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

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Abstract. Path planning of mobile robots is an important research content in mobile robot design. In view of the characteristics of classic ant colony algorithm, such as long distance, low efficiency and easy to fail into dead zone, a new pheromone updating algorithm and global/local pheromone distribution models are proposed. The grid method is used to construct two-dimensional plane space with obstacles and the simulation experiment is carried out. The simulation results show that under the improved algorithm, the robot path planning efficiency is high and the path distance is short, which verifies the validity of the model.

Keywords. Ant colony algorithm; robot; path planning; pheromone.

1. Introduction

With the development of artificial intelligence theory and technology, intelligent mobile robots are applied more and more in express parcel sorting, library book picking/delivering and warehouse intelligent handling [1-3]. The improvement of the complexity of mobile robot working environment also puts forward higher requirements for its path planning [4-6]. Therefore, it is of great practical significance to study the path planning of mobile robots [7].

Ant colony algorithm (ACA) is a kind of swarm bionic intelligent algorithm, which was first proposed by Italian scholar MaroDorigo [8]. However, it has some problems, such as long operation time, low efficiency, large average distance of planning path, and robots are easy to fall into U-shaped area. Some scholars put forward some improvement suggestions on the basis of classical algorithm [9]. In reference [10], in order to improve the convergence speed of the algorithm, a heuristic function with bidirectional search direction mechanism and scale coefficient guidance factor is proposed; In reference [11], in order to solve the problem of suboptimal, the heuristic factor of traditional ant colony algorithm is improved, and the survival mechanism is proposed; In reference [12], a new heuristic function is constructed to improve the performance of the algorithm; In order to improve the convergence of the algorithm, a new pheromone concentration setting model was established in reference [13].

This paper improves the path distance of traditional ant colony algorithm, changes the pheromone distribution rules, establishes the pheromone distribution model, and compares the path length of the improved algorithm with that of the classical algorithm through simulation experiments, which proves the effectiveness of the improved algorithm. The experimental results show that the improved algorithm is still applicable in more complex raster maps.
2. Classical Ant Colony Algorithm

The core of ant colony algorithm is to simulate the foraging behavior of ants in nature, that is, the path selection from nest to food. This is not done by one ant, but by several ants passing through the previous ants in the path in batches, leaving behind a substance called pheromone. The ants perceive the pheromone concentration and determine the direction. Set as $m$ is the number of all ants in the ant colony algorithm. At the moment $t$, the transition of ants named $k$ from one node which named $i$ to another node which named $j$ is determined by the pheromone concentration $p^k_{ij}(t)$.

$$p^k_{ij}(t) = \begin{cases} \frac{[\tau_{ij}(t)]^\alpha[\eta_{ij}(t)]^\beta}{\sum_{k \in \text{allowed}_j} [\tau_{ij}(t)]^\alpha[\eta_{ij}(t)]^\beta} & j \in \text{allowed}_i \\ 0 & j \notin \text{allowed}_i \end{cases}$$

(1)

Among them, $\text{allowed}_i$ represents the node set that ants which named $k$ can choose when they move to the next node at the moment $t$. The set can be called taboo list also. $\alpha$ is pheromone heuristic factor and represents pheromone weight. $\tau_{ij}(t)$ is the information density function at the moment $t$. $\beta$ expresses the expected heuristic factor. $\eta_{ij}(t)$ is the distance heuristic function. The formula is as follows:

$$\eta_{ij} = \frac{1}{d_{ij}}$$

(2)

$$d_{ij} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}$$

(3)

$d_{ij}$ is the distance from current node to next node. When $m$ ants complete a path search, they complete an iteration and calculate the path length $L$ of each ant. And update pheromone according to equations (4)-(6). Because pheromones in the path will evaporate naturally, let the volatilization coefficient be $\rho(0 < \rho < 1)$.

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

(4)

$$\Delta \tau_{ij}(t) = \sum_{k = 1}^{m} \Delta \tau^k_{ij}(t)$$

(5)

$\Delta \tau^k_{ij}$ is the pheromone left by ant $k$ between node $i$ and node $j$ in this search. Ant cycle model is used in this paper according to equation (6), where $Q$ is the pheromone strength and $L_k$ is the path length of the ant $k$ in this search.

$$\Delta \tau^k_{ij} = \begin{cases} \frac{Q}{L_k} & \text{from } i \text{ to } j \\ 0 & \text{otherwise} \end{cases}$$

(6)

3. Simulation Environment Modeling

The grid method is used to model the mobile robot’s active environment. The black area represents the obstacle, and the white area represents the passable area of the robot. The robot is represented by the particle, that is, the influence of the size of the robot is ignored. Referring to the actual environment, the small obstacle with the size less than half a grid is ignored; Obstacles that exceed half of the cut are regarded as a grid size. In this way, the position of obstacles in the grid map designed according to
the actual environment is closer to the actual working environment of the robot. Take the 20*20 grid map as an example, as shown in figure 1. Label each grid. The grid numbers from the top left to the bottom right are 1, 2, 3... 400. Set the start grid position (node $i$) and end grid position (node $j$) of the robot. When the robot moves to a grid, remove the last grid direction, and select any non obstacle grid moving in the direction near the current position.

![Figure 1. 20*20 grid map.](image)

### 4. Improved Ant Colony Algorithm

Applying ant colony algorithm to path planning, the important point that affects the quality of path planning is the distribution of pheromones in the path. In view of the shortcomings of the classical ant colony algorithm, this paper mainly proposes the optimization algorithm for the initial distribution of pheromones, update rules and volatilization rules, and establishes the dynamic distribution model of pheromones.

#### 4.1. Optimization of Initial Pheromone Distribution

The initial pheromone concentration of classical ant colony algorithm is a constant, which makes the path lose a priori message, increases the calculation amount of path information recognition, and changes the pheromone concentration distribution by using the prior knowledge of the path, that is, the grid pheromone concentration in the direction far away from the end node is increased, Ants can find a certain basis in the direction of forward, can move towards the direction of a shorter path from the end node, shorten the length of the planned path. The distribution rule of initial information degree is as follows equation (7).

$$\theta_i = \begin{cases} P & j = i - n - 1 \\ 2P & i = j - n = j - 1 \\ 4P & i = j - n - 1 \end{cases} \tag{7}$$

Equation (7) is based on the simulation of the actual situation after the establishment of the grid map. n is the number of rows of the grid, and $\theta_i$ represents the pheromone concentration in each direction of the path from grid $i$ to grid $j$. P is a constant. From the formula, it can be seen that the highest concentration of pheromone is in the line path between the starting point and the end point, and the opposite direction is not strengthened. According to such rules, the distribution of pheromone and the direction of robot movement are combined to make a distinction.

#### 4.2. Optimization of Pheromone Updating Rules

The advantages and disadvantages of ant colony algorithm to identify the path depend on the pheromone update rules. For shorter paths, more pheromones will be preserved in the same time. In order to optimize pheromone updating rules, local pheromone updating rules are added to update pheromones immediately (that is, the ants walk several times and update several times) according to equation (8).
In the equation (8), \( \sigma (0 < \sigma < 0.5) \) is the local pheromone volatilization coefficient. \( \Delta r_{ij}^{k} \) is the total amount of pheromones released by the \( k \)th ant in all the routes. \( \Delta r_{ij} \) represents the pheromone change of path \((i, j)\) in a single cycle. That is the sum of pheromones released by all ants passing through the path. In order to highlight the advantages of the shortest path, \( L_{\text{min}} \) is defined as the shortest path found at present. Then it optimizes the global pheromone (pheromone after all ants complete one iteration) according to equation (9).

\[
\tau_{ij}(t+1) = (1-u)\tau_{ij}(t) + u\Delta r_{ij}
\]

\[
\Delta r_{ij} = \begin{cases} 
\frac{Q}{L} + \frac{Q}{L_{\text{min}}} & (i, j) \in \text{bestpath} \\
\frac{Q}{L} & \text{otherwise}
\end{cases}
\]

In equation (9), \( u (0.5 < u < 1) \) is the global pheromone volatilization coefficient. \( L \) is the length of path searched by the current ant, and \( L_{\text{min}} \) is the shortest path. The improved pheromone update rule is always based on distance information, which greatly improves the performance of the algorithm.

### 4.3. Optimization of Pheromone Volatilization Rules

Pheromones released by ants are constantly volatilizing. The way to find the optimal path is not to continuously accumulate pheromones. For example, when a path has too many pheromones, it will ignore the consideration of other paths and fall into local suboptimal. Pheromone volatilization rules also have a strong influence on the efficiency of the algorithm and the ability of global path search. When volatilizing, we should not only keep the appropriate path information, but also avoid excessive volatilization, which results in the selection barrier for subsequent ants. Taking the path length as the dominant factor, the following rules are applied according to equation (10).

\[
\eta_{ij} = 1 - \frac{L}{L_{\text{min}}} \times \zeta
\]

In equation (10), \( L \) is the length of the path searched by the current ant, and \( L_{\text{min}} \) is the shortest path found at present. \( \zeta (0 < \zeta < 0.5) \) denotes the pheromone Volatilization Coefficient, which can effectively inhibit the excessive volatilization concentration. The improved information degree volatilization rule can dynamically give different weights to the volatilization concentration of different length path positions, which can store the optimal path information, and will not have excessive impact on the subsequent path selection of ant colony, so it can meet our requirements for the use of the algorithm.

### 4.4. Implementation Process of Improved Algorithm

The process of applying the improved ant colony algorithm is as follows in figure 2.
5. Simulation Experiment
The improved algorithm is compared with the classical ant colony algorithm in route planning and route distance. The initial parameters of the two algorithms are the same, the number of ants is 50, the maximum number of iterations is 500, the start grid position is 1, the end grid position is 400 (or 900), the pheromone weight factor is 1, the heuristic factor is 5, the pheromone volatilization coefficient is 0.4, and the pheromone enhancement coefficient is 100. Several experiments are carried out in a 20*20 grid map, and the simulation results of one experiment are shown in figures 3 and 4.

Figure 2. Flow chart of improved ant colony algorithm.

Figure 3. Path simulation and path length convergence curve of classical ant colony algorithm 20*20 grid map.
Figure 4. Improved ant colony algorithm 20*20 grid map path simulation and path length convergence curve.

It is not difficult to see from the figure that both algorithms can successfully search the path from the starting point to the end point, but the path length of the improved algorithm is small and the algorithm converges fast, as shown in table 1.

Table 1. Simulation comparison of two algorithms in 20 * 20 environment.

| Algorithm                  | Shortest path length | Average number of iterations | Average operation time (s) |
|----------------------------|----------------------|-----------------------------|----------------------------|
| Classical ant colony       | 30.00                | 200                         | 70.91                      |
| Improved ant colony        | 29.01                | 45                          | 63.28                      |

In the more complex 30*30 grid map in figures 5 and 6, the improved algorithm can complete the path planning. Compared with the classical ant colony algorithm, it shortens the path distance and improves the convergence speed.

Figure 5. Path simulation and path length convergence curve of 30*30 grid map based on classical ant colony algorithm.
Figure 6. Improved ant colony algorithm 30*30 grid map path simulation and path length convergence curve.

6. Conclusion
Based on the classical ant colony algorithm, an improved ant colony algorithm for mobile robot path planning is proposed. The improved algorithm establishes a new pheromone distribution model based on the path distance, which is used to improve the initial pheromone distribution, pheromone update rules and pheromone volatilization rules. The simulation results show that the advantages of the improved algorithm are mainly reflected in the reduction of the planned path distance and the number of iterations, which improves the performance of the algorithm. It provides an idea for the research of path planning of mobile robot.

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