A Comprehensive Cost Function Path Planning Algorithm for Sliding Prediction Based on Terrain Slope

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Abstract. In this paper, the terrain gradient algorithm and the slip prediction algorithm are studied in the three-dimensional path planning process. The slope, aspect and slip of the terrain affect the path planning to a certain extent. At the same time, the ant colony algorithm The selection of each of the relevant parameters was explained. By introducing the cost function of terrain passability, combined with the ant colony algorithm, the path planning algorithm was optimized to improve the efficiency of path planning.

1. Introduction

S.H.Liao et al. [1] mentioned the research methods and development trends of robot path planning technology. According to different understanding of environmental information, robot path planning can be divided into model-based global path planning and model-based local path respectively. The global path planning refers to the planning of the path of the robot under the condition that all the operating environments have been mastered. It is also called the static path planning. Sensor-based local path planning refers to the path planning in the case where all or unknown operating environment information is unknown. The path planning is also called dynamic path planning.

Global path planning algorithms mainly include A* algorithm [2], genetic algorithm [3], neural network method [4], etc. Local path planning algorithms mainly include artificial potential field method [5], fuzzy logic control method, hybrid method, etc. These algorithms have been well used in the two-dimensional environment, but their own characteristics and deficiencies have made their application to 3D path planning problems limited.

Ant colony algorithm is a heuristic algorithm, which has positive feedback, self-organization, distributed computing and strong robustness. Traditional ant colony algorithm has slow convergence speed in solving path planning, and it is easy to fall into local optimum. The resulting path is not the best. Literature [6] proposes an improved ant colony algorithm based on gradient optimization Adadelta algorithm to increase the randomness of the initial pheromone due to the shortcomings of traditional ant colony algorithm in slow path planning and lack of initial pheromone in the 3-D environment path of intelligent machines. The literature [7] adopts different expectation value mechanisms to update the information hormone adaptively in the way of volatility coefficient, and add the inflection point parameter as one of the criteria for the evaluation path. Literature [8] introduced the concepts of optimal solution and worst solution, changed the way of updating global pheromone, and improved the efficiency of global search. Based on the above research foundation, this paper
designs the heuristic search in ant colony algorithm. At the same time, it considers the updating strategy of three-dimensional topographic gradient pheromone, and introduces the integrated cost function \( f(p,n) \) of slip information into ant colony algorithm. The fitness value function. Matlab software was used to simulate the experiment. The experimental results were analyzed to verify the feasibility and applicability of the improved algorithm.

2. Ant Colony Algorithm

Let the number of ants in the ant colony be \( m \), and the distance between the node \( i \) and the node \( j \) be denoted as \( d_{i,j} \). In the movement process, the ant \( k \) selects the next move point according to the pheromone concentration of the path, and the initial time The location path pheromone is all the same constant. At a certain moment \( t \), the probability of selection of ant \( k \) from node \( i \) to node \( j \) follows the following formula [9].

\[
p_{i,j}^{k}(t) = \frac{\tau_{i,j}^{\ast}(t) \eta_{j}^{\ast}(t)}{\sum_{j \in \text{allowed}, \tau_{i,j}^{\ast}(t) \eta_{j}^{\ast}(t)}}, \quad j \in \text{allowed},
\]

Among them, \( \tau_{i,j}^{\ast}(t) \) is the concentration of pheromone on the path of node \( i \) to node \( j \) at time \( t \), \( \eta_{j}^{\ast}(t) \) and \( \eta_{j}^{\ast}(t) \) is the heuristic information of node \( i \) to node \( j \). It is generally \( \eta_{j}^{\ast}(t) = \frac{1}{d_{i,j}} \) defined as, \( \alpha \) is the pheromone heuristic factor, and \( \beta \) is the expectation. Heuristic factors, which are used to adjust the degree of influence on the decision., allowedk denotes the next set of feasible nodes.allowedk\(\{0,1,\ldots,n\}\)-Tabuk, Tabuk(k=1,2,...,m)is a collection of taboos.

In order to continuously screen the path information, the pheromone volatile factor \( \rho (0 < \rho < 1) \) was introduced into the ant colony algorithm. When the ant completes a cycle, the pheromone on the path is updated according to the following formula.

\[
\begin{align*}
\Delta \tau_{i,j}^{k}(t) & = \sum_{k \in \text{allowed}} \tau_{i,j}^{k}(t) \\
\tau_{i,j}^{k}(t+1) & = (1 - \rho) \tau_{i,j}^{k}(t) + \rho \Delta \tau_{i,j}^{k}(t)
\end{align*}
\]

\( \Delta \tau_{i,j}^{k}(t) \) indicates the amount of pheromone remaining on the path \( ij \) after the current cycle of the ant \( k \), and \( \Delta \tau_{i,j}(t) \) represents the sum of the pheromone amount remaining on the path \( ij \) for all ants in the current cycle.

\[
\Delta \tau_{i,j}^{k} = \begin{cases} 
\frac{Q}{L_{k}}, & (i,j) \in L_{k} \\
0, & \text{otherwise}
\end{cases}
\]

Among them, \( Q \) represents a constant of the initial pheromone quantity, \( L_{k} \) represents the path length of the \( k \)th ant in this cycle.

3. Terrain Passivity Cost Function Based on Slip Degree

Slip is a measure of the ability of a lunar rover to move or advance in a given terrain. It is defined as the difference between the control speed and the actual speed in the direction of each degree of freedom of the car body with the control speed as a standard. Because of different terrain types, the terrain has different slip characteristics. Therefore, each terrain has a separate slip model. The slip model is a non-linear approximation function of the terrain slope mapping to slip. Therefore, based on the terrain slope information, the slip can be predicted, the slip cost of the terrain is obtained, and the slip cost of each grid in the map is generated. Sliding maps. The slip cost of each grid can be used as an input to the terrain passivity cost function. First, the terrain classification algorithm is used to classify the terrain based on the terrain texture and color information. Then, a neighborhood analysis
method based on the analysis window is used to extract deeper terrain information, such as slope, terrain roughness and topographic relief, etc., which are used to describe the terrain. Characteristic terrain factor; According to the terrain type of known terrain type, the terrain slip model S=S(Xlongit, Xlateral). Among them, Xlongit, Xlateral, Respectively, the terrain is based on the horizontal and vertical slopes of the robot's movement direction. Finally, the slip prediction algorithm is used to predict slip.

The terrain pass-through cost function is a function for evaluating terrain passability. This function considers factors such as terrain slope, terrain roughness, and ladder obstacles. Here, the sliding cost considerations are taken into consideration to form a slip-based map. The terrain passes the cost function. Use this function to evaluate the path's passability between two points.

In path navigation, combining ant colony algorithm is the commonly used 3D path planning algorithm. Here, the above-mentioned terrain cost function is comprehensively considered to form a comprehensive cost function f(p,n), after modeling, sensing data, etc. are not deterministic factors, and the ant colony algorithm is adopted to adapt the value function, and an ant colony algorithm is used for path planning.

A generalized cost function that incorporates the extended slip practicable cost function ftrav triangle into the uncertain information such as the consideration from the node p to the node n edge of the undirected weighted graph created from the grid environment is:

\[ f(p, n) = f_1 \cdot f_{trav}(p, n) + f_2 \cdot f_{risky}(p, n) + f_3 \cdot f_{guide}(p, n) + f_4 \cdot f_{smooth}(p, n) \]  

(4)

Here, ftrav(p,n) is the passability cost function from node p to node n, frisky(p,n) Potential risk cost function, fguide(p,n) Path-directed cost function (whose cost value is negative), fsmooth(p,n) Path smoothness cost function, F1, F2, F3 and F4 are the weights of ftrav(p,n), frisky(p,n), fguide(p,n) and fsmooth(p,n) respectively. Then, the extended slip feasibility passability cost function ftrav triangle is incorporated into the comprehensive cost function f(p,n).

The integrated cost function f(p,n) incorporating the slip information is incorporated into the fitness function of the ant colony algorithm:

\[ f'(p, n) = f(p, n) + f_0(p, n) \]  

(5)

f(p, n) is an improved fitness function of the algorithm function, f(p,n) is based on the slip prediction integrated cost function, and f0(p,n) is the basic ant colony algorithm fitness function.

4. Four Experiments and Analysis

A. Initialize the program and create an environmental model of the 3D terrain.
B. Set the starting point and end point of the path search in the 3D model, determine the search direction of the ants, and place all the ants on the starting point. Initialize the iteration number NC_max of the ant ant colony algorithm and the number of ants M.
C. Apply the passability cost function to the fitness value function of the algorithm to calculate the fitness value of each path
D. The ants begin to search for the next node, and each time a search is completed, the pheromone on the path is updated iteratively accordingly.
E. Repeat the above steps to determine whether the final number of iterations has been reached. If yes, end the search and output the optimal 3D path. Otherwise, continue execution.

In order to verify the pass-through cost function of terrain gradient and slip prediction in this chapter, the ant colony algorithm is used to further optimize the path algorithm and simulate it with Matlab software. The simulation environment is 21×21×21 a three-dimensional topographic map. As shown in Figure 1, the corresponding search starting point and target point are set. According to the ant colony algorithm parameter selection idea, the number of populations is set to 21, the maximum number of iterations is 200, and the \( \alpha \) value is 1; The \( \beta \) value is 1.5 and the \( \rho \) value is 0.25.
Figure 1. Path planning diagram of the basic algorithm.

Figure 2. Path planning diagram of improved algorithm.

The results show that a comprehensive algorithm that incorporates the terrain pass-through cost function can effectively obtain the optimal path, can accurately predict the pathability of the path between two terrain points, reduce the running time and number of iterations of the algorithm, and improve the search ability and convergence speed.

Table 1. Comparison of Path Length Results of Two Algorithms (/km).

| Compare items           | Experiment 1 | Experiment 2 | Experiment 3 | Experiment 4 | Average |
|------------------------|--------------|--------------|--------------|--------------|---------|
| Basic ant colony       | 48.23        | 47.38        | 46.59        | 48.65        | 47.71   |
| algorithm              |              |              |              |              |         |
| Improved ant colony    | 37.32        | 36.42        | 34.31        | 37.56        | 36.40   |
| algorithm              |              |              |              |              |         |

Four groups of experimental data were randomly selected for comparison. The comparison of the optimal path length obtained by the two algorithms in Table 1 shows that the path length of the improved algorithm has been improved to some extent, and the passability has been introduced. The
function makes the algorithm pay more attention to the tortuosity of the path and avoiding the robot search to generate the invalid movement distance in the process of searching for the path. It can be seen from Table 2 that the algorithm has obtained certain time efficiency in finding the optimal path. improve. Because on the basis of considering the terrain passability, the efficiency of the path planning of the improved algorithm is more stable, and subsequent search will not be performed on some unreasonable paths.

**Table 2.** Comparison of Finding Path Time Results for Two Algorithms (/s).

| Compare items                  | Experiment 1 | Experiment 2 | Experiment 3 | Experiment 4 | Average |
|-------------------------------|--------------|--------------|--------------|--------------|---------|
| Basic ant colony algorithm    | 43.27        | 44.38        | 43.59        | 44.65        | 43.97   |
| Improved ant colony algorithm | 34.21        | 32.42        | 30.20        | 35.46        | 33.07   |

The number of iterations required by the obtained path length of the algorithm reflects the convergence performance of the algorithm to a certain extent. Through the number of iterations of the optimal path length obtained by the two algorithms of Table 3, it can be seen that the convergence speed of the algorithm is also obtained. A great improvement.

**Table 3.** Comparison of Finding Path Iterations for Two Algorithms.

| Compare items                  | Experiment 1 | Experiment 2 | Experiment 3 | Experiment 4 | Average |
|-------------------------------|--------------|--------------|--------------|--------------|---------|
| Basic ant colony algorithm    | 211          | 209          | 205          | 206          | 207.75  |
| Improved ant colony algorithm | 172          | 168          | 163          | 166          | 167.25  |

5. **Conclusion**

In this paper, some preliminary explorations of the three-dimensional path planning problem are carried out, and some researches are carried out based on the path planning of the basic ant colony algorithm. For the basic ant colony algorithm, there is a long search time in the path planning process. On the general deficiencies of the path quality effect, the terrain slope between nodes and the slippage problem generated during the movement of the robot are considered in the three-dimensional terrain, and a terrain passability cost function is introduced to the basic ant colony. The algorithm fitness has been improved. The experimental results also show that the improved algorithm has been effectively improved in the length and time of the path search. It can be seen that the improved algorithm in this paper has certain feasibility in the actual process.

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