Mobile Robot Path Planning Based on Multi-parameters Optimization Ant Colony Algorithm

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Abstract

The basic ant colony algorithm for mobile robot path planning has many problems, such as lack of stability, algorithm premature convergence, more difficult to find optimal solution for complex problems and so on. This paper proposes four improvement measures. 1. Apply genetic algorithm to optimization and configuration parameters of the basic ant colony algorithm; 2. Apply max min ant method to change pheromone update strategy; 3. For the ants fall into the trap causing stagnation problem, this paper proposes ant fallback strategy; 4. Add orientation function to enhance ant efficiency, reduce the time complexity of the algorithm. Simulation results show that the improved optimal path length significantly less than the basic ant colony algorithm and volatility is smaller, stability significantly improves. The stability of improved ant colony algorithm is superior to the basic ant colony algorithm, which verifies the effectiveness of the improvement measures.

Keywords: Ant colony algorithm, Mobile Robot, Path planning, Genetic algorithm

1. Problem description and definition

Mobile robot path planning is an important research field of robotics. It refers to that, the mobile robot in a work environment with obstacles, based on one or some optimization criterion, search for a motion path from the initial state to the target , state and the path is the optimal or near optimal, safe, obstacle avoidance[1].

In recent years, many scholars are committed to Path planning study based on intelligent method. The application of intelligent algorithms mainly includes ant colony algorithm, fuzzy methods, neural networks and genetic algorithms. [2-4] these methods improve the performance of path planning, but also exists the problem that the search space is large, algorithm is complex, efficiency and stability is poor and so on. This article considers the problems of ant colony algorithm in path planning, proposes an improved ant colony algorithm.

Robot movement environment which is studied in this paper is known two-dimensional flat space, and don’t take obstacles and the robot height information into consider. In the process of environment description, all the obstacles in the environment have done pretreatment which extend out each obstacles of the maximum radius of a robot. This allows considering the robot as a particle, thus ensuring the safety and greatly reducing the complexity of path planning algorithms.

This study aims to:
- In the known static environment, find a collision-free path connect the start and the end.
- Obstacle avoidance, meanwhile make the length of the path as short as possible
- Algorithm's time complexity is as low as possible, good stability.

2. Environmental modeling

Environmental modeling is an important part of the robot path planning. The essence of environmental modeling is, based on the known environmental information, through extraction and analysis of relevant characteristics; convert it into the feature space which robot can understand. There are many ways of environmental modeling, such as, grid method, vertex image method, and generalized cone method, the link diagram method, topology methods, geometric information method, etc. Grid method has been applied in many robot systems, and is a more successful method.
This article mainly uses grid method to divide the robot environment, two-dimensional grid represents environment, and encodes the grid from top to bottom, from left to right.

As shown in Figure 1, the grid is divided into two kinds, One is free grid, represented by white; the other is obstacle grid, represented by black. Robot can only move in the free grid, and must avoid when encounter obstacles grid.

Robot must according to the environment map to create a corresponding matrix which represents the state of each grid (free grid or obstacle grid). Only this, Robot can understand the environment. In this environment expression matrix, free grid is represented by 1, and obstacle grid is represented by 0. Each obstacle can occupy a grid, or can occupy multiple grids, less than one grid is also expressed by one grid.

3. Description and simulation of the basic ant colony algorithm

According to the basic principles of ant colony algorithm and path planning requirements, the basic idea can be simply described as follows: firstly, Set the basic parameters of the ant colony algorithm, including Information inspiration factor $\alpha$, and hope inspiration factor $\beta$, pheromone intensity $Q$ and evaporation coefficient $\rho$, etc. [5] Then put m ant at the starting point of the map(Number is 0), each ant take the starting point as the current node’ applied probability selection function, select the follow-up node, if the follow-up node which is to be selected, include the end node (number is N), end this tour, get a complete path. After each ant end the travel, partially update pheromone, and compare with the current optimal path. If the path obtained is shorter than the optimal path, then replace the optimal path with the current path. When all N ants end the tour, global pheromones update. At this point, iteration completes NC increment. When the NC reaches the maximum, or algorithm stagnation, the algorithm is complete.

We apply the grid method to establish a $20 \times 20$ environmental map. Use the basic ant colony algorithm to simulate, the specific process is as follows:

- Parameter setting. All parameters which are to be selected, refer to empirical values, Information inspiration factor $\alpha$ and hope inspiration factor $\beta$ take the value 1, pheromone intensity $Q$ takes the value 100. Evaporation coefficient $\rho = 0.2$.
- Initialization. Take pheromone $\tau_{ij}^0 = 10$ at time $t_0$.
- Pheromone updates strategy. Only when find the shorter path than the current optimal path, we can update the pheromone, and replace current optimal path.
- Cycles. Take the count of ants $m=100$, Maximum number of iterations $N_{C_{\text{max}}}=30$.
- Apply base ant colony algorithm to simulate, the obtained optimal path planning is shown in Figure 2.
Simulation results analysis: Repeat this experiment 50 times, calculate the program’s average solution, optimal solution and the worst solution, and evaluate the performance of the algorithm. In these 50 experiments, 22% appears algorithm stagnation, 14% appears the phenomenon of early convergence. Seen from the experimental data, Basic ant colony algorithm does not find the theoretical optimal path. And in the running process, there is the problem of robustness.

4. The improvement of improved algorithm

For the problem which exists in the basic ant colony algorithm, this paper proposes four improvement measures, and simulates it.

4.1. Apply genetic algorithm to optimize the relevant parameters

The parameters of ant colony algorithm have a crucial importance of evaluating the algorithm performance. But for the problem of the parameters selected, because in the absence of the corresponding strict theoretical analysis as a basis, currently there is no general solution possible. [6] For each specific problem model, the best combination of the main parameters is different. Most of the existing method of parameter settings is for a specific problem, is obtained through repeated tests, and can not be promoted as a general method. In this paper, information inspiration factor $\alpha$, hope inspiration factor $\beta$, pheromone intensity $Q$, these three parameter’s possible range is relatively large ($0 \leq \alpha \leq 5$, $0 \leq \beta \leq 5$, $10 \leq Q \leq 10000$). If determine the best combination through the experimental method, we need a lot of simulation and analysis. Genetic algorithm in solving parameters optimization problems, has good operability and high efficiency, this paper introduces genetic algorithm to optimize the parameters of the ant colony algorithm [7][8].

Genetic algorithms include selection, crossover, mutation and other operators; the step that using genetic algorithm to optimize parameter which is used in this paper, is shown in Figure 3.
The obtained best parameters configure is: \( \alpha = 0.5556 \), \( \beta = 0.8730 \), \( \rho = 0.3 \), \( Q = 1000 \).

**4.2. Max min ant method to improve pheromone update strategy**

When using the basic ant colony algorithm to do path planning, there will be premature convergence, the reduce of algorithm optimization capability and so on. This paper introduces Max min ant method to improve pheromone update strategy. In the basic ant colony algorithm, when an ant finds a better optimal path, allow this ant to improve pheromone. The improved ant colony algorithm based on this update strategy, update on the global pheromone after completing each iteration. [9][10] Pheromone update function is shown as formula (1). Meanwhile, in order to prevent the pheromone is too low, set the minimum value of pheromone. After each global pheromone update, detect path whose pheromone is too low, and reset these pheromone as the default minimum. In this paper, we set \( \tau_{\text{min}} = \tau_{\text{max}} / 5 \).

\[
\tau = (1 - \rho) \tau + \Delta \tau \frac{Q}{L} (\tau_{\text{max}} - \tau)
\]

**4.3. Increase probability selection function**

In order to accelerate the convergence of the algorithm, this paper set the orientation function, and adds this function to ants’ optimization probability computing.

Orientation function is calculated as follows:

\[
d_n = \sqrt{(x_{\text{max}} - x_n)^2 + (y_{\text{max}} - y_n)^2}
\]

After adding the orientation function, also take the distance between optional path and end point as a evaluation standard of measuring whether the node is good. Therefore, add the distance factor \( \gamma \) in probability selection function. The new probability selection function is as formula (3). When...
ants select follow-up node, respectively calculate the distance between the optional node and the end node, then the probability computing function is:

$$P^k_j(t) = \begin{cases} \frac{[\tau_{ij}(t)]^\alpha \cdot [\eta_{ij}]^\beta \cdot [d_{ij}]^\gamma}{\sum_{k \in \text{allowed } k} [\tau_{ik}(t)]^\alpha \cdot [\eta_{ik}]^\beta \cdot [d_{ik}]^\gamma}, & \text{if } j \in \{\text{allowed } k\} \\ 0, & \text{else} \end{cases}$$  \hspace{1cm} (3)

4.4. Fallback strategy

Once the ants enter, they will be caught into corners of concave obstacles, and will stagnate, and thus they never reach the end. This is shown as figure 4.

![Fig 4. Schematic diagram of ant caught into dead corner](image)

This paper introduced fallback strategy, that is, When the ants has no follow-up node to choose, they can choose two steps back, at the same time, put the selected node before which led ants into the dead corner, the taboo list, avoid further into a dead corner.

4.5. Simulation of the improved algorithm

Parameter. Parameters select the best configuration values obtained by the genetic algorithm, $\alpha = 0.5556$, $\beta = 0.8730$, $\rho = 0.3$, $Q = 1000$

Setting pheromone’s maximum and minimum: $\tau_{\text{max}} = 100$, $\tau_{\text{min}} = \tau_{\text{max}} / 5$.

Pheromone updates strategy. Only when find the shorter path than the current optimal path, we can update the pheromone, and replace current optimal path.

Cycles. Take the count of ants $m=100$, Maximum number of iterations $N_C_{\text{max}}=30$.

Apply improved ant colony algorithm to simulate, the obtained optimal path planning and convergence figure is shown in Figure 5.

![Fig 5. Improved ant colony algorithm complex map planning path figure](image)
4.6. The Comparison of simulation results compared

After applying above methods to optimize the basic ant colony algorithm, this paper compares path planning results of the improved ant colony algorithm and the basic ant colony algorithm, and analyzes the various performance parameters. Table 5 mainly compares and analyzes algorithm results before and after optimization, including optimal path length, worst path length, average path length, and maximum number of iterations, minimum number of iterations, and average number of iterations and each parameter of algorithm performance evaluation. In order to evaluate whether the algorithm is excellent, this paper introduces the following evaluation indicators [11]:

1)  Best performance indicator

\[ E_0 = \frac{c_b - c^*}{c^*} \times 100\% \]

In this formula, \( c_b \) represent the best optimal value obtained by algorithm running many times; \( c^* \) represent the problem’ theoretical optimal value, When the theoretical optimal value is unknown; it can be replaced by the known best optimal value. Best performance indicator is used to measure best optimized rate of the basic ant colony algorithm to the problem. The lower value means the better optimization performance of ant colony algorithm.

2)  Time performance indicator

\[ E_T = \frac{I_a T_0}{I_{max}} \times 100\% \]

In this formula, \( I_a \) represent, after algorithm run several times, the average number of iterations which meet the termination conditions; \( I_{max} \) represent given maximum number of iterations; \( T_0 \) represent the average computation time of algorithm iteration. Time performance indicator is used to measure the basic ant colony algorithm’s search speed for problem solution, under the premise of the fixed \( I_{max} \), the smaller ET is, the faster convergence of ant colony algorithm is.

3)   Robust performance indicator

\[ E_R = \frac{c_a - c^*}{c^*} \times 100\% \]

In this formula, \( c_a \) represent the average value obtained by algorithm running many times; \( c^* \) represent the problem’ theoretical optimal value. Robust performance indicator is used to measure basic ant colony algorithm’s dependence on random initial value and operation.

Thus, integrated performance indicator of basic ant colony algorithm \( E \) can be expressed as a weighted combination of above three performance indicator

\[ E = \alpha_O E_0 + \alpha_T E_T + \alpha_R E_R \]

In this formula, \( \alpha_O \), \( \alpha_T \), \( \alpha_R \), respectively represent weighting coefficient of best performance indicators, time performance indicators and robust performance indicators, and \( \alpha_O + \alpha_T + \alpha_R = 1 \). The smaller E value is, the better the algorithm's overall performance.

Performance comparison of improved ant colony algorithm and basic ant colony algorithm in solving 20 x 20 grid map is shown in Table 1.
Table 1. Performance comparison of improved ant colony algorithm and basic ant colony algorithm

<table>
<thead>
<tr>
<th></th>
<th>Basic ant colony algorithm</th>
<th>Improved ant colony algorithm</th>
</tr>
</thead>
<tbody>
<tr>
<td>Optimal path length</td>
<td>367.2792</td>
<td>277.9899</td>
</tr>
<tr>
<td>The worst path length</td>
<td>497.9899</td>
<td>428.7006</td>
</tr>
<tr>
<td>Average path length</td>
<td>424.3233</td>
<td>319.2577</td>
</tr>
<tr>
<td>Maximum number of iterations</td>
<td>30</td>
<td>40</td>
</tr>
<tr>
<td>Minimum number of iterations</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>Average number of iterations</td>
<td>15.3400</td>
<td>25.2800</td>
</tr>
<tr>
<td>The number of premature convergence</td>
<td>11</td>
<td>1</td>
</tr>
<tr>
<td>Best performance indicator $E_0$</td>
<td>0.3699</td>
<td>0.0346</td>
</tr>
<tr>
<td>Time performance indicator $E_T$</td>
<td>0.5113</td>
<td>0.6320</td>
</tr>
<tr>
<td>Robust performance indicator $E_R$</td>
<td>0.5792</td>
<td>0.1882</td>
</tr>
<tr>
<td>Comprehensive performance indicator $E$</td>
<td>0.5096</td>
<td>0.3350</td>
</tr>
</tbody>
</table>

Fig 6. Comparison figure of improved ant colony algorithm and basic ant colony algorithm

5. Analysis and Conclusions

Through the analysis of Table 1, we can draw the following conclusions:

1) Improved ant colony algorithm’s search optimization capability has greatly improved than the basic ant colony algorithm. As can be seen by observing Table 1, improved ant colony algorithm’s three parameters: the optimal path length, the worst path length and average path length are all smaller than the basic ant colony algorithm, this means, we have found a shorter path.

2) Improved ant colony algorithm can avoid premature convergence. We provide simulation results whose iterations number is less than 5, is premature convergence. By analyzing the table 1, we can see that, premature convergence situation of improved ant colony algorithm is significantly less than the basic ant colony algorithm. At the same time, algorithm’ overall iterations number is greater, but effective searching optimization time is improved.

3) Stability of improved ant colony algorithm is much better. The robustness indicators of the improved ant colony algorithm $E_R$ is significantly less than the basic ant colony algorithm, this shows, stability of improved ant colony algorithm is much better.

4) Comprehensive performance of improved ant colony algorithm is much better. Comprehensive performance evaluation Indicators of improved ant colony algorithm $E_0$ is significantly less than the basic ant colony algorithm that shows; improved ant colony algorithm has better Comprehensive performance.

5) Comparing path planning obtained by the basic ant colony algorithm and improved ant colony algorithm, dotted lines in figure 6 represent path optimization map obtained by applying basic ant colony algorithm, and solid lines in figure 6 represent path optimization map obtained by applying improved ant colony algorithm. It can be seen by comparing, the path length of improved ant colony algorithm is much shorter.
algorithm are significantly smaller than the basic ant colony algorithm. And fluctuations of the path obtained by improved ant colony algorithm are relatively small. Stability of improved ant colony algorithm is significantly better than the basic ant colony algorithm. This also shows the effectiveness of the improved algorithm.

It is proved by simulation experiments, This paper, through a number of optimization for basic ant colony algorithm, make path planning ant colony algorithm for mobile robot has stronger searching optimization ability, greater stability and better comprehensive performance. The final path is more optimized. The algorithm for solving the problem of mobile robot path planning has some theoretical innovation and practical value.

6. Acknowledgment

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7. Reference