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Path Planning of UAV Delivery Based on Improved APF-RRT* Algorithm

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Abstract. The application demand for UAV in logistics distribution is vast and its accurate and rapid path planning research has practical value. Nowadays, the RRT algorithm is one of the most popular path planning methods for UAV delivery. Although the search of RRT is fast, the planned path is generally not the optimal path. The improved RRT* algorithm improves the way, but the convergence time is long. In this paper, we proposed an improved 3d path planning method based on RRT* based on APF. We introduced gravitation and repulsion in the APF algorithm based on the RRT* algorithm in this paper, and then we added the random point generated sphere to carry out random sampling of local space. Finally, we used MATLAB to compare the simulation results of the three algorithms and verify that the improved 3d path planning algorithm is improved in the aspects of path optimization and operation time.

1. Introduction

In recent years, UAV technology has shown a blowout development. UAV is not only used in landscape images capturing[1], but also patrol[2], traffic monitoring[3], logistics[4], and other fields. Since the outbreak of COVID 19, the UAV delivery service reduces the risk of infection and improves delivery efficiency.[5] Therefore, the research of UAV is of great considerable to production and living, and the optimization of the path planning algorithm is one of the core of the study. In the traditional path planning algorithms, genetic algorithm[6], artificial potential field method(APF)[7], and A* algorithm[8] have a common drawback that they need to model and describe the space and obstacles. Due to the complexity of calculation, they are not suitable to solve the path planning problem of UAV in high dimensional or complex environment.

However, sampling-based path planning algorithms, such as RRT[9] and RRT*[10], obtain the information of obstacles in the environment through collision detection of sampling points. They avoid the problem of direct description of space and can better solve the path planning problem of UAV in high-dimensional space or under complex constraints. Still, they come at the expense of other issues.

At present, no algorithm can quickly and accurately complete the UAV path planning problem. In this paper, we combined two popular algorithms to propose a fast expanding and optimal path UAV logistics distribution path planning algorithm.

2. Rapidly-exploring Random Tree, RRT

The basic idea of the RRT algorithm is to form a random tree by random sampling in the search space. We need to find the node closest to the sampling point on the random tree and then intercept a specific step in the direction to the sampling point as the new node and perform collision detection. If there is no collision, we add the new node to the random tree. By repeating the operation above, we can quickly search the free space until getting a collision-free path from the initial point to the target point.

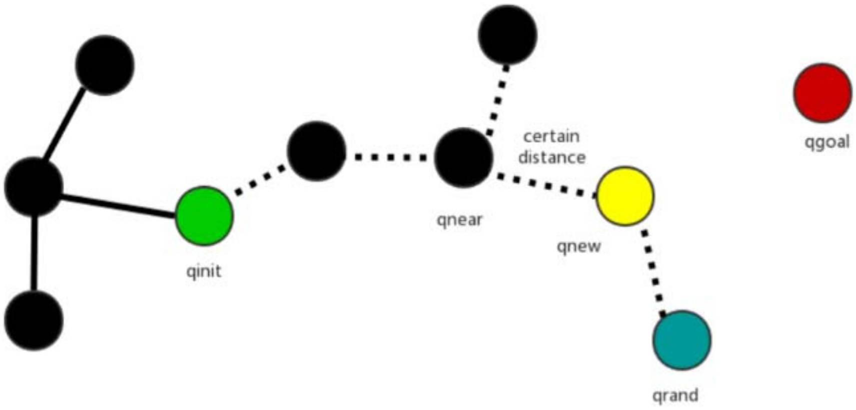

Figure 1. Schematic diagram of the RRT extension process

We can describe the RRT extension process as figure 1. Firstly, we need to set an initial point q_{init}, and then we randomly select a sampling point q_{rand}. Secondly, we find a point q_{near} closest to q_{rand} on a random tree and intercept a specific step from q_{near} to q_{rand} to obtain a new node q_{new}, and do collision detection from q_{new} to q_{near}, if no collision occurs, we add q_{new} to the random tree. We need to iterate continuously according to this rule until the distance between the new growth node q_{new} and the target state point q_{goal} is less than a specific set value, that is, the random tree has reached the target state point, and we have obtained a collision-free path from the initial root node to the target point.

A significant advantage of the RRT algorithm is "fast." Besides, the algorithm structure is simple, and it is easy to add non-complete constraints. However, the path of the RRT algorithm is generally far from the optimal path.

3. Asymptotically Fast Optimal Rapidly-exploring Random Tree, RRT*

The RRT* algorithm introduces the concept of a cost function based on RRT and improves the path through successive iterations. It solves the defect of the RRT algorithm and can obtain the optimal or quasi-optimal path.

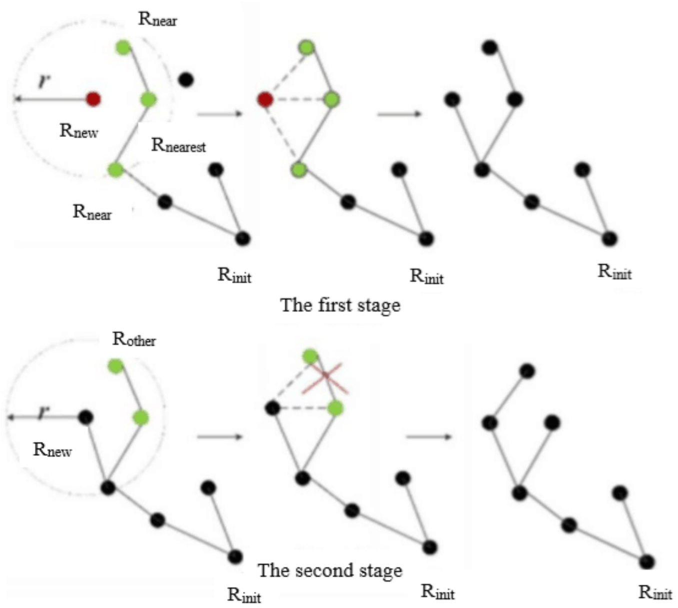

Figure 2. Schematic diagram of RRT * algorithm extension process

In the first stage, we add a new connection edge. First, we find q_{new} in the same way as the RRT algorithm. If there is no collision after the collision test, we can select the nearby nodes of q_{new}. The points falling in the circle with q_{new} as the center and R as the radius belong to the set of neighboring nodes. We set q_{min} as $q_{nearest}$, and the minimum path cost C_{min} as the sum of the path value from the initial point q_{init} to q_{min} and q_{min} to q_{new}. And we traverse all nodes in the set. If the path value of the new node is less than C_{min} and there is no collision, we can set q_{near} as q_{min}. Then C_{min} is the sum of the path value from q_{init} to new q_{min} and new q_{min} to q_{new}.
In the second stage, we obtain the optimal path-traverse other q_{other} in the set. If the total path value from q_{other} to q_{new} and from q_{new} to q_{init} is less than that of q_{near}, and there is no collision, then we define q_{other} as the parent node and delete the connection lines between the parent node and other q_{near}.
Although RRT* is asymptotically optimal with a heuristic search, the algorithm is still costly in terms of convergence time.

4. Artificial Potential Field, APF

The basic idea of APF is to assume that the target point has a gravitational effect on the UAV, while the obstacle has a repulsive effect on the UAV. Under the combined action of the two forces, the UAV approaches the target point and avoids the obstacle.

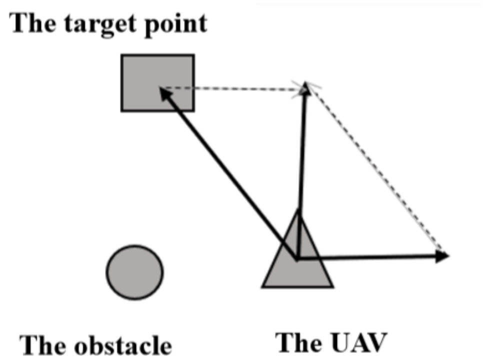

Figure 3. Schematic diagram of gravity and repulsion by artificial potential field method

The real distance between UAV and the target in the m-dimensional space affects possible function in the gravitational field. In contrast, the possible field function of the repulsive force is related to the Euclidean distance between UAV and the obstacle.
Considering the principle of superposition, we superpose the two potential field functions and obtain a composite potential field function of motion direction and pose. The vector force on UAV is composed of attractive force and repulsive force.
APF starts early, the algorithm is mature, the theory is simple, and the planned path is generally smooth and safe. However, in complex environmental information, there are many problems due to the particular position relationship between obstacles and target points. For example, the UAV will swing back and forth in a narrow environment.

5. Improved Path Planning Method Based on APF-RRT*

5.1. The Necessity of Multi-algorithmic Fusion

According to previous analysis of the basic principles of the RRT algorithm, we know that traditional RRT algorithm searches quickly and efficiently, for it has large randomness and completeness in probability. But due to the poor stability, it is difficult to map out the optimal global path. The improved RRT* algorithm improves the way of selecting the parent node on the original RRT algorithm and introduces the calculation of path cost to select the node with the smallest cost in the extended node field as the parent node. At the same time, it will update the connection of the nodes on the existing tree after each calculation of the total cost. Then the asymptotic optimal solution can be obtained. However, due to the increase of computational complexity, the convergence time of RRT* algorithm is a prominent problem. And the artificial potential field method (APF) introduced above has the advantages of conciseness, strong target orientation, and high real-time performance. Still, it is easy to fall into a local minimum.

Therefore, with the advantages of the two algorithms of APF and RRT*, it can not only jump out of the possible local minimum area of the potential field but also speed up the expansion and obtain the optimal global path.

5.2. The Principle of Improved Algorithm

Aiming at the problems of long convergence time and strong randomness in the RRT* algorithm, we introduce the idea of the traditional artificial potential field method that attractive force leads to exploration and repulsive force results in obstacle avoidance and generate a ball with random points to constrain the sampling space. According to the above ideas, we obtain a path planning method of UAV with improved RRT* algorithm based on APF, which solves the problem that the APF may fall into a local minimum and enhances the search efficiency and convergence speed of RRT*.

5.2.1. The idea that the target point generates gravitation. We construct a gravitational function $F_{gra}(q_{near}, q_{goal})$ based on the target point q_{goal} and a random expansion function $Expand(q_{near}, q_{rand})$ based on the randomly generated point q_{rand} to make the random tree extend toward the target point.

According to the randomly generated point q_{rand}, the neighbor node q_{near}, and the target point q_{goal}, we obtain two unit vectors $\overrightarrow{e_{nr}}$ and $\overrightarrow{e_{ng}}$ from the neighbor node to the randomly generated point and the newly growing node to the target point. The mathematical expressions are:

$$\overrightarrow{e_{nr}} = \frac{q_{rand}-q_{near}}{||q_{rand}-q_{near}||} \quad (1)$$

$$\overrightarrow{e_{ng}} = \frac{q_{goal}-q_{near}}{||q_{gaol}-q_{near}||} \quad (2)$$

Considering the mathematical definition of the gravitational function given in the APF introduced in the above section, we can define $F_{gra}(q_{near}, q_{goal})$ as:

$$F_{gra}\left(q_{near}, q_{goal}\right) = K_{att} * \overrightarrow{e_{ng}} \quad (3)$$

Similarly, we can define the random expansion function $Expand(q_{near}, q_{rand})$ as:

$$Expand(q_{near}, q_{rand}) = K_{epd} * \overrightarrow{e_{nr}} \quad (4)$$

Then the growth function $Grow(q_{near}, q_{goal}, q_{rand})$ of new growth node q_{new} is:

$$Grow\left(q_{near}, q_{goal}, q_{rand}\right) = F_{gra}\left(q_{near}, q_{goal}\right) + Expand(q_{near}, q_{rand}) \quad (5)$$

Finally, the mathematical expression of new growth node q_{new} is:

$$\mathrm{q_{new}} = q_{near} + Grow\left(\mathrm{q_{near}}, \mathrm{q_{goal}}, \mathrm{q_{rand}}\right) = q_{near} + K_{att} * \overrightarrow{e_{ng}} + K_{epd} * \overrightarrow{e_{nr}} \quad (6)$$

From the above expressions, the value of new growth node q_{new} is related to the target point q_{goal} and the randomly generated point q_{rand}, and the guidance of random tree growth can be enhanced or weakened by adjusting the gravitational factor K_{att}. And then, we can change the growth rate of the random tree by adjusting K_{att} and K_{epd}.

By introducing the idea of target point gravitation in APF, we can effectively reduce the useless search in the path planning of traditional RRT algorithm or RRT* algorithm and improve the convergence speed. However, merely introducing of gravitation may cause “obstacle trap” problem, that is, when the random tree is near the obstacle, and the obstacle is in the direction of the gravitational function $F_{gra}(q_{near}, q_{goal})$, many newly generated nodes may be tightly around the obstacle, which significantly affects the extended characteristics of the random tree and severely reduces the convergence speed. Therefore, we introduce the idea that obstacles generate repulsion.

5.2.2. The idea that obstacles generate repulsion. We construct a repulsion function $F_{rep}(v(i).coord, q_{new})$ based on the obstacle $v(i)$ so that the random number can avoid the obstacle and the "obstacle trap" problem.
Similar to the idea of the gravitational function, according to the geometric center coordinates of the obstacle (the obstacle is equivalent to a particle) $v(i).coord$ and the newly generated node q_{new}, we can obtain a unit vector $\overrightarrow{e_{vn}}$ pointing from the geometric center of the obstacle to the newly generated node, and its mathematical expression is:

$$\overrightarrow{e_{vn}} = \frac{v(i).coord - q_{new}}{||v(i).coord - q_{new}||} \tag{7}$$

The mathematical expression of the repulsion function $F_{rep}(v(i).coord, q_{new})$ of the newly growing node q_{new}, the mathematical expression is:

$$\mathrm{F_{rep}}(v(i).coord, q_{new}) = \begin{cases} K_{rep} * \overrightarrow{e_{vn}}, dist(v(i).coord, q_{new}) < r \\ 0 \quad\quad , dist(v(i).coord, q_{new}) \geq r \end{cases} \tag{8}$$

Where,

$$dist(x, y) = \big||x - y|\big| \tag{9}$$

We can update q_{new} according to the sum of the repulsive forces from all obstacles to the newly growing node q_{new}, and the expression is as following:

$$q_{new} = q_{new} + \sum_{i=1}^{n} F_{rep}(v(i).coord, q_{new}) \tag{10}$$

From the above expression, when the newly generated node is particularly close to the obstacle, it will avoid the obstacle by the repulsion function, to avoid many newly generated nodes surrounding the obstacle. And the repulsion factor K_{rep} can be adjusted to enhance or weaken the obstacle avoidance effect of the node, which can effectively improve the search efficiency and speed up the convergence.

5.2.3. Sampling space constraints. We construct the sampling function $Ball_{rand}(r_{rand}, \theta, \varphi)$ of generating a ball with random points.
We do random sampling in the sphere with a neighbor node q_{near} as the center of the field and a given length r_{near} as the radius. In this process, we adopt the relation of spherical coordinates to rectangular coordinates, and the sampling function $Ball_{rand}(r_{rand}, \theta, \varphi)$ of generating a ball with random points is expressed as follows:

$$\mathrm{Ball_{rand}}(r_{rand}, \theta, \varphi) = [r_{rand} sin\theta cos\varphi,\ r_{rand} sin\theta sin\varphi,\ r_{rand} cos\theta] \tag{11}$$

Where,

$$r_{rand} = U(0,1) * r_{near} \tag{12}$$

Then we can generate a new random point q_{rand} by the sampling function of creating a ball with random points. And the expression is:

$$q_{rand} = q_{near} + Ball_{rand}(r_{rand}, \theta, \varphi) \tag{12}$$

According to the above formula, random sampling can be realized in a sphere centered on the neighbor node q_{near}, so it is called generating balls with random points. The random points in the RRT and RRT* algorithms are scattered throughout the space, which causes a lot of useless searches. However, the algorithm proposed in this paper can randomly sample the local space by generating a ball with random points, reducing unnecessary pursuits and significantly improving the operation speed.
For the improved APF-RRT* path planning algorithm for UAV delivery, on the one hand, the search tree extends toward the target by introducing the idea of gravitation, on the other hand, the search tree can avoid obstacles by adding the concept of repulsion, which prevents "obstacle traps" and improves obstacle avoidance ability. Besides, we introduce the idea of generating ball with random points to avoid global random sampling, which significantly reduces useless searches and enhances efficiency.

6. Simulation

6.1. Simulation Environment Description and Parameter Settings

We tested three algorithms in the same simulation environment and set the parameters as follows:

Table 1. Settings of various parameters.

Parameters	Value
Simulation platform	MATLAB 2018a
Simulation space range	(640, 480, 400)
Starting position of UAV q_{init}	(0, 0, 0)
Target position of UAV q_{goal}	(640, 400, 180)
Number of iterations	2000
Gravitational factor K_{att}	3
Expansion factor K_{epd}	2
Repulsion factor K_{rep}	1.5
Sphere radius for random point generation r_{near}	300

6.2. Analysis of Simulation Results

According to the settings of the above parameters, 50 simulation experiments were performed on the traditional RRT algorithm, the RRT * algorithm, and the improved APF-RRT * algorithm proposed in this paper. In the experimental results, the blue columns on the map are obstacles such as simulated buildings, the black line represents the path search process of the random tree growth from the initial point to the target point, the green line represents the path from the parent node to the child node, and the red line is the final path. We have obtained the simulation results of path planning as shown in figure 4, figure 5, and figure 6, as well as the performance indicators of the algorithm shown in table 2:

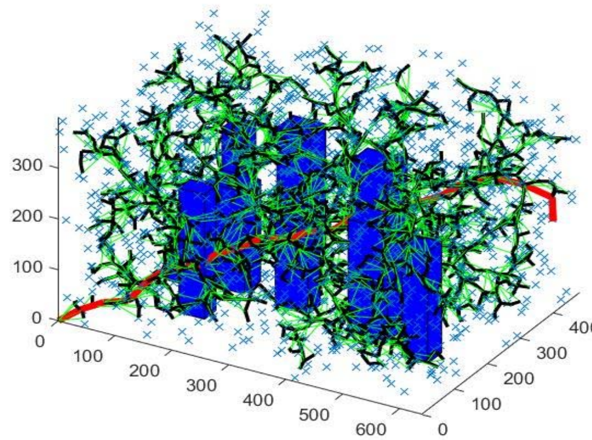

Figure 4. Simulation results of traditional RRT algorithm.

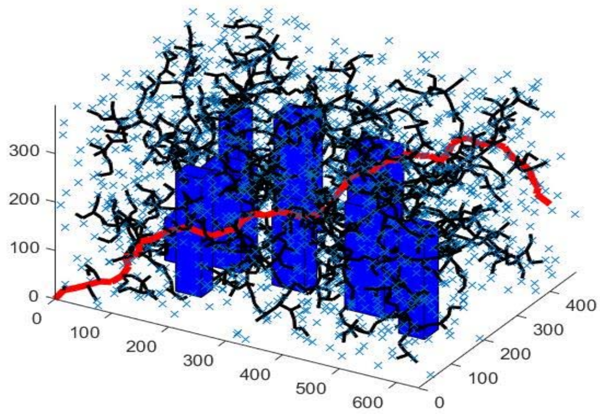

Figure 5. Simulation results of RRT* algorithm.

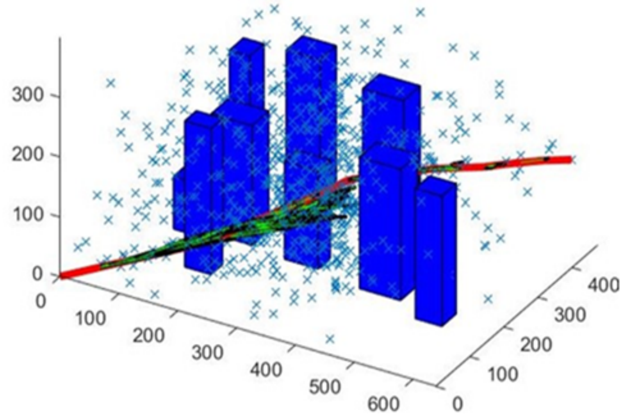

Figure 6. Simulation results of improved APF- RRT* algorithm.

Table 2. Simulation data of three algorithms.

Algorithms	Average number of nodes	Average path length	Average run time /s
RRT	1967	1107.1	283.634
RRT^*	1970	989.3	393.207
$APF\text{-}RRT^*$	432	787.6	32.365

As can be seen from the above table, among all the path planning methods of UAV, the average search time of the RRT* algorithm is the longest, and the final path planned by the RRT algorithm is relatively long. From figure 4 and figure 5, we can see that the sampling nodes of traditional RRT and RRT* algorithms are almost all over the state space in the planning process. The reason is that the generation of random sampling nodes in the traditional RRT algorithm is not purposeful and lack of guidance when expanding the search to the blank area, and its randomness is too large, which reduces the search efficiency, and its randomness makes the path not unique and optimal. According to figure 5 and table 2, the RRT* algorithm optimizes the path length by updating the path between the parent node and the child node and calculating the path cost to find a smaller value. From the simulation results shown in figure 6, we can know that the improved APF-RRT* algorithm can complete the path planning under the randomly distributed obstacle map, and most of the random sampling points generated in the search process are between the starting point and the ending point. Besides, the gravitational and repulsive potential fields lead to a smoother path. The results show that the optimization effect of the improved APF-RRT* algorithm is the most obvious and the best of the above three RRT algorithms, and has distinct goal orientation, which effectively solves the problem of slow convergence speed and low planning efficiency of the traditional RRT algorithm in a complex environment due to excessive randomness.

At the same time, from the experimental data in Table 2, we can see that the improved APF-RRT* algorithm completes the planning with the least number of extended nodes, the shortest path length and the least search time in the simulation process of randomly distributed obstacle 3D map, which is in line with the expected experimental results.

7. Conclusion

This paper studies the problem of path planning in UAV delivery, and proposes a 3D path planning method based on the improved APF-RRT* algorithm. First, we analysed the advantages and disadvantages of three popular path planning algorithms, the RRT algorithm, the RRT* algorithm, and the artificial potential field. Based on the RRT* algorithm, we introduced the idea of repulsion and gravity in the artificial potential field method and proposed APF-RRT* algorithm. Besides, we demonstrated the necessity and feasibility of the fusion algorithm. Finally, through a large number of MATLAB simulation experiments, we recorded the average number of extended nodes, the average path length, and the average search time, and compared the simulation results of the three algorithms. The simulation data shows that the improved APF-RRT* algorithm is the algorithm with the best simulation effect, and it effectively solves the problems of slow convergence and low planning efficiency of the traditional RRT algorithms due to excessive randomness in complex environments, which demonstrates the correctness and superiority of the improved APF-RRT* algorithm. This algorithm can provide a new solution for UAV delivery path planning.

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