Multi-target UAV path planning based on improved RRT algorithm

Xueping Ren, Li Tan*, Jiaqi Shi and Xiaofeng Lian

School of Computer Science and Engineering, Beijing Technology and Business University, Beijing 100048, China

E-mail: tanli@th.btbu.edu.cn

Abstract. When the Rapidly-exploring Random Tree (RRT) algorithm in the global path planning algorithm is used for autonomous online path planning of UAVs, there is a problem that the optimal path cannot be obtained. An improved RRT algorithm is proposed, including the dynamic constraints, heuristic search strategy, dynamic step fusion strategy, and the improvement of the selection method of changing new nodes under specific conditions. The simulation results show that the improved RRT algorithm can meet the premise of UAV dynamic constraints. Next, the optimal path planning for multiple goals is realized, especially in reducing the nodes in the random tree.

1. Introduction

With the promotion of computer technology and aerospace technology, UAV path planning plays an important role in the process of UAV combat mission. According to the requirements, the optimal flight path satisfying the constraints is not only the purpose of UAV path planning, but also the core part of UAV mission planning. At present, different researchers have proposed different methods to quickly and effectively plan UAV paths. There are two common path planning algorithms: one is the classic algorithm that needs to load environmental information in advance, such as A* (A-Star) algorithm[1], Artificial Potential Field method (APF)[2], Rapidly-exploring Random Tree (RRT) and other algorithms; the other is based on real-time measurement of environmental element information, and its own position information to calculate the relative relationship to plan the path of intelligent response algorithms, such as Genetic Algorithm (GA)[3], Ant Colony Optimization (ACO)[4], Cuckoo Search (CS)[5] and other algorithms.

RRT algorithm has been widely used in path planning in recent years due to its fast and efficient advantages[6]. RRT algorithm is suitable for solving the path planning problem of multi degree of freedom robots in complex environment. However due to the randomness of the extension point of the original RRT algorithm, the algorithm search is too average and the planning result deviates from the optimal solution[7]. In[8] uses target bias strategy and odor diffusion method to improve the selection of extended nodes, so that the growth of the random tree tends to the target point. The path length of the improved algorithm is shortened by about 22.1%. Literature[9] proposed a path planning algorithm for UAVs in complex environments based on RRT. It can search complex environments quickly and efficiently, and can also use random points where collision checks fail as an index to speed up exploration. For UAV path planning problem, literature[10] combines the environmental potential field with the original RRT algorithm to optimize the sampling and expansion strategy, so the
efficiency of path planning is greatly improved. The research on path planning based on the existing RRT algorithm focuses mostly on finding the optimal (shortest) path. In practical applications, it is hoped that it can meet a variety of constraints (especially the power of UAVs). Under the premise of learning constraints), the running time, the number of random nodes, the turning angle, and the path length are optimized at the same time.

2. Traditional RRT algorithm

The RRT[11] is a path planning algorithm based on random sampling proposed by S.M LaValle in 1998. The node expansion of this algorithm does not require preprocessing, and it can quickly search for unknown areas based on current environmental information. It is a probabilistically complete algorithm that can be applied to mobile robot motion planning and UAV trajectory planning[12]. The traditional RRT algorithm process is as follows:

Suppose the pose space is C, the start node is Qstart, the target node is Qgoal, the minimum step size is s, and the initial random tree is T. The algorithm takes Qstart as the root node, randomly generates the sampling point Qrand in the pose space C, and then traverses all the nodes in T to find the node Qnear closest to Qrand as the extended node. At this time, it is judged whether the connecting line of Qnear and Qrand intersects the obstacle. If they intersect, the random sampling point Qrand is regenerated in the pose space C; otherwise, the robot moves from Qnear to Qrand with the minimum step s to reach the new node Qnew, and at the same time The new node Qnew is added to the T. Repeat the above steps, the algorithm ends when the robot reaches the target node Qgoal or exceeds the maximum number of iterations.

3. Improved RRT algorithm

3.1. Dynamic constraints

3.1.1. Maximum range constraint. During the entire flight of the UAV, the navigation distance is limited by the amount of fuel, so there is a maximum range[13]. Let \( L_k \) denote the navigation distance of the kth segment, there are k nodes in total, and the range of the UAV must satisfy:

\[
\sum_{i} |L_k| \leq L_{\text{max}} \tag{1}
\]

Among them: \( L_{\text{max}} \) is the maximum range of the drone.

3.1.2. Turning angle constraint. During the flight, the UAV will inevitably make a turn, which will undoubtedly be restricted by the turning angle. Set a maximum turning angle \( \alpha_{\text{max}} \), and then delete those new nodes that do not meet the maximum turning angle during the node expansion process. When the formula \( \alpha < \alpha_{\text{max}} \) is satisfied, the newly expanded node meets the requirements and is added to the tree.

\[
\alpha = \arctan \frac{Q_{\text{near}} - Q_{\text{root}}}{Q_{\text{near}} - Q_{\text{root}}} - \arctan \frac{Q_{\text{new}} - Q_{\text{near}}}{Q_{\text{new}} - Q_{\text{near}}} \tag{2}
\]

3.2. Heuristic search strategy

RRT algorithm has search average, wastes a lot of computing time and resources, and has low efficiency. And deviation from the optimal solution. So a heuristic search strategy is adopted. That is, set a threshold probability in advance, and the system randomly generates a random number and compares the two values. If \( p > \text{probility} \), Qrand is randomly generated in the robot state space, otherwise...
Qrand=Qgoal. In this way, it not only retains the advantages of the original RRT algorithm, but also speeds up the search speed and greatly improves the search efficiency.

3.3. Dynamic step strategy
In order to make the UAV be able to quickly plan the optimal trajectory, the step size should change dynamically with the distance from obstacles, so as to ensure that the UAV can not only avoid obstacles but also have the optimal trajectory. Therefore, it is necessary to adopt a method that can dynamically adjust the step length. The dynamic adjustment of the step length is conducive to obtaining a better path, which is more in line with actual flight conditions[14]. The step length formula is as follows:

\[
Q_{\text{new}} = Q_{\text{near}} + \frac{P_1(Q_{\text{new}} - Q_{\text{near}})}{||Q_{\text{new}} - Q_{\text{near}}||} + \frac{P_2(Q_{\text{goal}} - Q_{\text{near}})}{||Q_{\text{goal}} - Q_{\text{near}}||}
\]

(3)

When there is an obstacle in the connection between Qrand and Qnear, set P1>P2. Otherwise P1<P2.

3.4. New node selection method
In the traditional RRT, the coordinates of Qnew are usually obtained from the line between Qnear and Qrand at the distance from Qnear step s or calculated according to some specific formula. The Qnew nodes calculated by this method are usually random. This paper proposes a new node selection method, that is, when there are no obstacles in the connection between Qnear node and Qrand node, no longer based on the coordinate position of Qnear node and Qrand node Information, to recalculate the Qnew node, but directly treat the Qrand node as the Qnew node.

3.5. Improved RRT algorithm description
The algorithm uses Qstart as the root node, adopts a heuristic search strategy in the pose space C, generates sampling points Qrand, and then traverses all nodes in T to find the nearest node Qnear to Qrand as the expansion node. At this time, it is judged whether the connection line between Qnear and Qrand intersects with the obstacle. If they intersect, the dynamic step strategy is adopted to generate the Qnew node in the pose space C, and then it is judged whether the Qnew node intersects the Qnear node. If they intersect, a random sampling point Qrand is regenerated in the pose space C; if they do not intersect, a new Qnew is obtained. Otherwise, directly treat the Qrand node as a Qnew node. The Qnew node obtained from the appeal again judges that it is appropriate to meet the drone motion constraints. If the condition is satisfied, Qnew becomes a new node in T. Conversely, the random sampling point Qrand is regenerated in the pose space C. Repeat the above steps, the algorithm ends when the robot reaches the target node Qgoal or exceeds the maximum number of iterations. At this point, backtracking from the target node Qgoal to the initial node Qstart, the path can be obtained. The improved RRT algorithm is as follows:

Algorithm 1: Improved RRT algorithm
Input: Qstart, Qgoal and Obstacle Location information
Output: A path from the starting point to the target point
for j=1:k
p=rand();
if p<=probability
random point as target point;
else random points are randomly generated; Qnear=Near(Qrand,T);
if Qrand and all nodes in the tree have no barrier
Qnew = Qrand;
else use formula (3) calculate the value of Qnew, among them (P1>P2);
if $Q_{\text{new}}$ has obstacles to nodes in the tree
continue;
if !DynamicConstraint()
continue;
else add new nodes to the random tree;

4. Simulation experiment

Based on the above algorithm design, this article uses Matlab to perform simulation experiments on an ordinary PC with a processor Intel(R) Core(TM) i7-8550U CPU @1.80GHz 2.00GHZ and a memory size of 8.00GB. Set the obstacle environment into two types: one is a simple environment with only one obstacle, and the other is a complex environment with multiple obstacles. Because the RRT algorithm is a random algorithm, this paper has done comparative experiments with the original RRT and RRT*. Ten simulation experiments were performed for each algorithm, and the average value was taken in a simple obstacle environment. The experimental results are as follows.

Table 1. Simulation results of different RRT algorithms in a simple obstacle environment.

|                  | RRT  | RRT* | Improved RRT |
|------------------|------|------|--------------|
| nodesTotalNumber | 452.4| 242.7| 23           |
| totalPathLength(cm) | 1.766447| 1.561202| 1.517941    |
| pathNodesNumber  | 17   | 14.3 | 12.1         |
| NodeUtilization(%) | 4.435| 7.867| 61.759       |
| Time(s)          | 49.10325| 36.1374| 6.041489    |

We can clearly see that the improved RRT algorithm has obvious improvements over the traditional RRT and RRT* algorithms in terms of the number of nodes in the random tree, node utilization, and path length. The RRT algorithm is a random algorithm. In order to test the applicability of this improved RRT algorithm, we conducted simulation experiments on this algorithm in a variety of obstacle environments, and compared it with the other two algorithms. The experimental comparison results are shown in Figure 1.

Figure 1. Simulation results of different RRT algorithms in multi-obstacle environment.

In order to prove the effectiveness of the proposed method of changing the selection of new nodes to the RRT algorithm under certain conditions, the experimental arrangement is as follows. On the basis of the RRT,RRT*, only the selection of new nodes is added, and they are respectively compared with RRT,RRT* algorithm has done a comparative experiment, the experiment environment is a multi-obstacle environment. As can be seen from the figure below, the new node selection method shows better performance than the RRT and RRT* algorithm. The experimental results are as follows:
Table 2. Simulation results of different RRT algorithms in a multi-obstacle environment.

|                          | RRT   | Improved RRT | RRT*  | Improved RRT* |
|--------------------------|-------|--------------|-------|---------------|
| nodesTotalNumber         | 68.5  | 56           | 39.7  | 36.7          |
| totalPathLength(cm)      | 1.857 | 2.35103      | 1.735 | 2.133907      |
| pathNodesNumber          | 10.4  | 13           | 15.4  | 14.5          |
| NodeUtilization(%)       | 40.59 | 23.21        | 44.002| 39.509        |
| time                     | 7.818947| 7.106387     | 13.698787| 11.456732 |

5. Conclusions
Traditional RRT algorithm has strong randomness and cannot find an optimal path planning that can realize multiple targets. This paper presents an improved RRT path planning algorithm. The algorithm can realize multi-objective optimal path planning under the dynamic constraints of UAV. The dynamic constraint, heuristic search strategy, dynamic step size strategy and the selection method of changing new nodes under certain conditions were added into the RRT algorithm, which effectively shortened the running time and finally found an optimal path satisfying the multi-objective constraint.

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