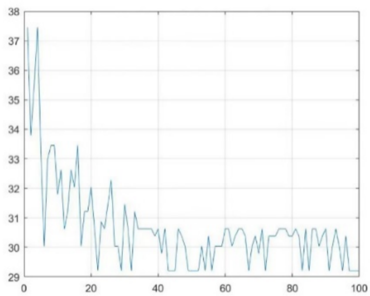
In order to verify the feasibility and effectiveness of the improved ACO algorithm, the improved ACO algorithm in this chapter is compared with the traditional ACO algorithm. MTALAB2022a programming software is chosen to program the improved ACO algorithm and conduct simulation experiments. The operating system is Windows 11, the processor is AMD R7-6800H CPU, the memory is 16 GB, and the start point and the end point are set at the upper left and lower right of the raster decomposition graph respectively. Basic algorithm parameters: number of iterations K= 100 ; Number of ants M= 50 ; Pheromone importance factor α = 1. 2; Starting position factor ε = 0. 4; endpoint position factor μ = 0. 6; Heuristic function significant factor β = 8; Degree of pheromone volatilization ρ = 0. 6。

5.2 Raster Decomposition Map Simulation

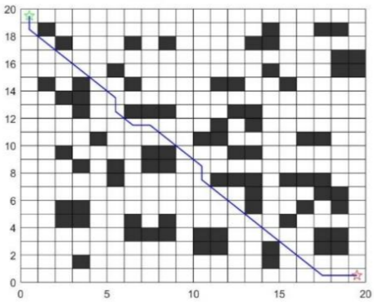
Based on the parameter indexes given in the table, simulation experiments are carried out on the classical ACO and the improved ACO algorithm using the grid decomposition graph of 20×20 fixed obstacles, and the results are shown in Fig. 3 and Fig. 4, and the results are compared. From the simulation results, the optimal path length and the number of iterations of the improved ACO algorithm are 28. 62 m, which are 9.39% less than that of the classical ACO algorithm. The simulation results show that the convergence speed of the improved ACO algorithm is higher than that of the classical ACO algorithm, and at the same time, it is easy to see that its indexes are more superior.



(a) Convergence curves

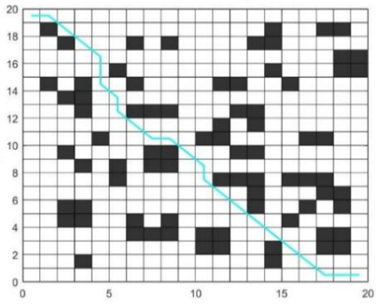


(a) Convergence curves



(b) Trajectories

Fig. 3. Trend and movement of convergence curve of classical ant colony algorithm



(b) Trajectories

Fig. 4. Trend of convergence curve and movement trajectory of improved ACO algorithm

6 CONCLUSION

In summary, this paper through two groups of comparison experiments in the 20 × 20 raster decomposition map of the optimal path length of path planning, the number of iterations to find the optimal path and other data, it shows that the improved ant colony algorithm can effectively reduce the number of iterations of the optimal path to speed up the convergence speed, increase the smoothness of the planning trajectory and other aspects are better than the classic ant colony algorithm, and the classical ant colony algorithm in dealing with the more complex maps will be In addition, the classical ant colony algorithm will have various problems when dealing with more complex maps, which proves the practicality of this algorithm in solving the path planning problem[9]. This improvement can enable the robot to select paths more accurately and ensure its stable operation and safe operation in various complex environments[10].

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