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

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Abstract. Due to the influence of full traversal environment, the path length obtained by existing methods is too long. In order to improve the performance of path planning and obtain the optimal path, a full traversal path planning method for omnidirectional mobile robots based on ant colony algorithm is proposed. On the basis of the topology modeling schematic diagram, according to the position information of the mobile robot in the original coordinate system, a new environment model is established by using the Angle transformation. Considering the existing problems of ant colony algorithm, the decline coefficient is introduced into the heuristic function to update the local pheromone, and the volatility coefficient of the pheromone is adjusted by setting the iteration threshold. Finally, through the design of path planning process, the planning of omnidirectional mobile robot's full traversal path is realized. Experimental results show that the proposed method can not only shorten the full traversal path length, but also shorten the time of path planning to obtain the optimal path, thus improving the performance of full traversal path planning of omnidirectional mobile robot.

Keywords: AGV; Path planning; Transition probability

1. Introduction
In recent years, the field of artificial intelligence has developed rapidly, and mobile robot path planning [1] has been widely used in autonomous driving, logistics sorting and transportation and other fields. The path planning of mobile robots has been widely studied at home and abroad. Common algorithms include genetic algorithm, neural network algorithm, A* algorithm, etc. Each optimization method has its own advantages, but also has obvious disadvantages [2]. AntColony algorithm is used to solve assignment problem, traveling salesman problem and vehicle routing problem [3,4]. It adopts distributed parallel computing mechanism, has many advantages, such as strong robustness, easy to combine with other algorithms, etc., and has been widely concerned by researchers. However, the ant colony algorithm also has the disadvantages of slow convergence speed, low search efficiency and long time, and easy to fall into the local optimum, which is not conducive to the efficient and high-precision solution of optimization problems. Aiming at the above problems, this paper proposes an improved ant colony algorithm, which improves the local part of the algorithm to improve the search efficiency and optimization ability.
2. Problem description and environment modeling

When the mobile robot undertakes a task, it first establishes the environment model according to the surrounding environment information, and then uses its own algorithm to locate and avoid the obstacles in the environment, so as to obtain the optimal path. To optimize the path of mobile robot, it is necessary to carry out the digital modeling of the robot's motion space, that is, the transformation between the motion space and the mathematical model, so as to facilitate the recognition and analysis of the robot. The robot path planning problem in this paper satisfies the following conditions: 1) the robot motion space is a two-dimensional finite space, and the position of obstacles in the space is known; 2) Obstacles are randomly distributed in the robot motion space, and their size does not change, so their height is ignored; 3) The collision between robot and robot or between robot and obstacle is not considered; 4) The starting position and target position of the robot are known. Finally, through path planning, the mobile robot can find the optimal path in the built environment model.

The raster method is simple and easy to implement, and it is a commonly used method for environment modeling in robot path planning [5,6]. A grid of the same size is used to divide the working area of the robot's motion space, and the robot is idealized into a particle point to ensure that all the resting positions of the robot are in the center of the grid. The grid in the two-dimensional motion space is divided into black grid and white grid. The white grid represents the walkable grid and is represented by 1. The black grid represents the obstacle grid, denoted by 0. Divide the two-dimensional space created into equal parts and number each grid in the order from left to right and top to bottom [7]. Fig. 1 shows the environment model constructed by the grid method.

![Figure 1. Environmental model](image)

The coordinate mathematical expression of each grid point is:

\[
\begin{align*}
x_i &= b \times (\text{mod}(i, MM) - 0, 5) \\
y_i &= b \times (MM + 0.5 - \text{ceil}(i/MM))
\end{align*}
\]

Where \(b\) is the side length of the grid; mod is the remainder; \(MM\) is the map dimension; ceil is rounded to positive infinity; \(x_i, y_i\) are the coordinate positions of each grid.

3. Traditional ant colony algorithm

Ants, searching for a food source, release a pheromone in their path and sense the pheromone left by other ants. The pheromone concentration represents the distance of the path. The higher the pheromone concentration, the shorter the distance of the corresponding path; otherwise, the longer the path. Ants often preferred pheromone concentration at larger probability higher path and release a certain amount of pheromone, to enhance the pheromone concentration of this path, and at the same time path pheromone
concentration will gradually decay over time, the choice of ants paths form a positive feedback, in the end, the ants will be able to find a optimal path from the nest to the food source, Namely, the shortest distance [8]. Fig. 2 is the optimization schematic diagram of ant colony algorithm.

FIGURE 2. Optimization principle of ant colony algorithm

The execution steps of robot path planning in traditional ant colony algorithm can be described as follows: using grid method to build robot environment model and initialize parameters. When the ant transfers from the current node $i$ to the next node $j$ according to the pheromone concentration in each position (initial pheromone concentration is constant, that is $\tau_0 = C$), the position of node $j$ is selected according to the functional equation (2):

$$
P_{ij}^k = \frac{[\frac{\tau_0(i,j)}{\eta_0(i,j)}]^{\alpha} [\frac{\eta_0(i,j)}{\tau_0(i,j)}]^{\beta}}{\sum_{k \in \text{allow}_k} [\frac{\tau_0(i,j)}{\eta_0(i,j)}]^{\alpha} [\frac{\eta_0(i,j)}{\tau_0(i,j)}]^{\beta}}, \quad j \in \text{allow}_k
$$

(2)

Where $\tau_{ij}(t)$ is the pheromone concentration between grid nodes $i$ and $j$; $\eta_{ij} = 1/d_{ij}$ is the heuristic function, which indicates the expected degree of ants walking from node $i$ to node $j$. $d_{ij}$ is the distance between grid nodes $i$ and $j$; $\text{allow}_k$ is the set of nodes to be visited in the next step; $\alpha$ It is the pheromone importance factor; $\beta$ It is the importance factor of heuristic function.

After a certain period of time, when all the ants of a certain generation have finished their path finding, the pheromone concentration is updated according to equations (3) to (5) $\tau$:

$$
\tau_0(i,j)(t+n) = (1-\rho)\tau_0(i,j)(t) + \Delta \tau_0(i,j)
$$

(3)

$$
\Delta \tau_0(i,j) = \sum_{k=1}^{n} \Delta \tau_0^k(i,j)
$$

(4)

$$
\Delta \tau_0^k(i,j) = \begin{cases} Q/L_k, & \text{if } k \text{ ants pass the path } i \text{ in this cycle} \\ 0, & \text{otherwise} \end{cases}
$$

(5)

Where $\Delta \tau_0^k(i,j)$ is the pheromone concentration of ants on the path from grid $i$ to grid $j$; $Q$ Is pheromone volatilization coefficient; $Q$ is the intensity coefficient of pheromone increase; $L_k$ is the path length of ant $k$ from the starting point to the target point. Until the specified number of iterations is reached, the optimal solution is obtained and the optimal path is output.
4. Improved ant colony algorithm

4.1. Heuristic function
Heuristic function in ant colony algorithm $\eta_{ij}(t) = 1/d_{ij}$, which indicates that the expected degree of ants walking from node $i$ to grid $j$ is related to the distance between nodes. If the number of iterations is too small, the algorithm may not be able to find the optimal path. However, with the increase of the number of iterations, the time-consuming of the algorithm increases, resulting in slow convergence speed.

In this paper, the influence of heuristic function on the algorithm is studied $\eta_{ij}(t)$ is improved to guide the direction of ants from grid $i$ to grid $j$, and enhance the expectation of walking. The improved heuristic operator is $\eta_{ij}(t) = (1/d_{ij})^{3}$, which greatly increases the effectiveness of the algorithm, improves the efficiency of the algorithm, shortens the convergence time, and makes the ant faster to search the optimal path.

4.2. Improvement of initial pheromone concentration
In the initial parameter stage of the algorithm, when setting the pheromone concentration matrix $T_{au}$, all possible paths are set to the same value, but the path finding of the ant colony algorithm is the process of ants from the beginning to the end, so the pheromone concentration value can be set higher than other positions in the path of the beginning and the end, and around it, which can help to enhance the attraction of the optimal path to the ant colony, Accelerate the convergence speed of the optimal solution.

4.3. Pheromone volatilization factor $\rho$
The improvement of the ant colony will leave pheromone on its walking path, and the pheromone concentration will not remain unchanged, but will volatilize with time. Pheromone volatilization factor represents the volatilization rate of ant colony pheromone. The pheromone volatilization speed of traditional ant colony algorithm is constant in the routing process. The volatilization factor of ant colony algorithm is related to convergence speed and global search ability $\rho$. If the value of $\rho$ is too small, the ants will choose the path they have passed again and fall into local optimum; On the contrary, if $\rho$ is too large, the global search ability of the algorithm will be improved, but the iteration time of the algorithm will be greatly increased, resulting in the decrease of convergence speed. The improved pheromone volatilization factor proposed in this paper is related to the iteration times, so that the pheromone volatilization factor is reduced $\rho$. The number of iterations $k$ obeys Gaussian distribution. Improved pheromone volatilization factor $\rho$ by:

$$\rho(k) = \frac{1}{\sigma \cdot 2\pi} \cdot \exp\left(\frac{(k-\mu)^2}{2\sigma^2}\right) - \alpha$$  \hspace{1cm} (6)

Here K is said to obey the parameter $\sigma, \mu$. Where $\sigma, \mu, \alpha$ can be adjusted adaptively according to the number of iterations; this paper $\sigma, \mu$ The values are 7.4 and 90 respectively; $k$ is the number of iterations.

In this way, ants have different pheromone volatilization factors in different iterations $\rho$. According to the number of iterations, the algorithm is divided into pre, middle and post. In the early stage of ant colony routing, that is, when the number of iterations is in $[0, 0.4k]$, the pheromone volatilization factor is small and shows an increasing trend, and the path selection of ant colony is mainly based on the initial pheromone concentration; With the increase of iteration times, pheromone volatilization factor increases $\rho$. When the number of iterations is in the range of $[0.4k, 0.7k]$, the amount of pheromone on each path reaches a certain degree, and the pheromone volatilization factor is higher $\rho$. In other words, pheromone volatilization of each path is fast, which is convenient for ant colony to carry out global search; When the number of iterations is in $[0.7k, k]$, the pheromone volatilization factor decreases $\rho$. With the number of iterations $k$ decreasing, that is, in the later stage of the algorithm, the ant colony has basically found
the optimal path and reduced the pheromone volatilization factor $\rho$ Accelerate the convergence speed of the optimal path.

5. Simulation and analysis

In order to verify the performance of the optimization algorithm, the correctness and effectiveness of the improved ant colony algorithm are tested on MATLAB, and the actual effect of path planning using traditional ant colony algorithm and improved ant colony algorithm is compared. Using grid method to build two-dimensional grid map, the environment model is $20 \times 20$ grid. The unit grid length is 1, the total length is 20, the robot is set to (0.5, 19.5), and the end point is (19.5, 0.5). During the experiment, the number of ants ($m$ value) was set to 60. Set simulation parameters: 200 iterations, pheromone importance factor $\alpha = 1$, Heuristic function importance factor $\beta = 6.8$, pheromone increase intensity coefficient $Q = 1$, pheromone Volatilization Coefficient of traditional ant colony algorithm $\rho = 0.5$. Improved ant colony algorithm $\rho$ For the above adaptive parameters, the traditional ant colony algorithm and the improved ant colony algorithm set the same number of ants. In this paper, the traditional ant colony algorithm and the improved ant colony algorithm are simulated and tested several times, and the test results are shown in Table 1.

| ALGORITHM                        | CONVERGENCE ALGEBRA | OPTIMAL DISTANCE |
|----------------------------------|----------------------|------------------|
| TRADITIONAL ANT COLONY ALGORITHM | 166                  | 30.4589          |
| IMPROVED ANT COLONY ALGORITHM    | 31                   | 28.2132          |

It can be seen from table 1 that the convergence algebra and optimal distance of the improved ant colony algorithm are reduced compared with the traditional ant colony algorithm, the convergence algebra of the improved ant colony algorithm is reduced by 135 generations, and the optimal distance is reduced by 2m.

In order to analyze the test process and simulation results more intuitively, the convergence algebra of the optimal path and the trajectory of the mobile robot are visualized, as shown in Fig. 3.

As can be seen from Fig. 3 (a1) and (b1), both algorithms can plan obstacle free path for mobile robot. From the trajectory diagram of robot path, traditional ant colony algorithm is better
The improved ant colony algorithm has less turns and smoother trajectory. From the point of convergence algebra, the traditional ant colony algorithm has slow convergence speed, unstable convergence performance and low search efficiency. The improved traditional ant colony algorithm obviously improves the convergence speed, the convergence performance is more stable, the search efficiency is higher, and the global optimization ability is improved, which shows that the improved ant colony algorithm has obvious advantages in mobile robot optimization.

6. Concluding remarks
This paper analyzes the shortcomings of traditional ant colony algorithm by establishing the environment model, and improves the traditional ant colony algorithm in terms of pheromone heuristic function, pheromone initial value and pheromone volatilization factor. Through MATLAB simulation, the simulation results show that the improved ant colony algorithm has obvious improvement in convergence speed, global optimization, and optimal path distance compared with the traditional ant colony algorithm, which proves the effectiveness and feasibility of the algorithm.

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