UAV Path Planning Method Considering Safety and Signal Shielding Risk

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***Abstract*—In order to meet the needs for the safe operation of unmanned aerial vehicles (UAV)s in cities, this paper proposes a multi-objective path planning method based on a particle swarm optimization algorithm. Firstly, a complex urban environment model is constructed by using the grid method. Then, taking the total length of the UAV path and the minimum flight risk as objectives, the multi-objective path optimization problem is established under the condition of taking into account the obstacle avoidance requirements and performance constraints of the UAV. Finally, the optimization problem is solved by a multi-objective particle swarm optimization algorithm and the path curve is smoothed by cubic B-spline. The simulation results show that the multi-objective path planning method proposed in this paper is more reasonable than the method that only considers the lowest security risk or the shortest path.**

***Keywords*—Multi-objective particle swarm optimization; path planning; cubic B-splines**

I. Introduction

With the continuous development of the electronic economy business, the number of people's online shopping has increased greatly, which also brings problems such as traffic congestion, high labor cost, a more complex service scene and so on. In recent decades, the UAV industry has been growing continuously. UAVs are utilized in urban environments for various purposes, including traffic monitoring [1], photography, and weather forecasting [2]. They are also a core component of Urban Air Mobility (UAM) [3] and future smart city plans [4, 5]. Along with the progress of relevant hardware and software, UAV delivery technology comes into being. At the same time, for the "last kilometer" problem that has plagued the industry for many years, the adoption of UAV delivery is the only feasible plan at present. Drone delivery can alleviate traffic congestion, improve delivery efficiency, and make great contributions to the sustainable development of the express delivery industry. As the premise of delivery, UAV path planning is a top priority issue that we should solve.

According to the classification of algorithms, path planning problems can be divided into traditional classical algorithms and swarm intelligence algorithms. The first kind of algorithms, such as naive Bayes classifier [6], according to Bayes' theorem, based on variable independence hypothesis and maximum likelihood estimation method[7], takes into account stable classification efficiency and insensitive sensitivity to missing data; Or backtracking algorithm [8], which is based on the main theories such as depth-first search [9]and recursion[10], takes into account both systemicity and jumping, and has the advantages of high search efficiency and strong adaptability. Based on this theory, Khan et al. [11] adopted a backtracking optimization algorithm to significantly improve the overlay path smoothing technique. The second type of algorithm, such as the ant colony algorithm [12], adopts the theory of simulating ant foraging, and extracts distributed, global optimization and adaptive features by revealing the selection, renewal and coordination mechanism, taking into account the advantages of fast convergence speed and dynamic path changes in the later period, and improves the planning quality. Based on this theory, Dentler et al. [13] proposed a chaotic ant colony improvement algorithm for path planning in dynamic environments to further shorten the path length. Calik [14] adopted multi-agent structure ant colony optimization algorithm to improve the obstacle avoidance effect for path planning problem in complex multi-obstacle environment.

Or genetic algorithm [15], which adopts the theory of biogenetics to reveal the laws of biological natural selection and genetic mechanism, takes advantage of its global search ability, adaptability, parallelism and other characteristics, takes into account the advantages of wide application range and high flexibility, and improves the quality of planning. Based on this method, Pehlivanoglu et al. [16] adopted a vibration genetic algorithm for path planning in low population environment to speed up the generation cycle.

Although the above methods have achieved beneficial results, they are rarely involved in the consideration of flight safety and signal shielding. Therefore, Banerjee [17] proposed an objective function construction method considering flight safety, using a linear Bayes algorithm to solve the dual-objective optimization problem that takes into account flight safety and shortest path. Ahmed et al. [18] put forward an improved particle swarm optimization algorithm to achieve the best obstacle avoidance effect and the shortest operating path. Levasseur [19] developed a surrogate model (Kriging method and neural networks) that considers wind conditions and various types of uncertainties to calculate the probability of drone impact on the ground. Jin [20] proposed a two-dimensional drone flight safety path planning method based on ground fitting. This method calculates the dynamic density of outdoor pedestrian populations using building volume, residential population, and grid area, thereby designing safe path planning for drones in urban environments.

The aforementioned research works plan routes by considering flight safety factors and constructing safety objective functions based on wind conditions, building volume, population density, and vehicle density. However, these studies do not address issues related to the proximity and avoidance of flight-restricted zones due to signal blocking, and therefore, cannot solve problems such as loss of communication or control

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caused by signal blocking during flight. Signal blocking is a crucial issue in various application scenarios such as wilderness rescue, cave exploration, and military reconnaissance. Consequently, it is necessary to design safety objective functions that account for signal blocking in the path planning process to achieve both the shortest path and the highest safety.

Therefore, based on the practical requirements of designing safety objective functions that consider signal shielding mentioned above, this paper proposes a path planning method for multi-target UAVs based on particle swarm optimization algorithm. The full text is arranged as follows: Section 1 briefly reviews the researches on path planning;

In the second section, a three-dimensional static urban environment model is established based on the three-dimensional raster method under the constraints of the UAV itself, considering the factors such as security risk and signal shielding, and the path optimization problem is described.

In the third section, a new objective function construction method is proposed, which takes into account security risks, signal shielding and shortest path, and uses particle swarm optimization to optimize multiple objective functions, and then smooths the path curve by means of cubic spline curve fitting scatter points.

In the fourth section, a set of Pareto solutions of evenly distributed flight path and safety risk are obtained through simulation examples, and the effectiveness of the proposed method in terms of shortest path and safety optimization is verified by considering safety wind comprehensively.

The fifth section gives the full text conclusion.

II. Environment Modeling and Optimization Problem Description

Environmental modeling is the first problem to be solved in the course of UAV flight path planning. Its purpose is to establish a mathematical model describing the starting point and end point, obstacle position, flight environment information and constraints, and provide an algorithm model for describing the path optimization problem and simulation verification.

A. Establishment of 3D Environment Model

In this paper, it is assumed that the largest external cuboid in the three-dimensional model is the protection area of obstacles, and the UAV track intrusion represents the collision path is not feasible. In this hypothesis, the irregular urban obstacles are regarded as regular columns, so that the planned path reduces the difficulty of the overall path planning and meets the obstacle avoidance requirements. As the input condition of the UAV path planning algorithm, the 3D environment model needs to obtain the flight environment information before the UAV executes the flight task, including the distribution and height of buildings, crowd density, traffic flow density, etc.

In this paper, the three-dimensional histogram shown in Fig. 1 is established to simulate the urban environment. The three-dimensional grid method [21] is adopted to divide the urban environment space into countless independent cells. If the range of the cell does not contain any obstacles, it is called a free grid. In the opposite case, if there are obstacles in the range of the grid, it is called the obstacle grid. The UAV can move freely in the free grid, but it cannot move in the obstacle grid. In order to reduce the calculation amount, no grid is set between each small surface, and the grasp of the granularity is adjusted to the shortest distance of the UAV.

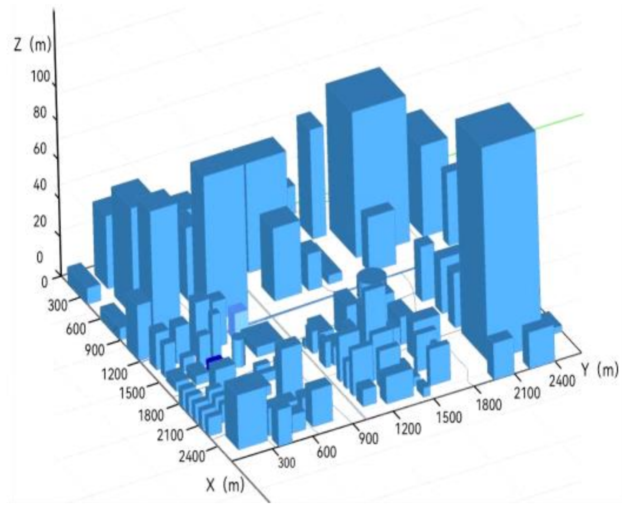

Fig. 1. Histogram of the three-dimensional building group environment.

Fig. 2. Top view.

B. Description of Optimization Problem

In the above environment, planning a path (see Fig. 2) that considers the dual goals of safety and shortest distance, the optimization problem can be described as:

$$\text{Objective function:} \quad \min F = (f_L, f_R)^T \tag{1}$$

Where f_L is the drone track length, which can be converted into the sum of distances of discrete points, the formula is as follows:

$$\min f_L = \sum_{i=1}^{n} \sqrt{(x_i - x_{i-1})^2 + (y_i - y_{i-1})^2 + (z_i - z_{i-1})^2} \quad (i = 1, 2 \ldots, n) \tag{2}$$

The starting coordinate point of the UAV is (x_0, y_0, z_0), and the coordinates of the middle waypoints are (x_i, y_i, z_i), f_R is a function to consider safety.

$$\min f_R = f_P + f_C + f_S \tag{3}$$

Where, f_P denotes the risk of drone crash for pedestrians, f_C denotes the risk of drone crash for vehicles, f_S denotes and the risk of signal shielding.

C. Constraints of UAV

$$d_{between} > r_{protect} \tag{4}$$

$$\arccos\left(\frac{\mathbf{a}_i^{\mathrm{T}}\mathbf{a}_{i+1}}{\|\mathbf{a}_i\|\|\mathbf{a}_{i+1}\|}\right) \le \theta_{\max} \tag{5}$$

$$\arctan\frac{|z_{i+1} - z_i|}{|a_i|} \le \beta_{\max}\,(i = 1, 2..., n-1) \tag{6}$$

$$h_{\min} \le z_i \le h_{\max} \tag{7}$$

Where, d_{between} indicates the distance between the UAV and the obstacle, and r_{propect} indicates the radius of the spherical protection area set for the UAV; $\mathbf{a}_i = \left(x_i - x_{i-1} \quad y_i - y_{i-1}\right)^{\mathrm{T}}$ is the projection vector of the i section of the voyage on the horizontal ground, $\theta_{\max}$ representing the maximum yaw Angle, $\beta_{\max}$ representing the maximum pitch Angle, $h_{\min}$ and $h_{\max}$ respectively representing the minimum and maximum flight height.

III. Multi Objective Particle Swarm Optimization Algorithm for Solving the UAV Path Planning Problems

A. Construction of Objective Function Considering Safety Risk

As can be seen from formula (3) above, the safety risk objective function in this paper includes three parts: the risk of UAV crash to pedestrians, the risk to vehicles [22] and the risk of entering the signal shielding area during flight. The mathematical models of these three parts will be established as follows:

1) The risk of drone impact on pedestrians on the ground: Due to the differences in the characteristics of different functional areas in the urban environment, such as the population density and shelter [23] coefficient of each functional area, the risk of UAV to pedestrians on the ground should be evaluated according to the different differentiation of the operation area during route planning, as follows:

$$f_R = \lambda QF \tag{8}$$

Where, λ represents the crash probability of UAV per hour, F represents the fatality rate [24] related to the kinetic energy of UAV, and Q represents the number of affected persons. The calculation formula is as follows:

$$Q = A\rho_p \tag{9}$$

Where, A represents the area of the drone and ρ_P represents the population density in the falling area.

The mortality rate F related to unmanned mobility is as follows:

$$F = \frac{1}{1 + \sqrt{\frac{\delta}{\varepsilon}}\left(\frac{\varepsilon}{E}\right)^{\frac{1}{4C_V}}} \tag{10}$$

Where, δ is the impact energy required for mortality to reach 50% when c=0.5, and ε is the critical value of impact energy required for death when c=0, C_v is equal to the masking coefficient, when there is no masking, C_v=0; When only trees exist, C_v=0.25; When there are numbers and low buildings, C_v=0.5; When tall buildings exist, C_v=0.75.

In formula (5), E represents the kinetic energy of the drone when it crashes, and the formula is as follows:

$$F_d = \frac{1}{2} R_L A_\rho V_{rel}^2 \tag{11}$$

$$\begin{cases} a = \dfrac{mg - F}{m} = g - \dfrac{R_L A_\rho V_{rel}^2}{2m} \\ = \int_0^t \left(g - \dfrac{R_L A_\rho V_{rel}^2}{2m}\right)dt = \sqrt{\dfrac{2mg}{R_L A_{\rho A}}\left(1 - e\dfrac{\lambda R_L A_\rho A}{M}\right)} \end{cases} \tag{12}$$

$$E = \frac{1}{2} m v^2 \tag{13}$$

Where, F_d represents the resistance of the UAV in falling, R_f represents the falling coefficient, ρA represents the air density, V_{rel} represents the falling speed of the UAV, m represents the mass of the UAV, g represents the acceleration of gravity, h represents the operating height of the UAV, and v represents the operating speed of the UAV.

2) The risk of drone impact on ground vehicles: The risk to the vehicle when the UAV is running is calculated as follows:

$$f_C = \lambda CY \tag{14}$$

Where, C represents the probability of the drone hitting the vehicle after falling, Y is the average death rate of each car accident, and C is determined by the ratio of the area of all vehicles on the road to the total area of the road, as shown in the following formula:

$$c = \frac{\bar{S}_{car}}{S_{road}} \times N_{car} N_{car} \tag{15}$$

Where, $\bar{S}_{car}$ is the projected vehicle area, is the number of vehicles, S_{road} is the road area, L is the road length, K is the traffic flow density, D_{road} is the width $N_{car} = KL, S_{road} = LD_{road}$

3) The risk of entering the signal shielding area during drone flight

$$f_s = \begin{cases} \frac{d_{in} - d}{d_{in}} & d \le d_{in} \\ 0 & d > d_{in} \end{cases} \tag{16}$$

Where, d_{in} indicates the radius of influence of the signal shielding area, and d indicates the distance between the UAV and the center of the signal shielding area.

B. Multi-Objective Optimization based on Particle Swarm Optimization

The multi-objective optimization problem can generally be expressed as a function

$$\min F(x) = (f_1(x), f_2(x), ..., f_M(x)) \tag{17}$$

Among $x \in \Omega, f(x) \in R^M, \forall_i = 1, 2..., M$

Where R^M is the target space and Ω is the decision space, which maps the decision space to the target space.

Compared with the single objective optimization problem, the most prominent problem of the multi-objective optimization problem is that there is a probability of conflict between different objectives in the multi-objective optimization problem, so it is difficult for the single objective optimization algorithm to have an effect on it.

In the dominance relationship between individuals, p and q are two distinct individuals in the population, which are called p dominate q, if the following conditions must be met:

$$f_k(p) \le f_k(p)(k = 1, 2, \cdots, r) \tag{18}$$

There exists at least one subobjective that makes p better than q, i.e. : $\exists m \in \{1, 2, ...r\}$, so $f_m(p) < f_m(q)$, then p dominates q. Where r is the number of subgoals, then p is said to be non-dominant, or non-inferior or dominant, and q is dominated. Expressed as p $\succ$ q, where '$\succ$ 'is the dominant relation [25].

The model proposed in this paper includes two factors: the flight path of UAV and the safety risk, in which the safety risk contains three objective functions. Due to the large differences in the order of magnitude and physical meaning of the two objectives of the flight path and security risk in the model, it is difficult to accurately assign weights and convert them into a single objective optimization problem. Meanwhile, for the UAV path planning, a set of Pareto solutions can be obtained to represent multiple optimal solutions, increasing the selectivity of the UAV path. Therefore, based on the multi-objective idea, this paper uses the multi-objective particle swarm optimization algorithm to solve the proposed multi-objective model.

Based on the advantages of PSO (particle swarm), MOPSO (Multi-objective particle swarm Algorithm) [26] uses the idea of external archiving and the principle of Pareto dominance [27] and follows the most basic equation to update its speed and position. When MOPSO deals with multi-objective problems, each iteration will produce a set of non-inferior solutions, which will be optimized through mutual learning among individuals, because the speed and position of each particle in the iterative process of PSO are constantly changing, and the fitness (objective function) will also change. Therefore, it is generally necessary to use an external archive to store the data of pareto optimal solutions and maintain the diversity of solutions. The steps of MOPSO method adopted in this section are as follows.

1) Data initialization, using raster method to generate environment models, initializing their speed and position, and given MOPSO parameters as follows:

$$P_i(x_i, v_i), \ i = 1, 2, \cdots, N \tag{19}$$

Use the generated $P_i(x_i, v_i)$ as the initialization particle and place them in external memory. X_i is the current position of the ith particle and V_i is the current velocity of the ith particle. Includes the inertia weight coefficient ω and learning factors C_1 and C_2, the initial population size N, the number of grids in each dimension D, the maximum increment level M, and the maximum number of iterations G.

2) Comparison: Each particle that is subsequently randomly generated is compared to the particles in memory, updating the particles in memory according to the following rules:

Comparison rule: If all fitness values (path and safety) of a particle in memory are greater than that particle, the particle in memory is deleted from memory; If there is a other particle in the memory, all fitness values are less than the particle, then the particle is not added to the memory, otherwise, the particle is added to the memory. Where, the fitness value is the value of two objective functions, the track path and the safety risk respectively.

3) Update of formulas: Collaboration and information sharing among individuals in the group to find the optimal solution. The particle swarm optimization algorithm only iteratively updates and stores the individual optimal solution and global optimal solution of each iteration through the velocity update formula and the position update formula. All particles adjust their speed and position according to the current individual extreme value found by themselves and the current global optimal solution shared by the whole particle swarm, so as to obtain the overall global optimal solution. Then the velocity and position update formula of particles [28] is as follows:

$$\begin{aligned} v_i(t+1) = \omega v_i(t) + c_1 r_1 (P_{best}(t) - x_i(t)) \\ + c_2 r_2 (G_{best}(t) - x_i(t)) \end{aligned} \tag{20}$$

$$x_i(t+1) = x_i(t) + v_{i+1}(t+1) \tag{21}$$

Where t is the number of update iterations and ω is the inertia weight coefficient. By dynamically changing the inertia of particles in flight, the purpose of global search capability and the purpose of balancing local search capability are achieved. C_1 and C_2 are the learning factors, used to adjust the speed, r_1 and r_2 are the random number on the interval [1,2], so as to increase the randomness of the algorithm. P_{best} is the optimal position of the particle during flight, and G_{best} is the global optimal position in the population. Where, P_{best} is obtained based on the dominant relationship of the current particle, if the current particle dominates, then take P_{best} as the current individual extreme value of the particle; If the two cannot be compared, the number of other particles dominated by the two in the group is calculated, and the number with more domination is taken as the individual extreme value, G_{best} is extracted from the optimal solution of Pareto frontier stored in external memory by roulette method [29].

After updating in the above formula, new particles are generated, the population is sorted by the dominant, the optimal Pareto frontier of the non-dominant solution is stored in the external memory, and the external memory is updated according to the comparison rules in step (2).

4) Repeat step (3) until the termination condition is reached. At this time, the data saved in the external memory is the Pareto frontier obtained by the algorithm. The change value of particle position is set. When the change of all particle positions is less than the threshold value, it is the termination condition, and the optimal Pareto frontier output is the final optimal scheduling result.

The overall framework diagram of the algorithm is shown in Fig. 3.

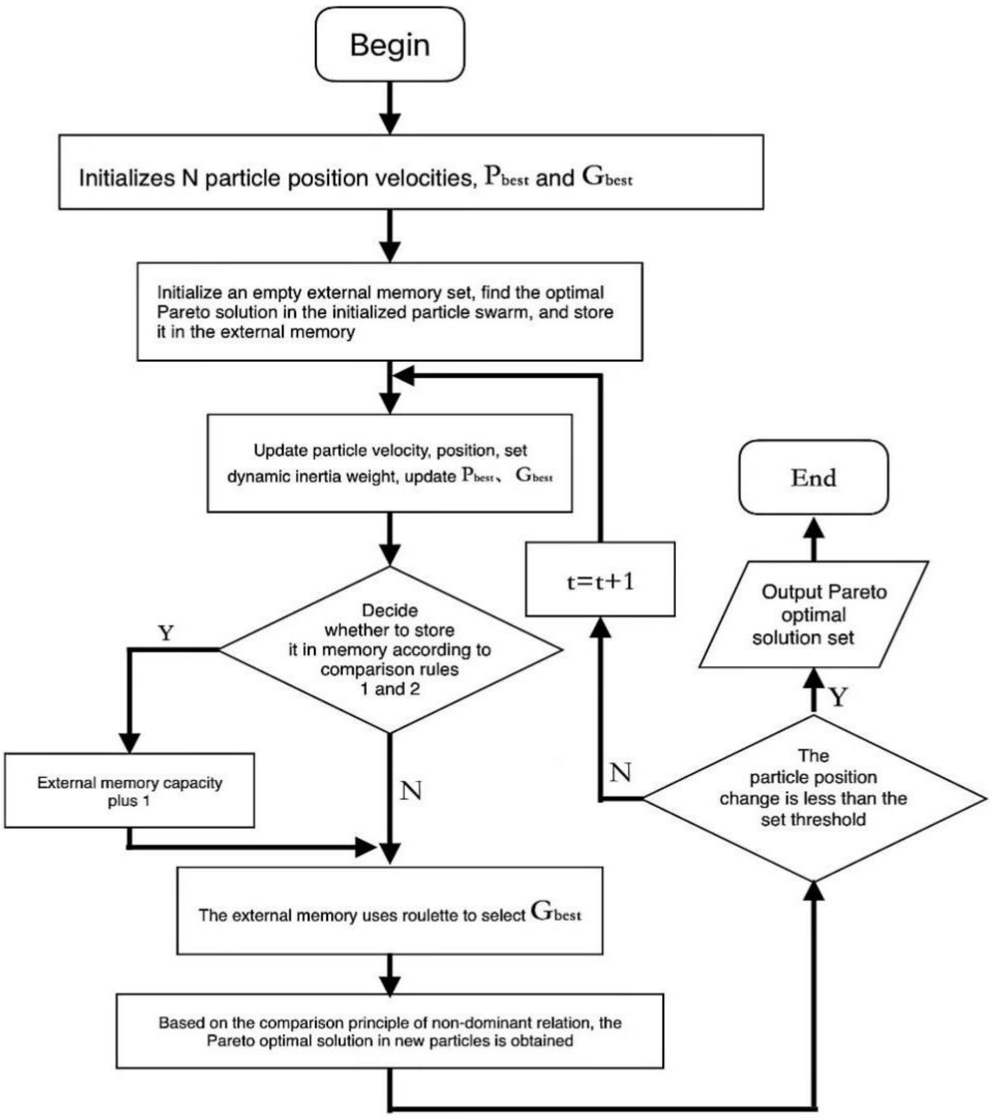

Fig. 3. Algorithm flow chart.

C. 3 Times B-Spline Interpolation Optimization

The planned path is not smooth or even out of reality. In order to keep the stability of the path in order to conform to the operation of the UAV in the city, the cubic spline interpolation is used to smooth the flight path of the UAV.

In this paper, cubic B-spline interpolation [30] is used to smooth the flight path of UAV, and the effect is shown in the figure. The path points that the UAV needs to pass through during flight are $P=(P_1,P_2...,P_n)$, and the coordinate of each point P_k in the three-dimensional coordinate system is (x_k,y_k,z_k). Then perform cubic spline interpolation on $(x_0,x_1...x_n),(y_0,y_1...y_n),(z_0,z_1...z_n)$ separately [31] to form a smooth flight path curve. Fig. 4 shows cubic spline interpolation curve.

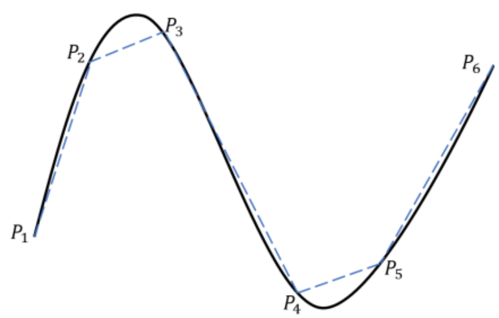

Fig. 4. Cubic spline interpolation curve.

Path smoothing basis function and control point:

Given spatial fixed points $P_i(i=0,1,...,m+n)$, curve segments can be obtained n times:

$$P(t)=\sum_{i=0}^{n}P_iF_{i,k}(t) \tag{22}$$

Where: P_i is the curve equation corresponding to the i^{th} control point, and $F_{i,k}(t)$ is a k-order B-spline basis function. Since the value represents the smoothness of the curve, the higher the value of k, the better the smoothness of the curve, but the greater the degree of calculation. In order to take into account the smoothness and complexity, this paper selects $k=3$ and obtains the basis function of cubic B-spline curve as follows:

$$F_{i,k}(t)=\frac{1}{k!}\sum_{m=0}^{k-i}(-1)^jC_{k+1}^j(t+k-m-j)^k \tag{23}$$

IV. Simulation Analysis and Verification

A. Simulation of Security and Signal Shielding Factors

1) Security: In the course of flight, the UAV should avoid the dense traffic and people as far as possible, reduce the harm caused by the UAV crash to urban roads and pedestrians, and improve the safety of the flight process. The distribution of traffic flow density of each road in the environmental model and the crowd density of the sidewalk is shown in Fig. 5.

The traffic flow density is set to (1,50), and the crowd density is set to (0.02,0.5). The depth of the color in Fig. 5 represents the density. The traffic flow in the intersection area is larger, while the crowd is densely distributed near the complex buildings.

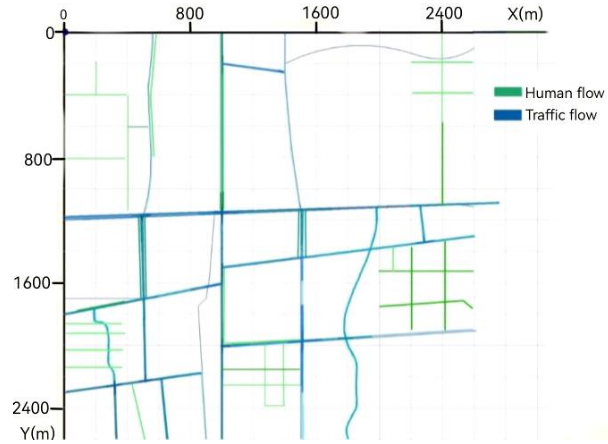

Fig. 5. Distribution of traffic flow density and human flow density.

2) Signal shielding: In the era of modern communication, the consideration of signal shielding area is particularly important. Ensuring that drone paths do not cross these areas reduces communication and navigation risks and improves flight safety. Among them, the signal shielding zones are randomly distributed in urban buildings with different radii, as shown in the Fig. 6.

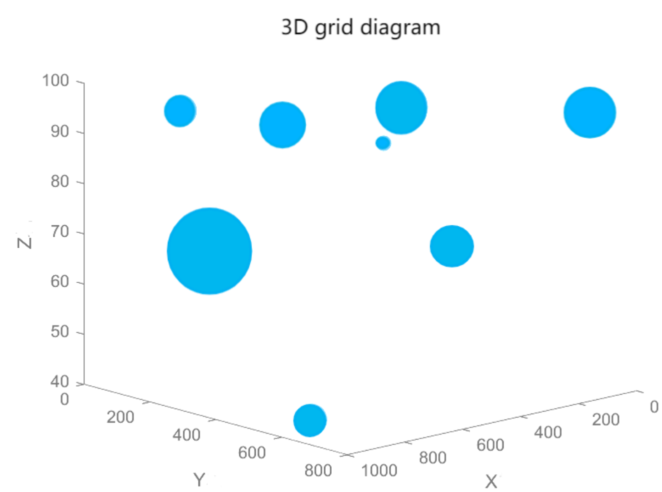

Fig. 6. Signal shielding area.

In summary, these characteristics indicate that MOPSO algorithm plays an important role in urban flight path planning of UAVs, and can fully consider factors such as safety, efficiency and route optimization. Through the analysis of the simulation results, we can further optimize the algorithm and improve the accuracy and reliability of the path planning to deal with various complex situations in the urban environment.

B. Path Planning Simulation

In this paper, the flight is designed to start from (0,0,0) and end from (2500,1560,30). In addition, the path planning also avoids areas with high human and vehicle flow, especially intersections, to reduce the risk of conflict with other traffic participants.

In this paper, the multi-objective model based on MOPSO will finally get a set of Pareto solutions, and Fig. 7 shows the distribution of this set of solutions. The fitness of the model is large because the height of each waypoint is considered in the model's flight path fitness. From the perspective of multi-objective programming, it can be seen that the distribution of this solution has good universality and uniform distribution, so the quality of this group of Parto solutions is good.

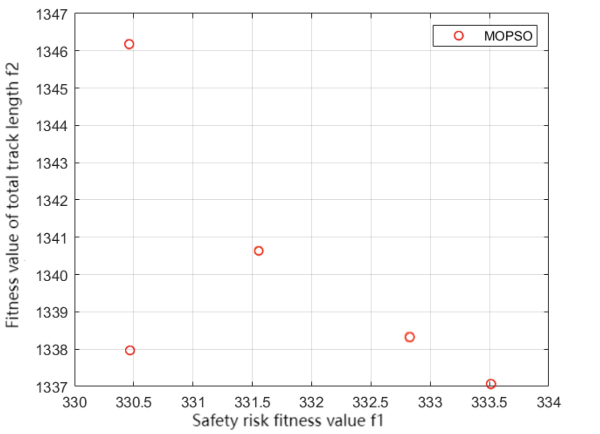

Fig. 7. Fitness distribution map.

Based on multi-objective planning, this method obtains a set of Parto solutions and five path schemes, in which the solution with the lowest security risk is the final path planning solution, as shown in Fig. 8 below, where the red trajectory 1 is the flight path of the UAV. The others can be used as alternative path schemes, providing operators with more path choices, better coping with various emergencies, and excellent adaptability in urban environment.

Fig. 8. Top view of path planning.

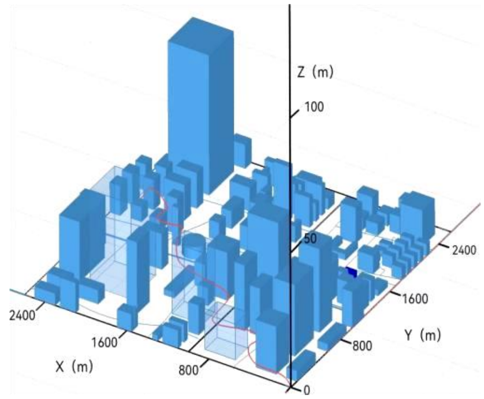

Fig. 9. Three-dimensional diagram of path.

C. Comparison Verification

In order to prove that the path generated in the urban environment model is the shortest and the safest, on this basis, this paper also gives three other comparison paths (see Fig. 9, 10 and 11) under different targets:

Trajectory 2: Only the shortest path is taken as the target, and the signal shielding area is not considered;

Trajectory 3: Only the safety is the goal, but the signal shielding area is not considered;

Track 4: Safety and shortest path is the goal, but the signal shielding area is not considered;

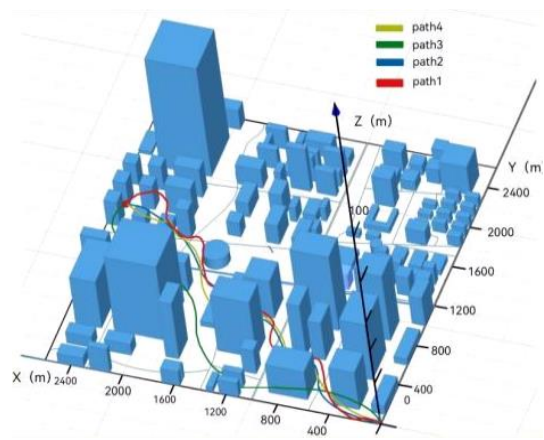

Fig. 10. Three-dimensional diagram of three different paths.

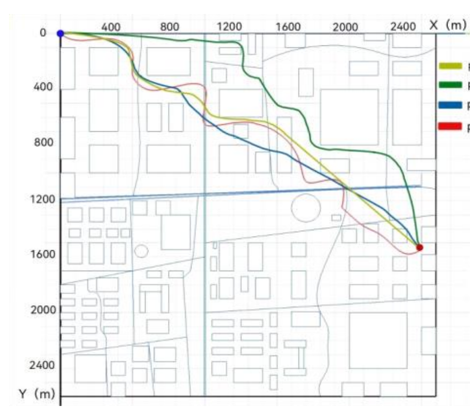

Fig. 11. Top view of three different paths.

D. Expected Result (Analysis)

Although Track 2 is 20.9% shorter than Track 1, it has a 19.5% improvement in fitness for pedestrian hazards and vehicle safety, as well as safety risks in signal-shielded areas.

Trajectory 3: Although aiming at safety, because the trajectory does not consider the distribution of urban signal shielding areas, the safety risk of this trajectory is increased by 6.3% compared with that of trajectory 1, and the total length is increased by 15.6%.

Trajectory 4: The safety risk is increased by 8.1%, but the total path length is shortened by 5.6%

To sum up, the new multi-objective function proposed in this paper comprehensively considers the path length and the security risk with signal shielding, and generates the optimal path when both are taken into account. Table I shows the path length and safety index of each trajectory.

TABLE. I. PATH LENGTH AND SAFETY INDEX OF EACH TRAJECTORY

Verify trajectories	Path length (m)	Safety risk
Track 1	4385.1	330.5
Track 2	3512.5	394.9
Track 3	4661.3	351.3
Track 4	4139.5	357.1

V. CONCLUSION

Aiming at the complex and changeable urban environment model, this paper proposes a multi-objective path planning method which considers the shortest path and the lowest security risk. In this method, the path length and safety risk of UAVs are taken as two major factors to construct the objective function, and the performance and obstacle avoidance requirements of UAVS are taken as constraints. The path optimization problem is established and a set of Parto solutions are obtained by using multi-objective particle swarm optimization algorithm. The simulation analysis results show that the proposed method can effectively reduce the risk by 19.5% or shorten the path by 15.6% compared with the shortest path or the lowest safety risk. The two requirements can be effectively taken into account. In addition, by taking the signal shielding factor into consideration, the security risk can be further reduced by 6.3%. The method proposed in this paper can be used to safely reach the destination in a relatively short path while avoiding the dense area of people and vehicles and the signal shielding area.

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