

Application of Improved Ant Colony Algorithm in Unmanned Vehicle Path Planning

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Abstract

Aiming at the defects of ant colony algorithm in unmanned vehicle path planning, such as low efficiency and easy to fall into local optimization, the state transition rule is improved, and the experimental simulation is carried out. The simulation results show that the algorithm can effectively improve the efficiency of path search and show good performance in unmanned vehicle path planning.

Keywords

Ant colony algorithm; Path planning; State transition rules .

1. Introduction

Unmanned vehicles have played an active role in assisting drivers in driving, relieving drivers' fatigue and reducing traffic accidents. At the same time, in the modern military war, the battlefield environment is getting worse and more complicated, it is more and more important to reduce the casualties of the combatants by replacing the combatants with unmanned vehicles to complete the tasks of battlefield reconnaissance patrol, danger investigation, equipment transportation and supply escort. Path planning is the first step for unmanned vehicles to perform various complex tasks. The problem of unmanned vehicle path planning in complex environment is an urgent problem to be solved. At present, a great deal of research has been done on path planning, including artificial potential field method, neural network algorithm, genetic algorithm, ant colony algorithm, etc. These algorithms play a positive role in path planning problems, but at the same time there are also problems such as low efficiency and local optimization. On the basis of the above research, this paper introduces ant colony algorithm into unmanned vehicle path planning, and improves the existing problems in traditional ant colony algorithm to improve the efficiency of unmanned vehicle path planning, and verifies the effectiveness of the algorithm through simulation experiments.

2. Principle of Ant Colony Algorithm

Studies have found that ants release a pheromone on the path they travel when searching for food sources and can sense pheromones released by other ants. The size of the pheromone concentration indicates the distance of the path. The higher the pheromone concentration, the shorter the distance of the corresponding path. In general, ants will give priority to the path with higher pheromone concentration with greater probability, and release a certain amount of pheromone to enhance the pheromone concentration on the path, thus forming a positive feedback. However, at the same time, the pheromone concentration on the path will gradually decrease with time. In the end, the ant can find the best path from its nest to its food source, that is, the shortest distance.

The basic idea of ant colony algorithm to solve path planning problem is: the feasible solution of the problem to be optimized is represented by the path traveled by ants, and all paths of the whole ant colony constitute the solution space of the problem to be optimized. Ants release

more pheromones on the path with shorter path. As time goes on, the accumulated pheromone concentration on the shorter path gradually increases, and the number of ants choosing the path also increases. Ants concentrate on the best path under the action of positive feedback, at which time the corresponding is the optimal solution of the problem to be optimized.

2.1. Pheromone Update

$$\begin{cases} \tau_{ij}(t+1) = (1-\rho)\tau_{ij}(t) + \Delta\tau_{ij}, \\ \Delta\tau_{ij} = \sum_{k=1}^n \Delta\tau_{ij}^k. \end{cases} \quad (1)$$

Where $\Delta\tau_{ij}^k$ represents the pheromone concentration released by the ant k on the node i to the node j , and its calculation is shown in formula (2); $\Delta\tau_{ij}$ indicates the sum of pheromone concentrations released by all ants on the node i to the node j .

$$\Delta\tau_{ij}^k = \begin{cases} Q/L_k, & \text{the ant } k \text{ from the node } i \text{ to the node } j \\ 0, & \text{else} \end{cases} \quad (2)$$

Where Q is a constant, which indicates the total amount of pheromones released by ants in one cycle; L_k is the length of the path that the first ant will take.

2.2. State Transition Rules

When the ant moves to the node i and selects the next node j , the transition probability formula is

$$p_{ij}^k(t) = \begin{cases} \frac{[\tau_{ij}(t)]^\alpha \cdot [\eta_{ij}(t)]^\beta}{\sum_{s \in allow_k} [\tau_{is}(t)]^\alpha \cdot [\eta_{is}(t)]^\beta}, & s \in allow_k \\ 0, & s \notin allow_k \end{cases} \quad (3)$$

where $\eta_{ij}(t) = 1/d_{ij}$ is the heuristic function, d_{ij} represents the distance from the node i to the node j , $allow_k, (k=1,2,\dots,m)$ represents the set of nodes that ant k is allowed to select at the next moment, α represents the influence index for ants to select paths, and β indicates the role of heuristic factors in the ant's path selection process.

Ants choose the optimal path according to the pheromone concentration and path length on each path. When searching, the pheromone concentration of each path is the same. Ants can only choose according to the path length when searching. Due to the positive feedback mechanism of ant colony algorithm, when searching to a certain extent, all individuals find completely the same solution and cannot further search the solution space, which is easy to fall into the local optimal solution.

3. Improvement of Ant Colony Algorithm

In order to improve the efficiency of ant colony algorithm in the process of path search and reduce the blindness of search, the state transition rule is improved. Parameters are added to the transition probability formula. The modified state transition probability formula is as follows

$$p_{ij}^k(t) = \begin{cases} \frac{[\tau_{ij}(t)]^\alpha \cdot [\eta_{ij}(t)]^\beta (\xi_{ij})^\mu}{\sum_{s \in allow_k} [\tau_{is}(t)]^\alpha \cdot [\eta_{is}(t)]^\beta (\xi_{is})^\mu}, & s \in allow_k \\ 0, & s \notin allow_k \end{cases} \quad (4)$$

Where $\xi_{ij} = 1/d_{ij}$, μ indicates the degree of influence of ξ_{ij} on the selection of the next node. It can be seen from the above formula, the closer the distance from the node i to the node j , the greater the value of ξ_{ij} . By introducing the parameter ξ_{ij} and μ , the algorithm can be prevented from falling into a local optimal state to some extent.

4. Path Planning for Unmanned Vehicles based on Improved Ant Colony Algorithm

The efficiency of the ant colony algorithm is improved by improving the state transition rule in the ant colony algorithm, and the improved ant colony algorithm is applied to unmanned vehicle path planning. The steps are as follows:

Step 1: Initialize relevant parameters, such as ant colony number c , pheromone importance factor α , heuristic function importance factor β , maximum iteration number $iter_max$, iteration number initial value $iter$, starting point $start$, ending point end , etc.

Step 2: Each ant selects the next node according to the state movement rule formula (4).

Step 3: When the ant k reaches the end point end , the information concentration on the road is locally updated according to the formulas (1) and (2) of the basic ant colony algorithm.

Step 4: Repeat steps 2 and 3 until all ants reach the end.

Step 5: Store that complete path information collected in the iteration into a database, namely, the optimal path between the two nodes found in the iteration.

Step 6: if $iter < iter_max$, make $iter = iter + 1$, and repeat steps 2 to 5 above; If $iter > iter_max$, the algorithm ends. In this way, the global optimal path from the start node to the end node is saved in the database.

5. Simulation Experiment

The simulation experiment is carried out by using MATLAB, and the obstacle distribution is known. The starting point of the unmanned vehicle is $(0,20)$, and the ending point is $(20,0)$. The obstacle is represented by a black square. The simulation results are shown in the figures.

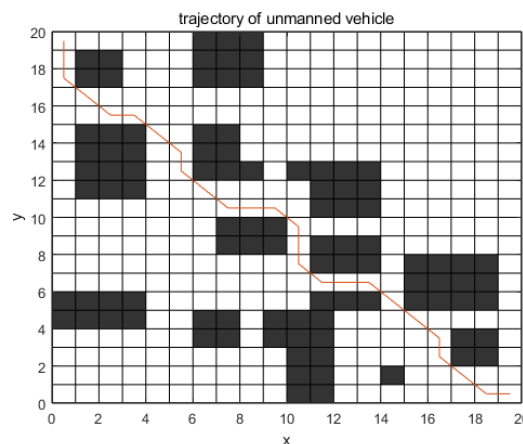


Figure 1: Trajectory of unmanned vehicle

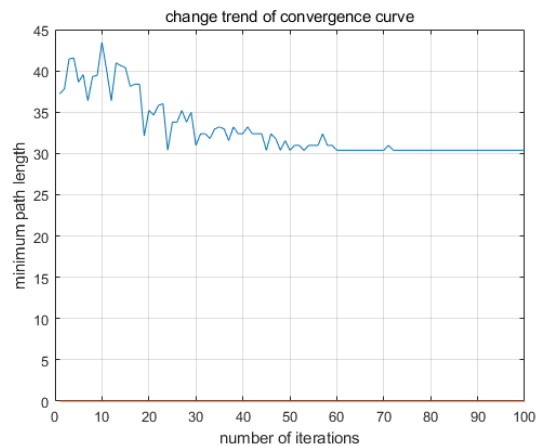


Figure 2: Change trend of convergence curve

6. Conclusion

The improved ant colony algorithm proposed in this paper has effectively solved the problem of unmanned vehicle path planning. Next, further consideration will be given to how to combine ant colony algorithm with other intelligent algorithms to further improve the efficiency of path planning and to study unmanned vehicle path planning in dynamic environment.

References

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