Motion Planning of Unmanned Aerial Vehicle Based on Rapid-exploration Random Tree Algorithm

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Abstract. In the study of route planning problems in complex environments, in order to reduce the flight cost of unmanned aerial vehicles (UAVs), it is necessary to achieve a better balance between planning time and path quality. This paper utilizes the Rapid-exploration Random Tree (RRT) algorithm for motion planning of a fixed-wing UAV and a multi-rotor UAV (i.e., a quad-rotor UAV), and gives the origin and destination locations on a 3-D map. By following aerodynamic constraints such as maximum roll angle, flight path angle, and airspeed, a collision-free and flight-friendly path is found through simulation. In addition, this paper employs a path smoothing algorithm to simplify the 3-D Dubins path and generates the shortest trajectory. The simulation results show that the RRT and the optimization method have faster convergence speed and shorter search time, reduce redundant planning points, shorten the planning track, and improve the track planning efficiency.

1. Introduction

Unmanned Aerial Vehicle (UAV) plays an important role in a lot of highly dangerous tasks cause of its advantages of little shape, cheap price, convenient use, low requirements for combat environment, strong battlefield survivability [1-2]. A route planning of the UAV is to find the optimal or sub-optimal flight route of the UAV from the starting point to the target point that meets certain performance indicators under certain constraints. However, when UAVs perform tasks in complex environments, some traditional algorithms have exposed their own shortcomings and deficiencies, which cannot find the needs of actual way planning.

For example, A* algorithm [3] adopts the method of expanding nodes for route planning. Due to the shortcomings of node expansion method itself, there is a problem of combined explosion in complex environment, resulting in the sharp expansion of time required for planning and low efficiency. Genetic algorithm [4] is in the state of blind search in the process of evolution due to the influence of unknown factors in complex environment, resulting in very low search efficiency. Ant colony algorithm [5] uses pheromone as the basis for path selection, which is easy to fall into the local optimal area, takes a long time, has low planning efficiency, and is not convenient for planning in a complex environment. The cross particle swarm optimization algorithm [6] first initializes a rough route from the starting point to the target point by using the threat avoidance technology, and then globally optimizes the rough route by using the cross idea of particle swarm optimization, so as to find an optimal path. However, the path it searches in complex environment is long, and it is easy to fall into local optimization.

The RRT algorithm has the characteristics that it does not need to construct the task environment, and a planned path can be obtained only through the random selection of the tree exploration direction points. The randomness of the exploration direction point selection ensures the global optimality of the search path. It is easy to model in the environment and easy to realize [7]. Therefore, more and more scholars choose the RRT algorithm for UAV route planning. However, when the distribution of threat sources in the mission environment is not clear, RRT tends to make the tree search fall into a local minimal area. Although, cause of the randomness by a exploration direction point selection, though the certain amount of iterations, tree exploration can get off the local minimum area, but it increases a amount of exploration failures and reduces the planning efficiency. Therefore, we should formulate different path planning schemes according to different UAV types.

2. Rapid-exploration Random Tree algorithm

The basic idea of rapid-exploration random tree is that in a two-dimensional workspace, the position coordinates and direction angles of UAV determine the pose state. As shown in Figure 1, for the convenience of description, we take a two-dimensional environment as an example. RRT is a general heuristic that can be used no matter what type of UAV, no matter how many degrees of freedom, no matter how complicated the constraints are, and the principle is simple.

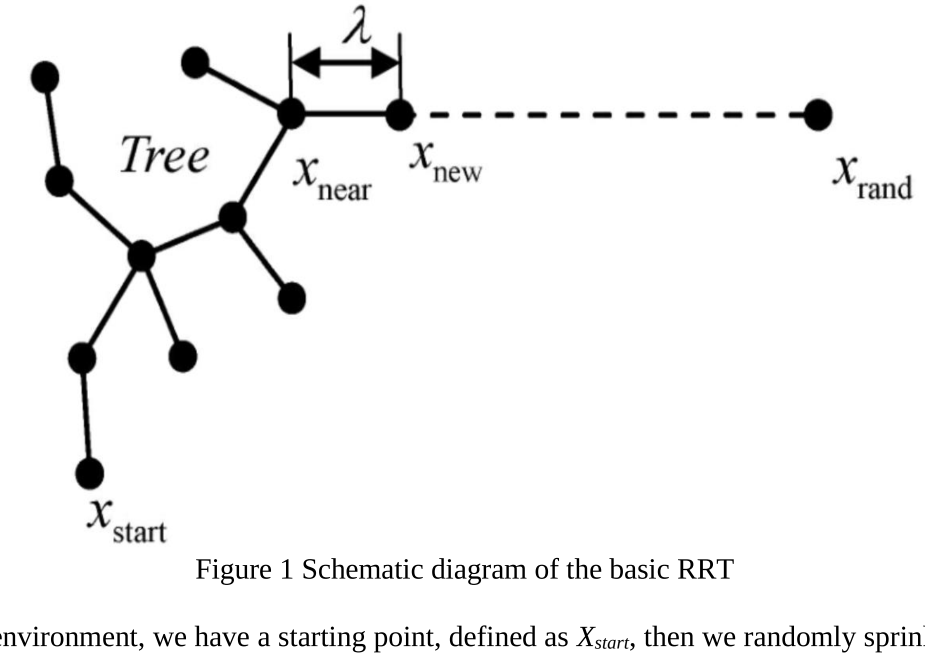

Figure 1 Schematic diagram of the basic RRT

First in environment, we have a starting point, defined as X_{start}, then we randomly sprinkle the point at environment to obtain a point X_{rand}. If X_{rand} isn't at the barrier zone, connect X_{start} with X_{rand}. We obtain the connecting line L. If L isn't at the barriers at all, move along L a certain distance from X_{start} to the direction of X_{rand} to get the update point, X_{new}. Then X_{start}, X_{new} and a line segment between them constitute the simplest tree. On the basis of the first step, Keep repeating, sprinkle points at environment, and obtain a point X_{rand} of a barrier-free area. Then discovered the point X_{near} closest to X_{rand} on the existing tree, and connect the two points. If there are no obstacles along the line, move a certain distance from X_{near} to X_{rand} along the line to get a new point, X_{new}, which is added to a current tree. Keep repeating the above process to a goal point (or a point near it) is increased to a tree, at which point we could get the way in the tree from the starting points to a goal point.

3. Experimental Results and Analysis

All simulations are based on the MATLAB@R2021a environment and the loaded map is a 3D occupancy map '*uavMapCityBlock*' containing a group of pre-generated obstacles, as Figure 2. In the experiment, we performed trajectory planning for a fixed-wing UAV and a multi-rotor UAV (specifically, a quad-rotor aircraft). The initial position for UAV is (150, 50, 70), the target position for (40, 200, 66). For the RRT algorithm, Maximum number of tree nodes equals 10000, Maximum Iterations equals 400, Max Connection Distance equals 50. The maximum roll angle of the UAV is equal to $\pi/6$, airspeed equal to 6, the flight path angle limit range is [-0.1 0.1].

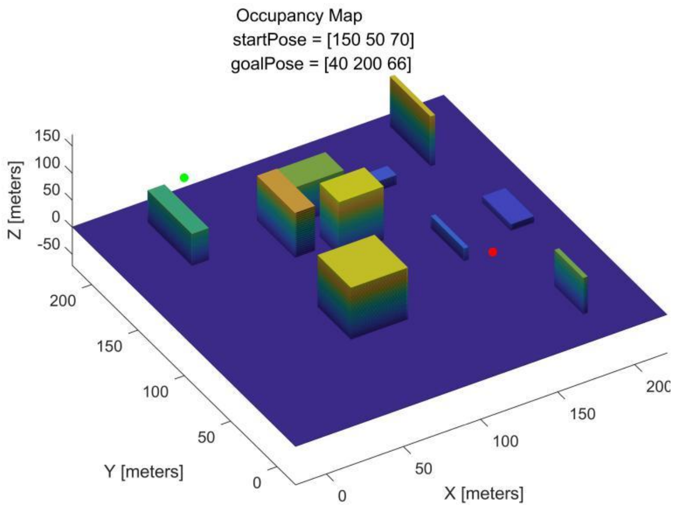

Figure 2 A 3D occupancy map *uavMapCityBlock*.

3.1. Motion planning for fixed-wing UAVs

The fixed-wing UAVs should obey aerodynamic constraints such as maximum roll angle, flight way angle, and airspeed while moving between points. Rapid-exploration Random Tree algorithm progressively build a search tree from random sample of given state space. The tree finally span a search space and connect the start and goal states. We connect two states using the 'uavDubinsConnection' object function that satisfies the aerodynamic constraints, and also use the 'validatorOccupancyMap3D' object function for collision examining between fixed-wing drone and environment. Among them, the two object functions 'uav-Dubins-Connection' and 'validator-Occupancy-Map-3D' come from the function library defined by MATLAB.

A state space is postulated as [*x, y, z, headingAngle*]. This article uses the '*UavDubinsConnection*' object by way of a UAV's kinematic model that constrained by the maximum roll angle, airspeed, and flight way angle. The last line represent a heading angle in a range [$-\pi$, π] radians. Specifically, UAVStateSpace (Bounds = [-20 220; -20 220; 10 100; $-\pi$, π]). We use the setWorkspaceGoalRegion function to renewal the goal pose with its surrounding area.

We create a planner RRT object though designating a state space and a state validator by way of input. This article sets the Max Connection Distance, Goal Bias, and Max Iterations attribute of the planner object, specifies the custom objective function. The objective function decides the way has reached a goal if Euclidean distance to a goal is below the threshold of 6 m. We show RRT-based way planning in 3D space. This paper interpolates the decided way in view of UAV Dubins connection and plots the interpolated state by way of the green line. We use a provided helper function '*SimulateUAV*' to simulate UAV flight, which requires way-points, airspeed, and time to target. The assist function uses a fixed-wing guidance model to assume drone behavior in view of control inputs produced by way-points, plotting the simulated state as a red line.

There will be some unnecessary turns in the originally decided path as UAV move to the goal.Therefore, we use a way smoothing algorithm 'UAVPathSmoothing' to simplify 3-D Dubins paths [8]. The smooth ways made though this process enhance the tracking characteristics of fixed-wing simulation models. We set a fixed-wing UAV model using some new smoothed points, the smoothed paths are much shorter and show improved tracking overall, see Figure 3.

The last set of experiments showed the difference between a planned path and a smooth path with only a small section of the intermediate process.Therefore, we changed the coordinates of the starting point and conducted another set of experiments with obvious contrast, as shown in Figure 4.

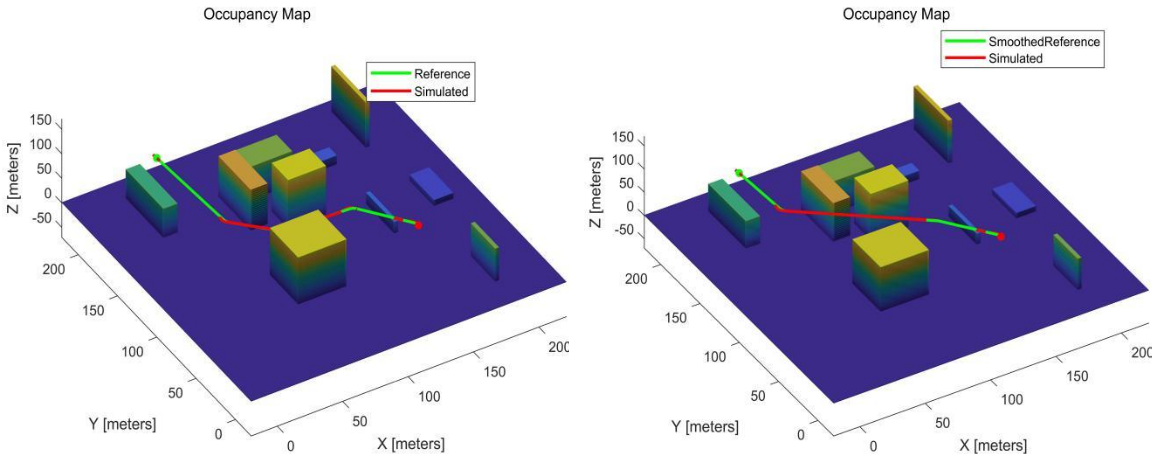

Figure 3 UAV trajectories simulated by planned paths and smoothed paths.

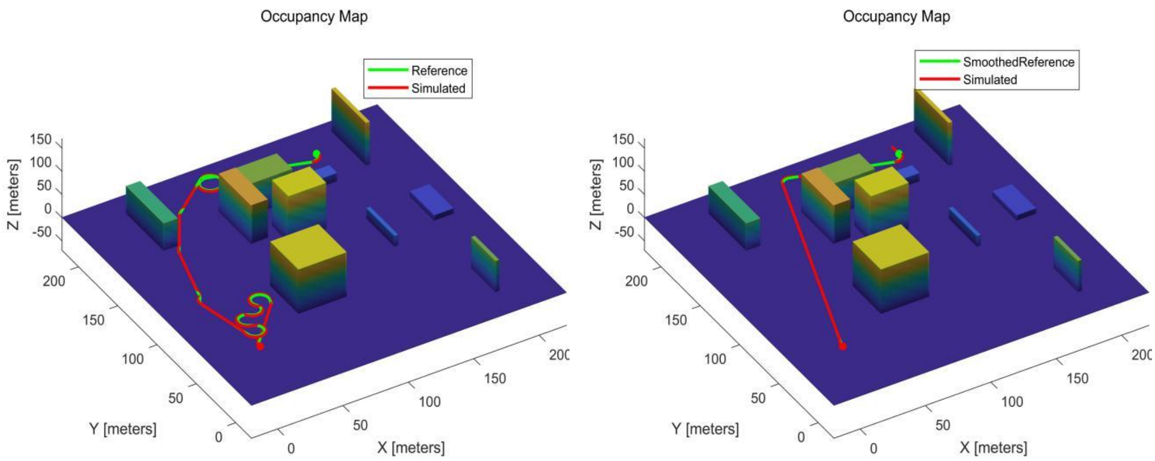

Figure 4 UAV trajectories simulated by planned paths of change location.

3.2. Motion planning for multi-rotor UAVs

In this section, we are going to plan a path through RRT using 3D straight line connections and fit a minimum trajectory through the obtained waypoints. We use the SE(3) state space for path planning and the 'validatorOccupancyMap3D' object for collision checking between the multi-rotor drone and the environment. Specifically, start_Pose = [12 22 25 0.7 0.2 0 0.1]; goal_Pose = [150 180 35 0.3 0 0.1 0.6], as Figure 5.

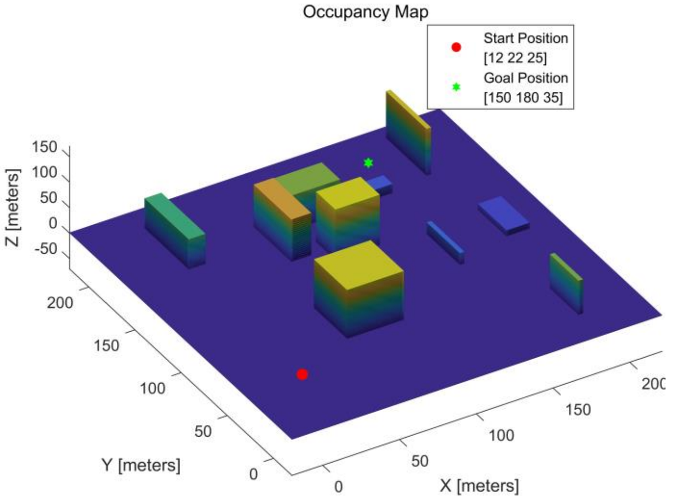

Figure 5 The 3-D occupancy map of multi-rotor UAVs route plan..

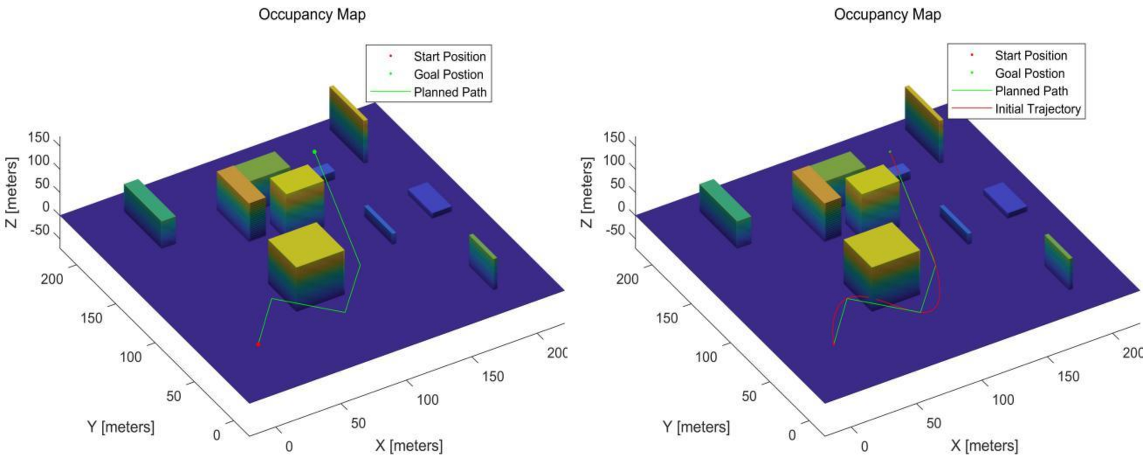

Figure 6 The minimum smooth trajectory of multi-rotor UAV.

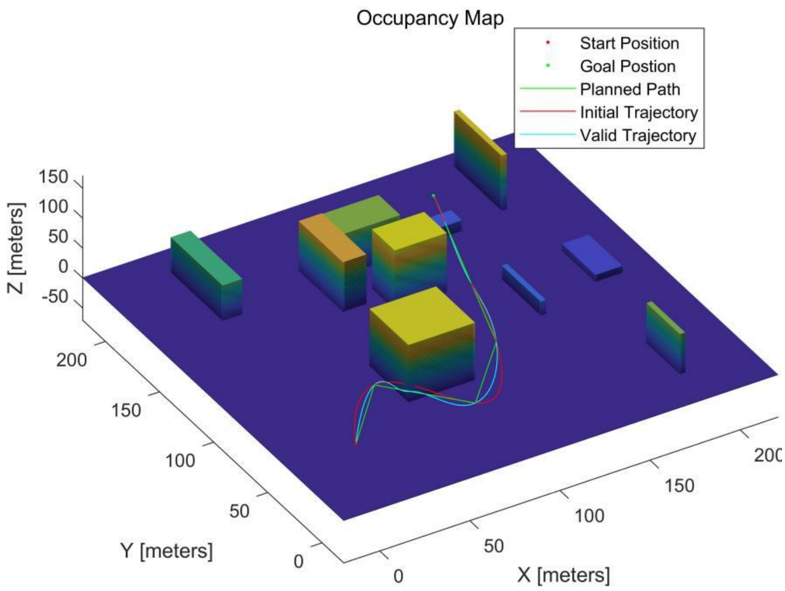

Figure 7 The minimum smooth and valid trajectory of multi-rotor UAV.

This article creates a 'plannerRRTStar' object though specifying a state space with a state validator as input. We establishment the 'Max Connection Distance', 'Goal Bias', 'Max Iterations', 'Continue After Goal Reached', and 'Max NumTree Nodes' properties of the planner object to optimize the waypoints returned.planner. Max Connection Distance = 50; planner. Goal Bias = 0.8; planner. Max Iterations = 1000; planner. Continue After Goal Reached = true; planner. Max NumTree Nodes =10000. Finally, we performed path planning according to the above parameters to generate the minimum UAV trajectory, as Figure 6.

The originally planned path has some sharp corners when navigating towards the goal. A smooth trajectory is generated by fitting the obtained waypoints to the minimum snap trajectory. For a preliminary estimate of the time it takes to reach each waypoint, the UAV is assumed to be moving at a constant speed. Then, the resulting flight trajectory has some invalid state. We have to modify the waypoints so that the resulting trajectory is unobstructed. The waypoints are inserted iteratively until the entire trajectory is valid, as shown in Figure 7.

4. Conclusion

In this paper, the motion trajectory planning of fixed-wing UAVs and multi-rotor UAVs is carried out using Rapid Exploration Random Tree (RRT). Through the simulation results, the proposed scheme reduces redundant planning points and shortens the planning trajectory. In future research, we will carry out shortest path planning and simulation of adding loads (such as packages or first aid supplies) to multi-rotor or fixed-wing UAVs to further improve the practical application scenarios of UAVs. In addition, for the algorithm level, new methods such as reinforcement learning are planned to be used.

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