Path Planning of UAV in Cities Based on Improved RRT Algorithm

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Abstract. With the development of UAV technology and low-altitude economy, path planning is an important link for UAVs to perform tasks in urban mission space. In urban environments, UAVs face many challenges, such as complex building layouts, large amounts of green belts and so on. RRT (rapidly exploring random tree) algorithm serves as a stochastic search method that employs randomly generated samples to expand its tree structure incrementally, enabling efficient exploration of task spaces. Aiming at the shortcomings of traditional RRT algorithm, such as long exploration time and poor quality of path, some improved algorithms and strategies for RRT algorithm in the past were summarized, and a new improved RRT algorithm named RRT-FieldPrune combining artificial potential field guided exploration and pruning strategy was proposed. After performing multiple simulation and using the mean value as the final result, the results are then contrasted against the traditional RRT algorithm, The algorithm named RRT-FieldPrune proposed in this paper saves 73.0% in path search time, reduces the path by 20.86%, and 91.30% of the bending times are eliminated, significantly improving the path quality and reflecting better performance.

Keywords: UAV; Path Planning; RRT; Artificial Potential Field; Pruning Strategy

1 Introduction

With the innovation of UAV technology and desire for a more convenient lifestyle from people, the development of low-altitude economy has been strongly supported [1]. However, the variety of buildings and facilities in cities brings many challenges to the flight of drones. In order to make the UAV better serve the human society, planning an economic, safe and efficient path becomes has an essential link. There are various path planning algorithms [2-4], among which, the UAV with traditional RRT algorithm has strong adaptability to the complex environment, and the logic of the RRT algorithm is relatively simple, but there are also shortcomings such as low path quality, large amount of invalid calculation, and difficulty in ensuring the path optimality at the same time. Cheng Haohao et al. [5] enhanced the traditional RRT algorithm by implementing a dynamic step approach, which reduces the flight distance while optimizing trajectory smoothness. TaiHuang et al. [6] developed an enhanced path planning method called

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PF-RRT, which achieves faster computation and higher path quality compared to traditional approaches. FanYang [7] et al. improved the path quality and solved the problem of local optimality by introducing ant colony algorithm to intervene in the selection of RRT next expansion points. This paper introduces an enhanced algorithm named RRT-FieldPrune, built upon the RRT framework, which directs the growth of the random tree by incorporating artificial potential field techniques [8-10], and then uses pruning strategy [11-12] to optimize the path. The path planning of UAVs using this strategy is simulated by MATLAB in cities with a certain height and an obstacle environment composed of various tall buildings, and the superiority and feasibility of this algorithm are compared and tested.

2 Improved RRT Algorithm

2.1 Application scenario and problem description

Assuming that drones perform transportation, monitoring and other tasks in the city at a certain height, and this height is higher than a large proportion of buildings, almost all power facilities and trees. The purpose is to reduce the cost of path planning and reduce the incidence of risk. However, as urban construction advances rapidly, there has been a marked increase in the number of high-rise buildings. The UAV often has to pass through a huge number of high-rise facilities or other buildings with complex shapes during the execution of tasks, which increases the difficulty of urban UAVs path planning. This paper will simulate the path planning of a UAV that maintains a certain height through a high-rise residential area. Fig 1. is the simplified two-dimensional task space, Set the point in the upper left as the starting point, set the point in the lower right as the end point, the black rectangle represents the residential building, and the size of the whole task space is $700 \times 700\ m^2$.

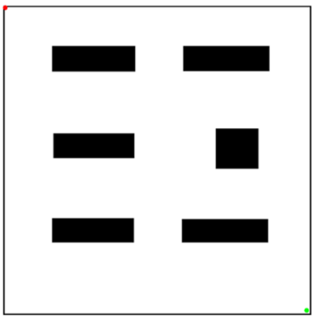

Fig. 1. The two-dimensional task space (Photocredit: Original)

In this paper, the actual situation is simplified into a two-dimensional task space. At the same time, the path planning problem of the UAVs passing through the high-rise community is also simplified into the problem of planning an optimal path avoiding all obstacles in this task space.

2.2 Current principles and limitations of RRT

RRT (rapidly exploring random tree) [11-12] algorithm explores sample points by search randomly in task space. The basic principle is to randomly expand new nodes in the task space from the root node, and continue to expand from new nodes until the random exploring tree expands to or near the end point. Fig 2. shows the traditional RRT expansion process.

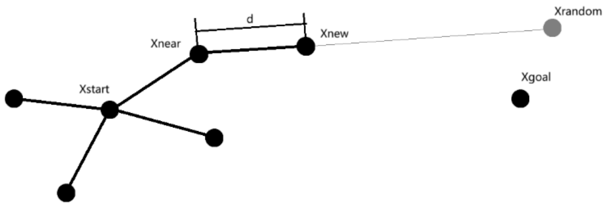

Fig. 2. Traditional RRT expansion process (Photocredit: Original)

In Fig 2., X_{start} is the starting point (extended random tree root node), a sampling point X_{random} is randomly selected within the specified search range in the state space, X_{near} is the nearest point toX_{random} tree, from the nearest point, along the direction of random sampling point to expand the extension distance d and determine a new node X_{new}, at the same time, judge whether the new node is inside the obstacle. If the new node is in the obstacle, it means that the UAV will hit the obstacle and the new node is not desirable. Otherwise, the node can be incorporated into the original random tree for subsequent expansion. This loop ends when the endpoint X_{goal} is incorporated into the random tree. Ultimately, the UAV's final path is selected as the path connecting the start and end points. The formula for calculating the new node is as follows.

$$X_{new} = X_{near} + d\,\frac{X_{random}-X_{near}}{|X_{random}-X_{near}|} \qquad (1)$$

The traditional RRT algorithm is able to find an achievable path quickly, and the logic of the algorithm is relatively simple, but there are also some shortcomings:

(1) The path quality is not high. The path created by RRT algorithm is unsmooth and including lots of turning points, which will increase the running time and energy waste of UAVs.

(2) Large amount of invalid calculation. Compared with the number of nodes in the whole random tree, the number of nodes connected to a final path is very small, indicating that numerous useless nodes will appear when the random tree is expanding, resulting in an increase in invalid computation.

(3) Path optimality is difficult to guarantee. RRT algorithm can generally search a feasible path, but because of its randomness and other defects, it is difficult to ensure that the path is the optimal path.

2.3 The intervention of artificial potential field

Because of the high randomness inherent in the traditional RRT algorithm, the random tree continuously produces a significant number of unnecessary branches, which wastes the memory computing space and the time of exploring the path. To solve this problem, according to the obstacles encountered by UAVs in the execution of urban transportation and other tasks, this paper uses the goal-oriented characteristics of artificial potential field to construct a gravitational field to improve the probability of random point selection near the end point, and then leads the random tree to take steps in the direction of the end point, thereby reducing the amount of useless computation and speeding up the solution speed.

In the process of random tree growth, an end-oriented gravitational field is constructed to guide it. This strategy is embodied in that when a certain node X is randomly expanded, the end point X_{goal} is regarded as a gravitational source, and this node is guided to the next step towards the direction of X_{goal}. Potential energy function and force formula are:

$$U_a(X) = \frac{1}{2}k_a \cdot d\left(X, X_{goal}\right) \quad (2)$$

$$F_a(X) = -\nabla U_a(X) = k_a \cdot (X_{goal} - X) \quad (3)$$

Where $U_a(X)$ is the gravitational potential energy of the current node X, k_a is the gravitational gain coefficient, and $d(X, X_{goal})$ represents the Euclidean distance between the current node X and the end point X_{goal}. Effect of gravitational field is embodied in the algorithm by increasing the sampling probability near the target point. The formula is as follows:

$$X_{random} = \begin{cases} X_{goal} + \mathrm{random}(-\mathrm{range}, \mathrm{range}), & p \\ \mathrm{random}(X_{min}, X_{max}), & 1-p \end{cases} \quad (4)$$

Where p is the probability of bias to the target point, range is the sampling range near the end point, and $random(X_{min}, X_{max})$ represents the random number generated within the range of $[X_{min}, X_{max}]$. Due to the action of the gravitational field, the node is biased in the direction of the end point and gradually approaches the end point as it expands to the next node. According to the analysis, the strength of gravity is directly related to the distance between the current node and the end point.

The purpose of this design is to reduce the probability of the random tree falling into the local optimum during the growth towards the end point.

2.4 Pruning strategy

RRT algorithm is random when expanding nodes. The generated path consists of multiple random nodes and is limited by a fixed step size. The overall path looks very tortuous and there are a number of turns, and the quality is obviously low. Although the original path shown in Fig 3 can reach the end point, it is very tortuous, and the direct application of this path will increase energy consumption and time cost, thus falling short of the criteria necessary for practical application. To find solution of this problem, this paper makes use of pruning strategy to further "pruning" the path generated by RRT algorithm, aiming to reduce the number of bends, shorten the path length and improve the path quality by cutting off some nodes.

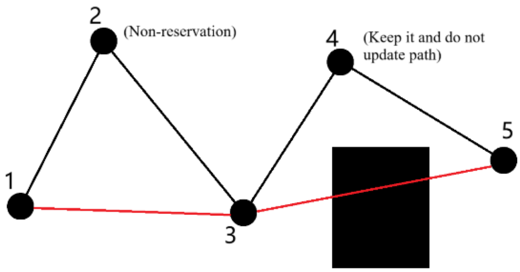

Fig. 3. Rationale of pruning strategy (Photocredit: Original)

The first principle of the strategy of pruning is that the sum of any two sides of a triangular is greater than the third, that is, starting from the beginning of the path, connecting the third node, and then connecting the third node and the fifth node, in that order. Here the previous three nodes as an example, the new connection formed by the first and third nodes connected and the skipped two-segment connection formed by the first and second nodes and the second and third nodes constitute a triangle, so the length of the new connection must be less than the sum of the length of the skipped two-end connection. Determine whether there is an obstacle on the new connection, if not, update and optimize the path, on the contrary, keep the node. As shown in Fig 3., the red line is the optimized path using pruning strategy. The optimization process of the pruning strategy namely shortens the path and also reduces the time consumed by the UAV to complete all the bends.

2.5 Simulation design

As this paper illustrates, the developed algorithm RRT- FieldPrune integrates the artificial potential field gravitational field-guided randomized search tree growth and pruning strategy. The process of simulation design steps is as follows:

Stage 1: Initialize the two-dimensional task space, confirm and mark the starting point X_{start} and the end point X_{goal} respectively, whose coordinates are (1, 1) and (700,700). The growth step d is determined according to the task space situation, and the starting point X_{start} is added to the random tree Tree_LIST.

Stage 2: Under the guidance of the gravitational field, samples are randomly sampled in the task space with the sampling point X_{random}. Select the node X_{near} closest to X_{random} in the random tree list to grow one step in the direction of connecting with X_{random}, and determine a new node X_{new}.

Stage 3: Obstacle determination is performed on the newly generated step, if there are no obstacles, it means that this step is safe. Add the new node X_{new} to the random tree Tree_LIST and continue to stage 2; if an obstacle is determined to exist, then the Tree_LIST will not be updated and stage 2 will continue. Ultimately, a path connecting the start and end points is identified and visualized within the task space.

Stage 4: The pruning strategy is used to optimize and alter the path. From the starting point, a triangle was constructed every three points as a group, and the obstacle was determined for the new connection. The program halts when the variation in the total path length following a single optimization is less than 0.1% of the total path length following the subsequent optimization. Output the final path. The overall flow of RRT-FieldPrune algorithm is demonstrated in Fig 4.

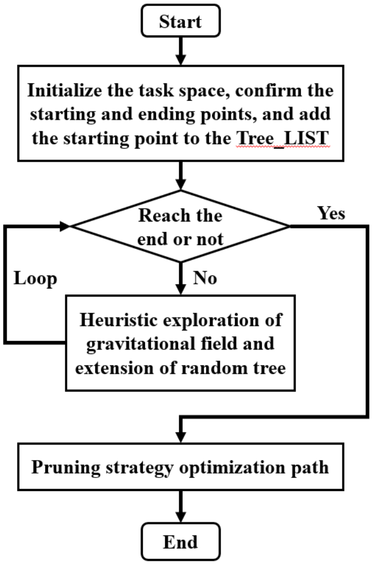

Fig. 4. Program Flowchart of RRT-FieldPrune (Photocredit: Original)

3 Analysis and Comparison of Simulation Results

This section mainly aims to demonstrate that the paths generated by the enhanced RRT-FieldPrune algorithm exhibit superiority over those produced by the traditional RRT algorithm in terms of computation time, overall path length, and bend count. The software used for this simulation is MATLAB R2024a, considering the randomness of the two algorithms, this verification will run the two algorithms 50 times respectively under the same parameter settings and the same task space, and take the average of the running results as the simulation results and make a comparison. To facilitate the comparison of time, the algorithm was set to be separated by 0.01 s for each two explorations.

Set the starting point to the upper-left corner of the task space (1,1), the end point to the upper-right corner (700,700), the expansion step size to 30, and the probability of deviation to the target point to 0.3. Compared with the traditional RRT and RRT-FieldPrune algorithms, the extended random trees exhibited in Fig. 5 (a), (b) and (c) are all extended by the traditional RRT algorithm, while those shown in Fig. 5 (d) are the extended random trees derived from the RRT-FieldPrune algorithm.

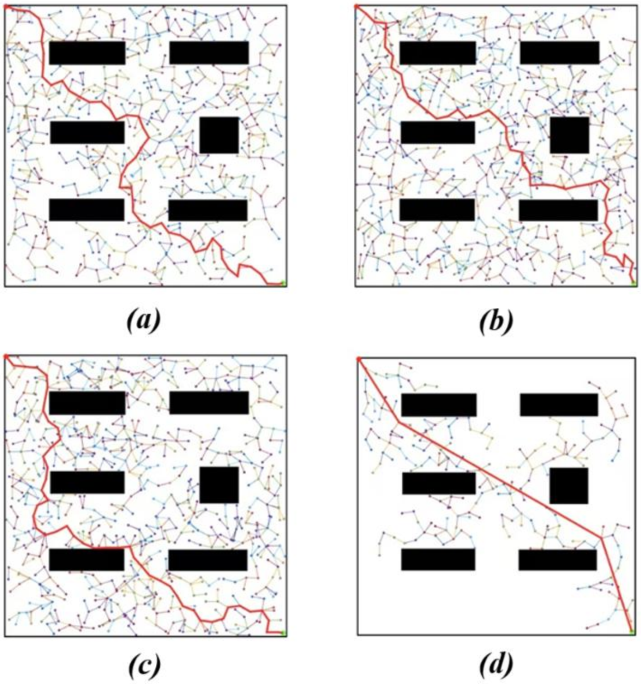

Fig. 5. Algorithmic Path Planning Comparison Diagram (Photocredit: Original)

Table 1 records the average computation time, total length, and number of bends of 50 path planning times conducted by traditional RRT algorithm and RRT-FieldPrune algorithm respectively.

Table 1. Simulation Results

Algorithm	Computation time/s	Total length /m	Bends
RRT	10.33	1365.37	46
RRT-FieldPrune	2.79	1080.61	4

The simulation results validate how the integrated and modified RRT-FieldPrune algorithm enhances the targeting of random tree expansion, reduces the ineffective branches and nodes, and shortens the searching time and the time needed to adjust the direction during the actual operation of the UAV by adding gravitational field and pruning, which enables urban UAV to perform better when performing tasks such as transportation.

4 Conclusion

Aiming at the defects of traditional RRT, this paper has proposed an improved RRT-FieldPrune algorithm, which guides the growth direction of random tree by gravitational field, and further optimizes the generated path combined with pruning strategy. After analyzing the simulation results, the effectiveness and superiority of the proposed algorithm are proved.

When contrasted against the traditional RRT algorithm, the enhanced algorithm demonstrates notable benefits in path planning. Due to the guidance of the gravitational field, the randomized search tree expands more purposefully in the direction of the area near the end point, reducing unnecessary exploration in the search process, thereby shortening the time of path generation and improving the path quality to some degree. At the same time, application of pruning strategy eliminates a large number of bends in the generated trajectory, further reducing the length of the path and the number of required nodes. This not only enhances the path performance but also decreases energy usage in practical applications to some degree. According to simulation data, the enhanced algorithm called RRT-FieldPrune outperforms the traditional RRT across three key metrics: time consumption, path length, and node count.

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