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RESEARCH ARTICLE

Four-Dimensional Trajectory Planning for Urban Air Traffic Vehicles Based on Improved RRT* Algorithm

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ABSTRACT In this paper, we propose a trajectory planning method for high-density flights in a complex environment with multiple buildings in the city. Moreover, a simulation study of four-dimensional trajectory planning for aircraft is conducted with different flight densities in an urban environment. In this paper, the Rapidly Exploring Random Tree Star (RRT*) algorithm is improved to adapt to urban air traffic, including node expansion angle constraint, dynamic collision detection, adapting to stratified airspace, and adding virtual obstacles. The urban environment model with multiple obstacles is established, the stratified airspace and flight parameters of the vehicle are set, and simulation experiments are conducted. The experimental results demonstrate the effectiveness of the proposed algorithms and the necessity of real-time and unified management of high-density flights in urban air traffic. The proposal of maximum aircraft density and airspace layer construction in the stratified airspace of the simulation environment is obtained. Lastly, a four-dimensional trajectory planning method for high-density flights in an urban multi-building environment is provided.

INDEX TERMS Improved RRT* algorithm, 4-dimensional trajectory planning, urban air traffic.

I. INTRODUCTION

The demand for urban transportation continues to rise as the scale of cities expands, and the population grows rapidly. Traditional ground transportation can no longer meet people's travel demands. In many large cities, the traffic demand is often much greater than the urban traffic capacity. New transportation modes must be developed [1] to solve the contradiction between traffic demand and supply in large cities, enhance traffic construction, and explore better traffic management modes. Compared with increasingly saturated land transportation, urban air traffic has a large development space, sufficient application potential, and a considerable market to be explored. Adding air traffic to the existing comprehensive three-dimensional urban transportation system can relieve the existing urban traffic pressure and improve the efficiency of urban traffic operations.

The Federal Aviation Administration (FAA) has structured airspace into six classes based on site distribution and airspace altitude. Urban air traffic is still in its early stage, and airspace classification should refer to the existing civil aviation airspace classification standards. However, the current research and practice of urban air traffic have proven that urban air traffic will fly in multiple classes of airspace in the future [2]. National Aeronautics and Space Administration (NASA) researchers have considered urban air traffic and airspace integration [3], [4]. Vascik [5] assessed the challenges and opportunities of introducing urban air traffic

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services and unmanned aircraft systems. Mueller [6] pointed out that it may soon enter the On-Demand Mobility (ODM) era with quiet, efficient, and largely automated air cabs.

The European Commission and the European Aviation Safety Agency (SEASA) [7] proposed the establishment of a public Unmanned Aerial System (U-Space), which provides a new set of digital and automated service procedures for UAVs regarding parameters such as route planning and air interaction. The Japanese Unmanned Traffic Management (UTM) Association and the New Energy Industry Technology Development Organization established the National UTM Project [8]. The project focuses on managing Unmanned Aerial Vehicles (UAVs) flight intelligence and operators. The Civil Aviation Authority of Singapore organization [9] proposed the Unmanned Aerial Control System TM-UAS to implement geo-fencing and conflict avoidance technologies.

Tang [10] pointed out that trajectory planning is a task that must be accomplished to conduct UAV autonomous flight. Moreover, it is an important contribution to improving UAV timeliness and reducing path selection costs. Whether man-piloted or unmanned, operational safety and efficiency must be considered in urban air traffic when conducting vehicle trajectory planning. Path planning is widely used in unmanned mechanical devices such as mobile robots [11] and in various transportation activities requiring high timeliness. In urban air traffic management, advanced flight path planning of an aircraft can avoid collision between an aircraft and an obstacle or two aircraft. Trajectory planning can improve flight safety and reduce the cost of secondary path planning. There are many mature path planning algorithms due to the continuous research in various disciplines and promotion by companies, such as ant colony algorithm [12], genetic algorithm, artificial potential field, particle swarm optimization algorithm, A* algorithm, Rapidly Exploring Random Trees (RRT) [13], and bee colony algorithm [14]. Furthermore, the dynamic reassignment model of multiple UAVs under swarm intelligence and emergency adjustment scenarios was also established [15], [16], [17]. Tang [18] proposed an anti-collision algorithm for multirotor UAVs based on geometric constraints and dynamic equations.

The intelligent optimization algorithm was invented by simulating natural biological phenomena. This algorithm has the advantage of relaxed requirements for optimization problems. The RRT algorithm [19] implements path search step by step by random sampling in space and is characterized by low algorithm complexity. Nevertheless, it does not consider the trajectory optimization problem. However, the applications of these algorithms are mostly static scenarios, and there are mergers of global static track planning with in-process local path re-planning. Tan et al. [20] proposed an ant colony particle swarm fusion algorithm. This algorithm was improved for the shortcomings of the ant colony algorithm and combined with the particle swarm algorithm for secondary trajectory adjustment. Static track planning is performed first in the track planning process. Then, path adjustment is performed by dynamic track planning.

In the future urban low-altitude airspace, the aircraft density will be much higher than that in traditional airspace. Establishing systematic aircraft path planning and airspace management systems must be accompanied by research on aircraft conflict and deconfliction to enable more aircraft to fly safely. There have been some relevant research and application results in the aviation industry [21], [22]. Pallottino [23] used a mixed integer linear programming approach to solve the two-dimensional conflict resolution problem. Alonso Ayuso [24] performed a linear approximation solution to minimize the velocity variation of the aircraft. Durand [25] combined a neural network algorithm to solve the conflict resolution method between two aircraft. Hao [26] proposed a four-dimensional trajectory-based multi-machine conflict detection and deconfliction method.

In this paper, the urban air traffic environment is simulated, and vertical takeoff and landing airports are set up [27]. The aircraft path planning algorithm suitable for urban air traffic environments is obtained by improving the Rapidly Exploring Random Tree Star (RRT*) algorithm, including node expansion angle constraint, dynamic collision detection, adaptive stratified airspace, and adding virtual obstacles. The information of all aircraft flying in the specified range of low-altitude airspace is recorded, including takeoff and landing times, locations, flight trajectories, and corresponding moments, and four-dimensional trajectory planning is performed for an aircraft. Path planning takes place before the aircraft takes off, allowing the aircraft to reduce the number of path adjustments caused by temporary avoidance during flight and ensure the safe and efficient simultaneous operation of multiple vehicles. Finally, the effectiveness of the proposed method is verified by simulation and comparison experiments.

II. SIMULATION OF PHYSICAL ENVIRONMENT MODELING

A. FLIGHT SPACE MODELING

The current urban air traffic is in the development stage, while the airspace division is still immature and mostly based on the existing airspace division for further refinement. The National Aeronautics and Space Administration (NASA) [4] proposed a development framework for urban air traffic airspace. It is believed that the future airspace involved in urban air traffic will include a portion of Class E airspace, i.e., a transition between Class A airspace and other airspace classes, in addition to the currently defined airspace in which light and small UAVs can fly below 120 m. The Dutch National Laboratory for Aeronautics (NLR) [28] provided a view of the application of free airspace, layers airspace, zones airspace, and tube airspace. The layered model of Metropolis [29] can reduce the relative speeds of aircraft at the same altitude level, improve the efficiency of direct flight

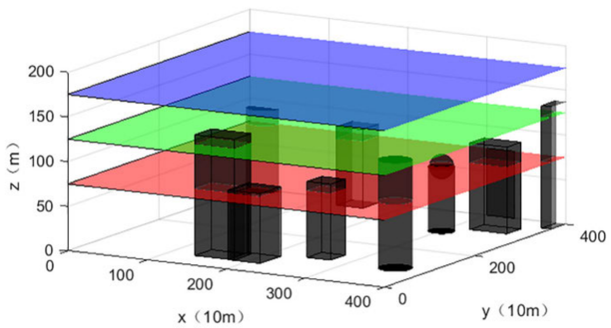

FIGURE 1. Schematic flight space model.

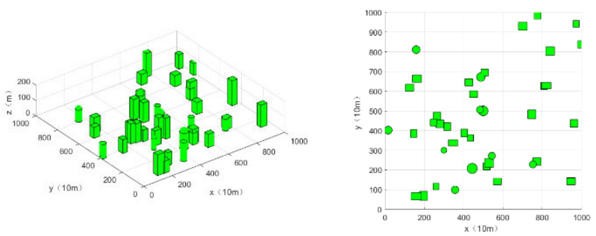

FIGURE 2. Obstacle model with a height of more than 70 m.

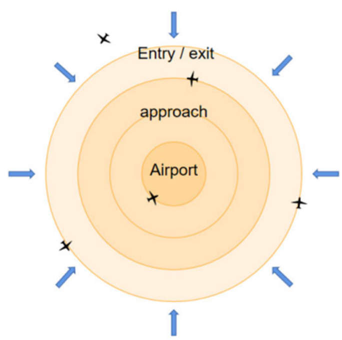

FIGURE 3. Vertical lift airport aircraft operation concept.

routes, and reduce plane flight conflicts. Hoekstra [30] further discussed the influence of different parameters on airspace capacity and safety degree in the highly stratified approach combined with the simulation method.

In this paper, a layered airspace structure is adopted, dividing every 50 m into a layer. Considering there are more tall buildings in the city, the flight activities of the aircraft will mainly be carried out at 50-200 m. The main flight altitudes for each level of airspace are plotted in Figure 1.

B. OBSTACLE MODELING

The fixed obstacles in this experiment are mainly buildings, and no airspace is set up in the experimental space that is not allowed to be occupied due to large aircraft takeoffs and landings. Wu [17] simplified the calculation by enclosing the building with cubes. Most of the buildings in the city

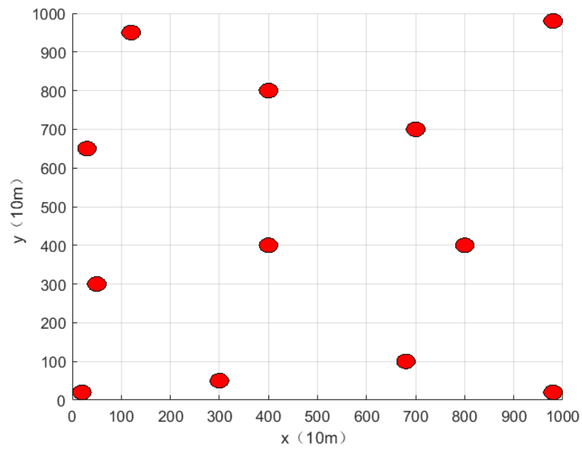

FIGURE 4. Vertical takeoff and landing airports distribution map.

are below 15 stories, but there are tall new buildings and a few ultra-high urban landmarks. In urban space, it is far more economical to have a fraction of the aircraft make short detours between buildings than to have all of them fly above the height of the tallest buildings in the city.

Forty groups of buildings over 70 m tall were set up in the model (including 26 over 80 m), and protected areas were set up for the buildings along their outer contours. The flight altitude is controlled near 75 m since the minimum flight altitude layer of the vehicle is 50-100 m. Moreover, buildings below 70 m do not affect vehicle path planning. Hence, they are not plotted. A three-dimensional view and a top view of the obstacle model are shown in Figure 2.

C. AIRPORT MODELING

With the continuous breakthroughs in UAVs and related supporting technologies, the takeoff and landing methods available for urban air traffic can also differ from the traditional takeoff and landing methods. Bertram [27] proposed a vertical takeoff and landing airport terminal area operation concept for e-VTOL aircraft, as shown in Figure 3. Furthermore, a Markov decision process based on urban air traffic self-organized terminal aircraft sequencing algorithm is constructed, which can handle the high-density terminal aircraft sequencing problem.

The e-VTOL aircraft can reduce the size of space that airports need to occupy, leaving more urban airspace for an aircraft to fly. In this paper, this type of vertical takeoff and landing airport is referred to during airport modeling, and a certain space for aircraft that need more landing space is reserved. A total of 12 vertical takeoff and landing airports are established by considering the top of some buildings as landing points. The distribution of airports is shown in Figure 4.

D. PHYSICAL ENVIRONMENT MODEL

The aircraft flight environment model has been constructed, including layered airspace, inaccessible space, and landing

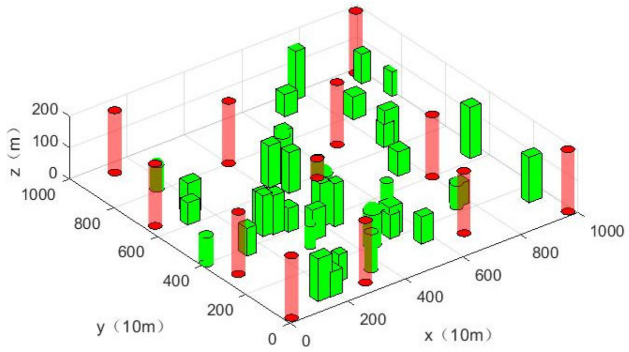

FIGURE 5. Physical environment model.

and takeoff airports. In subsequent experiments, the parameters of the protected area will be set based on obstacles and the flying machine. The constructed model is shown in Figure 5. The green diagram shows fixed obstacles such as buildings, and the red diagram shows vertical takeoff and landing airports and their restricted airspace.

III. PATH PLANNING BASED ON IMPROVED RRT* ALGORITHM

A. RRT* ALGORITHM

The principle of the RRT* algorithm is starting from a given starting point, randomly sampling in space, and building a path tree according to the given rules until it reaches the endpoint and finds the shortest path in the sampled path tree. After sampling, the nearest point on the path tree to the randomly sampled point is found, and it is determined whether it can expand the given step size without any obstacle. If the expansion is possible, the new points on the path tree are obtained according to the specified step length, and the nearest point is used as its initial parent node. The RRT* algorithm re-selects the parent nodes to improve the paths. Other parent nodes that make the distance from the starting point to the new node closer are re-found in a certain range around the new node. If they exist, the parent node corresponding to the nearest path is updated as the parent node of the new node, the nodes are again expanded according to the step size, and the path tree is updated.

B. NODE SAMPLING RULES AND EXPANSION RULES OPTIMIZATION

In urban air traffic, more than a single aircraft simultaneously fly, i.e., there is the possibility of aircraft intersection in the air. Therefore, it is necessary to carry out four-dimensional trajectory planning for aircraft to maximize the effectiveness and safety of the planned trajectory in the trajectory planning before takeoff and achieve higher operational efficiency.

A static map is often given in traditional RRT* algorithms, and path planning is performed in a fixed obstacle environment. Such a path planning method will generate many cases of re-routing due to detecting conflicts between aircraft in high-density aircraft operations, negatively impacting urban air traffic regarding flight safety, operational efficiency, and timeliness.

In this paper, the RRT* algorithm is improved by expanding the information of the path tree into points containing temporal and spatial information, which is expressed as $T_{m,n}(x, y, z, t)$. Here, $T_{m,n}$ is the point numbered n and the parent node numbered m in this path planning, x is the position of point $T_{m,n}$ in the x coordinate direction, y is the position of point $T_{m,n}$ in the y coordinate direction, z is the position of point $T_{m,n}$ in the z coordinate direction, and t is the time to arrive at point $T_{m,n}$ in this path planning. Only information $T(x, y, z, t)$ is reserved for the planned path, and information about the parent node is included in the path. Each point on the tree contains (x, y, z, t) provides more detailed and accurate information for the subsequent dynamic collision detection. This ensures the validity of dynamic collision detection results and enhances the feasibility of trajectory planning before departure.

C. FOUR-DIMENSIONAL PATH INFORMATION OPTIMIZATION

1) NODE SAMPLING OPTIMIZATION

One of the major differences between urban air traffic and traditional high altitude-controlled airspace is its complex geographic environment with many obstacles. Among various airspace structures, such as free airspace, regional airspace, stratified airspace, and pipeline airspace, many research results from the Delft University of Technology and the National Aerospace Laboratory of the Netherlands concluded that stratified airspace is currently the most suitable airspace structure for urban air traffic operations [28]. Chen [13] proposed an improved algorithm for the fast exploration of random trees. Balachandran [31] proposed a dynamic flight path planning algorithm for UAV over-the-horizon flight based on a fast exploration of a random tree.

In the proposed model, a hierarchical airspace concept structure is used to preferentially assign all aircraft in the initial determination layer to reduce the consumption of aircraft takeoff and landing when the aircraft density in the first space layer does not exceed a limited threshold. Priority is given to the pre-acquired reference trajectory, which is the shortest path between the start and arrival points. If no conflict arises, this path is used as the result of this path planning when the node sampling range is at the same altitude level. The path length is compared with the product of the shortest path multiplied by a factor of 1.25 after completing single path planning. The corresponding cross-layer navigation permission is opened if the planned path length exceeds the threshold. In this case, the node sampling range is not restricted to the same altitude level, and the aircraft will re-route for it in the multi-layer airspace range. The airplane density is controlled by limiting airplane takeoff when the airplane density is too high. Substantial detours and air safety accidents are avoided by waiting a short period.

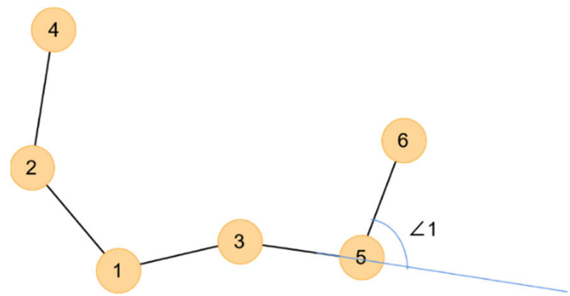

FIGURE 6. Angle constraint for node expansion.

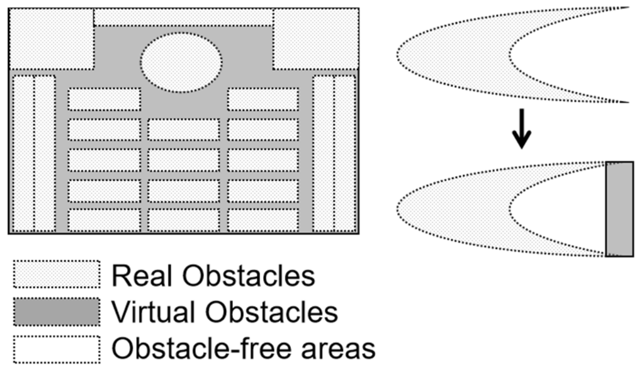

FIGURE 7. Virtual barrier design.

In addition, the node sampling of the original algorithm is random, whereas a completely random sampling has some blindness in finding the path. Therefore, a certain probability of bootstrapping the sampling direction can find a better path in a shorter time. The model in this paper sets a probability of 0.6 to expand in the target direction and generates random numbers to determine whether the new node expands in the target direction or other directions, which is shown in Eq. (2).

$$r = rand(0, 1) \tag{1}$$

$$T_{m_{i+1},i+1}(x, y) = \begin{cases} T_{end}(x_{end}, y_{end}), r \leq 0.6 \\ (rand(0, 1), rand(0, 1)) \times 1000, r > 0.6 \end{cases} \tag{2}$$

where r is the randomly generated number between 0 and 1, $T_{m_{i+1},i+1}$ is the R is the (i+1)th generated point on the path tree, and it's parent point is node m_{i+1}, T_{end} is the end of path planning.

2) NODE EXPANSION RULE OPTIMIZATION

Different aircraft may have various speed interval constraints, steering angle constraints, and hovering capacity constraints when flying in urban air. In this paper, the highest possible operational efficiency is considered. Therefore, the hovering capability of some aircraft is not considered in non-exceptional cases. An angle constraint is added to the node expansion, ensuring the smoothness of the planned trajectory and resampling if the angle between the sampled node direction and its parent node direction is greater than a threshold value.

The angle constraint added for the node extension is shown in Figure 6. The node is resampled if the angle difference between the sampled node direction and its parent node direction exceeds a threshold value of 60°. Node 6 in Figure 6 is taken as an example. Node 6 is new, and its parent is 5. The angle calculation is in Eq. (3), as shown at the bottom of the next page.

Node 6 in Fig. 6 is a new node whose parent node is 5. Still, it does not satisfy the requirement that the angle ∠1 between the sampled node's direction and the direction of its parent node is greater than a threshold value of 60°. Hence, it cannot grow and needs to be redefined as a new node.

When the aircraft can cross the altitude layer and obtain a shorter flight path, the node expansion process faces a flight process with altitude changes. The calculation of the horizontal node angle is consistent with Eq. (2), and the vertical speed limit is increased, which is elaborated in the following ''Experimental Simulation and Analysis''.

Dynamic collision detection is performed during planning to improve the feasibility of planning trajectories and reduce path re-planning due to conflicts during the flight. In this paper, the information record of the trajectory includes the spatial displacement and the corresponding moment. When a new trajectory planning expansion node is carried out, the positions of other aircraft are detected within a specified radius of 100 meters, with the current position of the planning aircraft as the center of the circle. If other aircraft are in range, the collision probability is high, and this node does not grow.

D. VIRTUAL BARRIER DESIGN

The flight space in urban airspace is narrow, the environment is complex, and the major fixed obstacles (such as buildings) have different geometries. If the path planning is done according to the actual shape of the building, it will increase the computation significantly. Primatesta [32] proposed a method to map the risks of drones flying over cities. Some methods simplify the calculation by enclosing the building with cubes [17].

Therefore, according to an error of two meters or less, most buildings are simplified into combinations of basic three-dimensional figures such as columns, cones, and spheres. Moreover, virtual obstacles are added to the periphery of three-dimensional figures to preserve a safe distance for aircraft emergencies.

The method of filling virtual barriers is directly used for some dense complexes that are difficult for aircraft to penetrate. These narrow and complicated passages are set as inaccessible areas for aircraft. Furthermore, virtual barriers are placed in parts with no other exits to prevent the path planning from entering the dense complexes and causing planning failure.

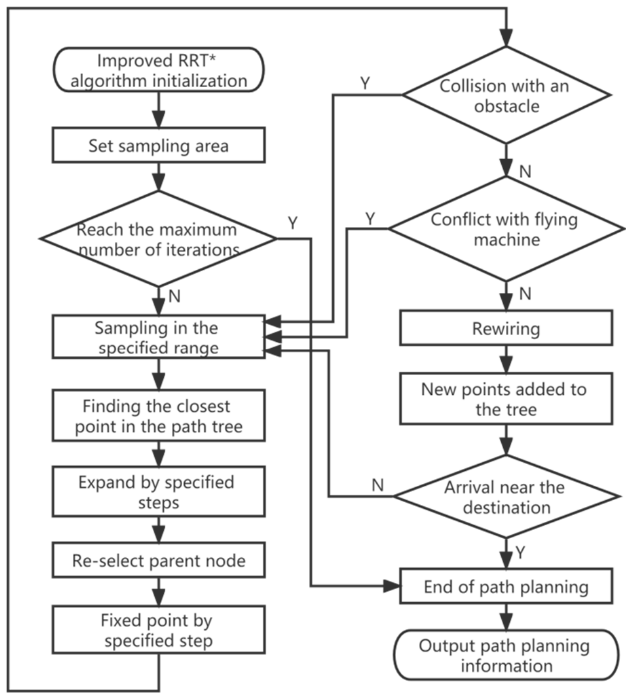

FIGURE 8. Flowchart of four-dimensional trajectory planning based on an improved RRT* algorithm.

Virtual barriers are set up as shown in Figure 7. The light gray part represents the real obstacle or forbidden space, the dark gray part is the virtual obstacle, and the white part is the area without obstacles. On the left side of Figure 7 is a cluster of dense buildings filled with barriers between the spaces between the buildings. In the right part of Figure 7, a virtual barrier is added to the specially-shaped building to ensure the aircraft is not flying inside. Such virtual obstacles can speed up path planning and reduce unnecessary computing costs.

E. PATH PLANNING PROCESS

The specific flow of the improved RRT* algorithm is shown in Figure 8, and the path-planning steps are as follows:

Step 1: Initialize the map environment, and set the airport and obstacle location.

Step 2: Set parameters such as safety distance, travel speed, and angle limit.

Step 3: Set 66 groups of starting point information and carry out path planning individually to obtain a reference track without the influence of other aircraft.

Step 4: Set the starting point information for this trajectory planning.

Step 5: Determine whether the reference trajectory is feasible or not. If feasible, go to step 9; otherwise, go to step 6.

Step 6: Perform trajectory planning in the current layer and obtain the available trajectory to step 9; otherwise, go to step 7.

Step 7: Open other altitude layers, perform route planning, and obtain a usable route or a route within 25% of the distance exceeded to enter step 9; otherwise, enter step 8.

Step 8: Delay the takeoff time, go to Step 5, and repeat the above operation until the maximum delay time is reached. If the path planning fails, record the cancellation flight information and go to step 4.

Step 9: Record the path planning information, go to step 4, and repeat the above operation until the maximum number of iterations is reached.

IV. EXPERIMENTAL SIMULATION AND ANALYSIS

A. SIMULATION DESCRIPTION

The experimental space is an urban space of 10 km x 10 km x 200 m, divided vertically into four main height layers of 0-50 m, 50-100 m, 100-150 m, and 150-200 m. There are three main spaces 50 meters in height for aircraft to pass. The priority is to fly in the 50-100 m layer, and the flight height is 75 meters due to the aircraft safety distance guarantee. There are 40 buildings in the city with heights over 70 meters (including 26 over 80 meters) defined in the experiment by combinations of rectangular, cylindrical, and spherical forms and different sizes. Twelve airports were established in the experimental area, one of which relied on high-rise buildings for takeoff and landing.

Moreover, restricted airspace was set up for each airport to prevent urban air traffic flights from entering restricted airspace. The total operating time of the aircraft is the sum of its takeoff, landing, and flight times. Since the terminal airport capacity is sufficient, the takeoff and landing times after each entry into the airport range are taken as the same mean value in this paper. The climb and descent speeds are set to 4 m/s, and the horizontal flight speed is set to 20 m/s.

Once a flight demand is generated, the reference path information is retrieved, and the feasibility of the reference path is evaluated. If feasible, the reference path is directly executed. If not, the path is planned according to the current flight plan being executed. The initial flight altitude is determined based on the airport information at the starting and ending points of the flight. The trajectory planning considering fixed obstacles such as buildings, airport no-go areas, and aircraft in flight is carried out without changing the altitude layer. The results of the trajectory planning are compared with the reference trajectory information obtained by calculation. The trajectory planning is executed if the consumption time and navigation distance exceed 1.25 times the reference trajectory. If the results of trajectory planning do

$$\angle 1 = arccos\frac{(x_{T_{5,6}} - x_{T_{3,5}})(x_{T_{3,5}} - x_{T_{1,3}}) + (y_{T_{5,6}} - y_{T_{3,5}})(y_{T_{3,5}} - y_{T_{1,3}})}{\sqrt{(x_{T_{5,6}} - x_{T_{3,5}})^2 + (y_{T_{5,6}} - y_{T_{3,5}})^2} + \sqrt{(x_{T_{3,5}} - x_{T_{1,3}})^2 + (y_{T_{3,5}} - y_{T_{1,3}})^2}} \tag{3}$$

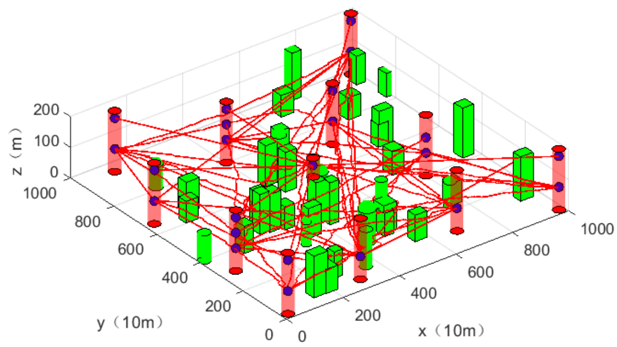

FIGURE 9. Aircraft path map corresponding to low-density flight demand.

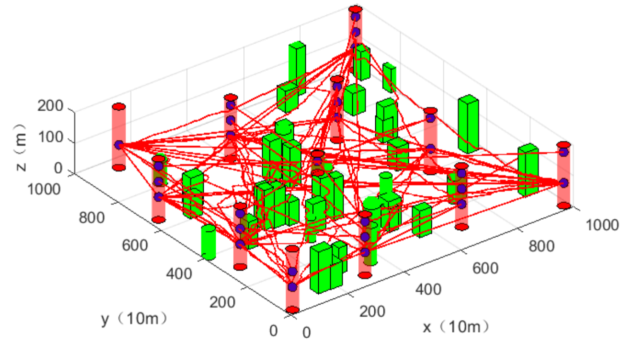

FIGURE 11. Trajectory map corresponding to medium-density flight demand.

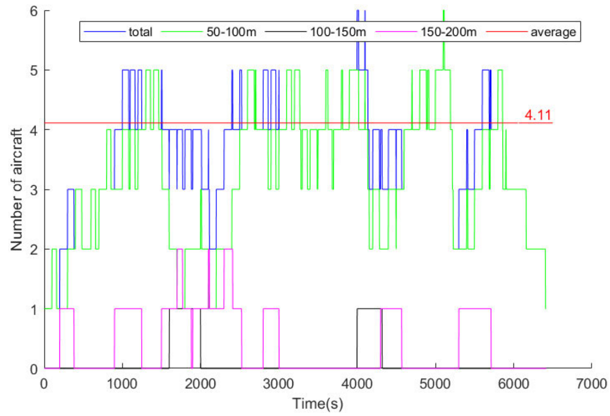

FIGURE 10. Statistical chart of the number of aircraft corresponding to low-density flight demand.

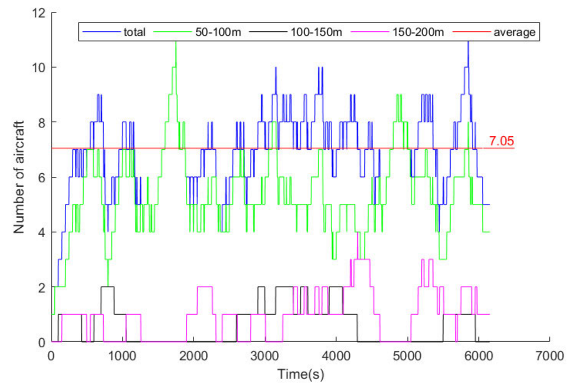

FIGURE 12. Statistical chart of the number of aircraft corresponding to medium-density flight demand.

not meet the execution requirements, avoidance is considered by changing the altitude layer, re-planning is conducted to obtain a better trajectory, and the trajectory qualification test is re-performed. If the condition-satisfying trajectory plan is still not obtained, avoidance by delaying the takeoff time is considered. The delay time will be counted in the total time, and the trajectory check will be performed again. If path planning cannot achieve the requirement by changing the altitude level and/or delaying the departure time, the aircraft density in the area of this path route is high at that period. The factor should be increased in such instances to reduce the path length requirement.

B. REFERENCE PATH INFORMATION ACQUISITION

Under the experimental conditions described in Section IV-A, let the paths from airport A to airport B and from airport B to airport A be the same. The best paths are solved in the first level of airspace for 66 combinations of takeoff and landing points at 12 takeoff and landing points in the environment. The obtained result is a nearly straight path after avoiding obstacles, which is used as a reference path whose starting point, time, distance, and path information are recorded.

C. EXPERIMENTAL RESULTS AND ANALYSIS

1) LOW-DENSITY FLIGHT DEMAND

Under the experimental conditions described in Section IV-A, the probability of generating a flight demand per second is set to 0.01, i.e., a new flight demand is generated in the region for an average of 100 seconds. In the simulation model, 60 sets of trajectory planning information were obtained in 6000 seconds, and 43 sets were directly used for the reference trajectory, as shown in Figure 9.

Intercepting the stable middle part of the acquired trajectory planning information shows that the number of aircraft in the experimental area is stable at 4.11 above and below, as shown in Figure 10. Hence, the probability of aircraft collision is low since the demand for urban air traffic is lower than its capacity under this flight demand.

2) MEDIUM-DENSITY FLIGHT DEMAND

The probability of generating flight demand per second is set to 0.02, i.e., an average of 50 seconds is required for a new flight demand to be generated in the region. The simulation model is run, and 120 sets of path planning information are obtained in 6000 seconds, of which 78 sets are reference paths. The number of aircraft flying into 100-150 m airspace has increased, as shown in Figure 11. According to

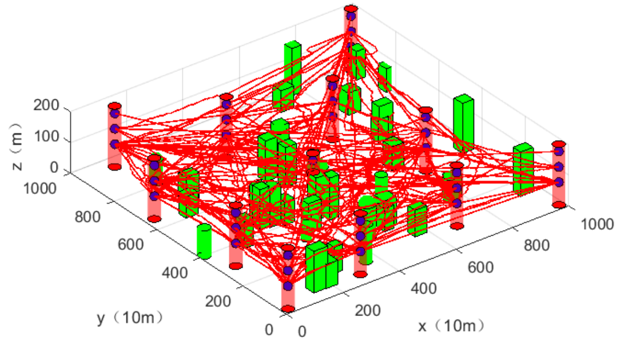

FIGURE 13. Trajectory maps corresponding to high density flight requirements.

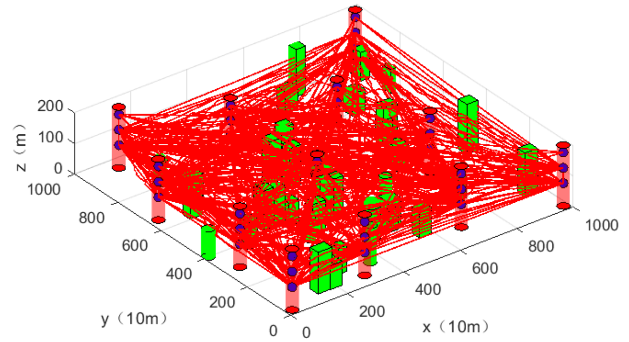

FIGURE 15. Path diagram corresponding to ultra-high density flight demand.

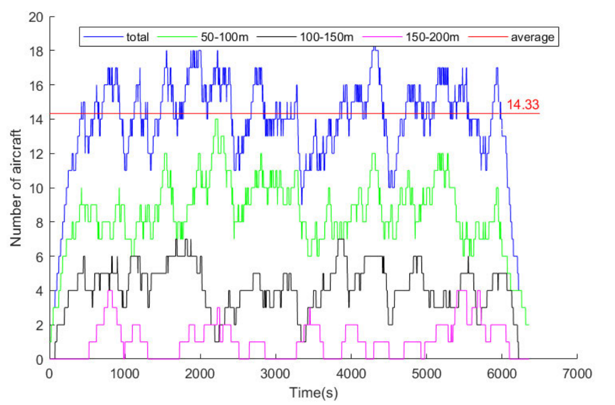

FIGURE 14. Statistical chart of the number of aircraft corresponding to the demand for high density flights.

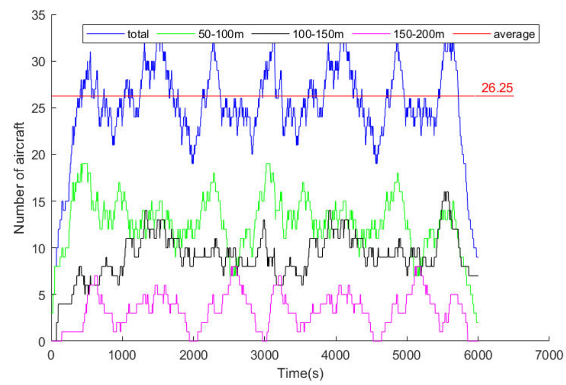

FIGURE 16. Statistical chart of the number of aircraft corresponding to ultra-high density flight demand.

the acquired trajectory planning information, the number of aircraft in the experimental area is stable above and below 7.05, with obvious fluctuations, as shown in Figure 12. Under this flight demand, the demand for urban air traffic is still lower than its capacity. However, the probability of aircraft collision increases, and the role of conducting integrated four-dimensional trajectory planning is gradually emerging.

3) HIGH-DENSITY FLIGHT DEMAND

The probability of generating flight demand per second is set to 0.04, i.e., an average of 25 seconds is required for a new flight demand to be generated in the region. The simulation model was run for 6000 seconds, and eight planning failures and 232 sets of path planning information were obtained. Of these, 101 groups used the reference path directly, six planning trips exceeded the path length threshold within 25%, and six delayed takeoffs. The number of aircraft flying into the 100-150 m airspace increased significantly, and there were cases of aircraft crossing layers to avoid other aircraft on the way to flight, as shown in Figure 13. According to the acquired trajectory planning information and by taking the middle section steady state, the number of aircraft in the experimental area is above and below 14.33 with obvious regular fluctuations, as shown in Figure 14.

4) ULTRA-HIGH-DENSITY FLIGHT DEMAND

The probability of generating flight demand per second is set to 0.1, i.e., an average of 10 seconds is required for a new flight demand to be generated in the region. In the simulation model, 600 sets of trajectory planning information were obtained in 6000 seconds, with 29 path lengths 1.25-1.5 times the reference trajectory and 112 delayed takeoffs, as shown in Figure 15. According to the obtained trajectory planning information and by taking the steady state of the middle section, the number of aircraft in the experimental area rises rapidly, with an average of 26.25 aircraft in the steady phase accompanied by large fluctuations, as shown in Figure 16. This indicates that the experimental airspace cannot sustain such a high density of flight demand. Hence, the capacity reaches saturation, with an airspace capacity of approximately 26 aircraft. At this time, the probability of aircraft collision is high, and aircraft queuing is common. Therefore, the need for coordinated 4-dimensional trajectory planning is high.

Based on the above experimental results, a comparison of the number of aircraft at the four flight demand densities shows that the fluctuation of the aircraft in the airspace increases with the flight demand density, which is the most obvious in the ultra-high-density flight demand scenario. The statistics are shown in Figure 17. In particular, the airspace

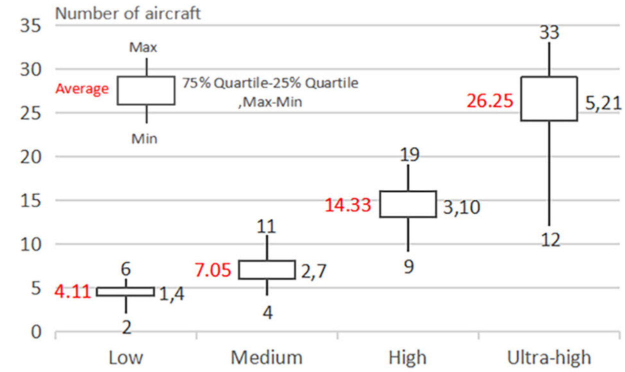

FIGURE 17. Analysis of the number of aircraft for the four densities of flight demand.

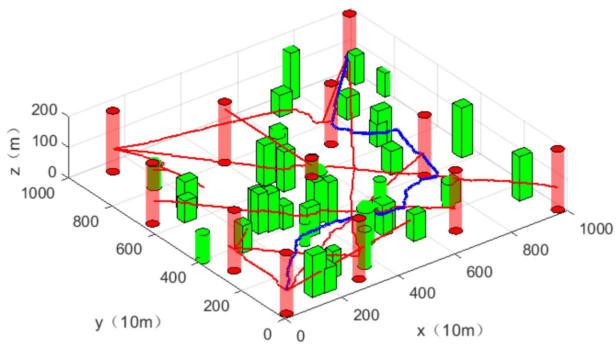

FIGURE 18. Analysis of the number of aircraft for the four densities of flight demand.

is already saturated during ultra-high-density flight demand. The number of aircraft in space is relatively large when dispersed and relatively small when gathered. The data in the figure are taken from the stable period of the above experimental results in units of the number of aircraft. The data above the box are the maximum number of aircraft, the data below are the minimum number of aircraft, the left side is the average value, and the right side is the difference between the two quartile values and the maximum and minimum values.

D. VERIFICATION OF ALGORITHM VALIDITY

According to the results of the four-dimensional trajectory planning simulations under the above four flight demand densities, when the density is small, the number of airspace layers can be distinguished without differentiation because the loss of airspace occupation is smaller than the resource consumption of aircraft path planning and control. With an increased density of flight demand, airspace stratification will increase the number of aircraft accommodated in urban airspace and allow for more accurate space occupancy planning when performing cross-level obstacle avoidance.

Next, the effectiveness and advantages of the algorithm are verified from two perspectives. The free-flight strategy based on static maps is simulated in the experimental section and compared with the proposed algorithm. The path planning based on the free flight policy of static map is carried out based on the low-density flight demand trajectory information obtained by the proposed algorithm. In Figure 18, the blue trajectory is the current path trajectory, and the red path is the aircraft path that may conflict with this planning.

TABLE 1. Comparison of actual and reference trajectory lengths for two path planning strategies at four flight demand densities.

Flight demand density	Traditional Strategy	Algorithm of this paper	Contrast
Low density	120.39%	101.39%	1.19
Medium density	117.85%	101.26%	1.16
High density	124.82%	104.17%	1.20
Ultra-high density	137.91%	108.35%	1.27

Experiments are conducted for the static map-based free flight strategy according to the proposed method at each flight demand density to verify the effectiveness of the proposed algorithm. The number of planning times equal to the number of valid trajectories in 1000-5000 seconds of the proposed algorithm is obtained. The length of the actual track is compared with the length of the reference track as follows:

$$LK = \frac{1}{n} \times \sum\nolimits_{i=1}^{n} \frac{l_{Real}}{l_{Reference}} \times 100\%, \tag{4}$$

where n is the number of calculated trajectories, l_{Real} is the trajectory length of the simulation run, and $l_{Reference}$ is the corresponding reference trajectory length. When the trajectory is shorter than the reference trajectory length, the elevation is taken as $LK = 1$. The results are shown in Table 1.

Data analysis in the above table shows that regardless of the flight demand, the algorithm in this paper has an advantage over the traditional free flight strategy based on static maps in terms of the flight path length of the vehicle. The experimental results of low-density and medium-density flight demands are similar, related to the aircraft's airspace capacity and flight altitude. The experimental results of high-density and ultra-high-density flight demand show a trend where the advantage is more obvious when the flight demand is higher. Simultaneously, more frequent emergency avoidance may lead to more safety accidents. The trajectory planning proposed in this paper minimizes the occurrence of emergency avoidance by trajectory planning before the departure of the aircraft, which also has advantages in improving the safe flight of high-density aircraft.

Other aircraft were taken as obstacles to carry out path planning and further verify the superiority of the proposed method while providing four-dimensional flight path information for the RRT* algorithm and Bi-RRT. When comparing these several path planning algorithms, the same simulation environment with the same simulation process is provided. The difference between the experiments is the use of different algorithms for path planning.

It should be noted that several experiments were repeated in this paper. There is not only one path length comparison between the actual path length and reference path length for

TABLE 2. Comparison of actual track length and reference track length of three strategies with four-dimensional information under four densities.

Flight demand density	RRT*	Bi-RRT	Algorithm of this paper
Low density	110.62%	121.77%	101.39%
Medium density	111.39%	124.58%	101.26%
High density	116.67%	127.92%	104.17%
Ultra-high density	122.98%	127.85%	108.35%

the three strategies. In addition, the reference paths are given in advance and are consistent. There are no different reference paths obtained by different algorithms.

The lengths of the actual flight path and a reference flight path were compared, and the results are shown in Table 2.

According to the data analysis, the aircraft path length obtained by the algorithm in this paper has certain advantages and provides four-dimensional information conducive to efficient path planning. The presented method can increase the maximum aircraft density in an area by carrying out four-dimensional path planning before takeoff.

V. CONCLUSION

This paper provides a four-dimensional trajectory planning method for high-density flights in urban multi-building environments. The proposed improved Rapidly Exploring Random Tree Star (RRT*) algorithm for urban air traffic considers dynamic obstacle avoidance between aircraft and overall aircraft management in the region based on the traditional static map path planning application. Different flight demand densities were set up in simulation experiments to perform four-dimensional trajectory planning simulations in an urban environment. Simulation experiments were conducted to obtain the airspace capacity of the experimental area and the number of aircraft at different flight demand densities. The effectiveness of the proposed algorithm and the necessity of real-time unified management of high-density flights were proved. Since the algorithm provided in this paper is used for aircraft pre-departure trajectory planning and does not consider sudden dynamic obstacle situations such as flocks of birds in the urban environment, the strategy and overall scheduling of the aircraft to deal with sudden moving obstacles in the urban environment still need to be investigated.

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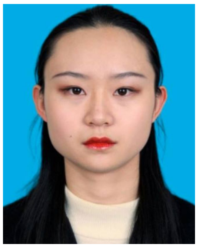

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