Cooperative Path Planning Algorithm of UAV in Urban Environment Based on Improved Pigeon Swarm Algorithm

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Abstract. For the urban environment with dense obstacles, narrow space and complex air flow, the UAV cooperative path planning method is studied. The selection method of cooperative path in urban environment is proposed. A multi UAV cooperative path planning method based on Cauchy mutation pigeon intelligent optimization algorithm (ECM-PIO) is proposed, which avoids the optimization deviation of the traditional pigeon swarm algorithm in the process of path optimization and overcomes the disadvantage that the traditional pigeon swarm algorithm is easy to fall into local optimization. The simulation results verify the advancement of the proposed cooperative path planning method of UAV in urban environment based on ECM-PIO.

Keywords: UAV · Cooperative path planning · Urban environment · PIO

1 Introduction

In order to get the optimal flight path for civil aircraft, the aircraft path planning problem was first proposed by the American Aviation Research Center, aircraft energy management technology and navigation technology were used to design the path planning method. At the beginning of the 21st century, path planning methods mainly based on random search algorithms, such as fast random search tree, probability path graph and Voronoi graph, which can almost give the optimal solution [1]. However, in some complex environments, such as unpredictable obstacles, these random search algorithms usually cannot obtain a feasible path. This problem promotes the development of path planning methods. In order to effectively and efficiently solve the path planning problem in complex environment, in recent ten years many traditional heuristic optimization algorithms, such as A* algorithm, D* algorithm and model predictive control (MPC) algorithm, were to develop more advanced path planning strategies [2].

In recent years, the problem of UAV cooperative path planning in 3D environment attracts much attention. On the other hand, there are more and more challenges to the heuristic optimization algorithm based path planning method due to the task requirements, the physical constraints of UAV and complex environment. They search slowly in

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complex environment and are easy to fall into local area, so they cannot give the optimal or suboptimal solution quickly and accurately. In order to solve this problem, artificial intelligence based path planning methods have been widely studied. These algorithms include simulated annealing algorithm (SA), genetic algorithm (GA), ant colony optimization algorithm (ACO), artificial neural network algorithm (ANN), pigeon intelligent optimization algorithm (PIO), bat algorithm (BA), artificial bee colony algorithm (ABC) and particle swarm optimization algorithm (PSO). These artificial intelligence algorithms can find the near optimal path with fast convergence speed in three-dimensional complex environment, but they often fall into local optimization [3]. In order to improve the result of artificial intelligence based path planning algorithm, many researchers make contributions. X. Wu optimizes the optimization process of traditional PSO algorithm by using the Metropolis criterion based on probability theory [4]. S. Li proposes an improved chromosome coding strategy for the traditional GA algorithm to avoid the search error and ensure the feasibility of the path [5]. J. Shahrabi designes a callback mechanism for the traditional ABC, which can obtain the shortest and safest path [6].

For multi-UAV path planning problem, collision avoidance and cooperation among agents should also be considered. S. Hamed takes the collision avoidance between UAV as a constraint condition, and obtains the optimal path through parallel genetic algorithm in two-dimensional and three-dimensional environments respectively [7]. Y. Zhang models the UAV path planning problem as a rolling optimal control problem, combined with the rolling time-domain optimal control theory and inverse dynamics optimization algorithm, proposed a cooperative path planning method for multiple UAV [8]. Aiming at the problem of simultaneous arrival of multiple UAV, Z. Zhen et al. take the time synergy as the constraint condition, proposed a cooperative path planning method based on fast random search tree, and realize the simultaneous arrival of multiple UAV by adjusting the length of paths [9]. L. Yuan et al. achieve this problem by adjusting the flight speed of UAV when the path planning is completed, this research is based on the decentralized control structure [10]. C. Ryoo designs a navigation control law to control the flight time of UAV for the cooperative attack task, ensuring that all UAV can form the formation within a given time [11].

This paper comprehensively considers key points of the cooperative path, and puts forward the process of path planning. The pigeon swarm intelligent optimization algorithm is used to design the cooperative path planning method, and the mutation operator is introduced to avoid falling into local optimization.

2 Cooperative Path Planning Method Based on Cauchy Mutation Pigeon Swarm Intelligence Algorithm (ECM-PIO)

Inspired by the navigation mechanism in the process of pigeon nesting, Professor Duan Haibin proposed the pigeon swarm intelligent algorithm in Beihang University in 2014. The navigation mechanism of pigeons in nature includes two different stages using different navigation tools. In the first stage, pigeons adjust the direction through geomagnetic field and solar altitude, and in the second stage, pigeons judge the direction and position according to the landmark information near the destination. Similar to the pigeon nest searching process, the pigeon swarm intelligent algorithm is also composed of two independent calculation stages, namely geomagnetic navigation stage and landmark navigation stage. In the first stage, pigeons update the position and speed of individuals through geomagnetic operators. In the second stage, the pigeon updates the state through the principle of landmark operator.

Cauchy distribution is a continuous probability distribution without variance and mathematical expectation. If the random variable x satisfies the probability density function of Cauchy distribution, it is called Cauchy distribution. The probability density function of Cauchy distribution is:

$$f(x; x_0, \gamma) = \frac{1}{\pi}\left[\frac{\gamma}{(x - x_0)^2 + \gamma^2}\right],\ x \in (-\infty,\ +\infty) \tag{1}$$

In Eq. (1), x_0 is the peak of the probability distribution and γ is the width of x when the probability is greater than half of the maximum probability. The Cauchy distribution in $\gamma = 1$ and $x_0 = 0$ is denoted as $X \sim C(1, 0)$. The corresponding cumulative distribution function is an incremental function:

$$F(x; 0, 1) = \frac{1}{\pi}\arctan(x) + \frac{1}{2},\ x \in (-\infty,\ +\infty) \tag{2}$$

2.1 Geomagnetic Optimization Stage with Cauchy Mutation Operator

The pigeon swarm intelligence algorithm uses the geomagnetic operator to find the global optimal individual in the search space, and then refers to the optimal individual to change the position and speed of the pigeon swarm. Using Cauchy mutation operator to optimize geomagnetic operator in the optimization stage can not only expand the search range of pigeons in the first stage of pigeon swarm intelligent algorithm, but also reduce the risk of falling into local optimization.

The value of Cauchy mutation operator c_1 follows Cauchy distribution:

$$\frac{1}{\pi}\arctan(c_1) + \frac{1}{2} = rand \tag{3}$$

The *rand* function can generate random numbers from 0 to 1, and the Cauchy mutation operator c_1 can be expressed as:

$$c_1 = \tan[\pi(rand - 1/2)] \tag{4}$$

In each iteration, the position of a single pigeon is updated according to the following rules:

$$X_i' = X_{i0} + c_1\left(X_{i0} - X_{gbest}\right) \tag{5}$$

where X_{i0} is the position of the i th pigeon, X_{gbest} is the pigeon with the highest fitness in the $N_c - 1$ th iteration, and X_i' is the position of the updated pigeon. In the next iteration, the position of the i th pigeon will be:

$$X_i = \begin{cases} X_i', f(X_{i0}) > f\left(X_i'\right) \\ X_{i0}, f\left(X_i'\right) > f(X_{i0}) \end{cases} \tag{6}$$

For the Cauchy mutation operator c_1 applied to the geomagnetic operator, when it is positive, the updated position X_i' will be far from the global optimal position X_{gbest}. After the action of Cauchy mutation operator, half of the pigeons will spread outward to find a better position, while the other half will not. Compare the pigeons in the updated position with the pigeons in the previous position, and retain the pigeons with high fitness, so as to ensure the quality of algorithm optimization and improve the diversity of pigeons.

2.2 Landmark Optimization Stage with Cauchy Mutation Operator

In the optimization stage of landmark operator in pigeon swarm intelligent algorithm, the population size will be reduced by half every iteration, and the pigeons will move to the center of the pigeon swarm. This rapid population reduction will lead to premature convergence of the algorithm, which will have a negative impact on the optimization ability of landmark operator. In order to avoid premature convergence or missing the optimal solution, the landmark navigation operator is improved by using Cauchy mutation operator, and then the positions of other pigeons are updated with reference to the positions of the optimal pigeons in the pigeon group. The Cauchy operator c_2 satisfies the Cauchy distribution, which can be expressed as:

$$c_2 = \tan\left(\frac{\pi}{2} rand\right) \tag{7}$$

The rules for pigeon location update are:

$$X_{i0}^{N_c} = X_{i0}^{N_c-1} + c_2\left(X_{gbest} - X_{i0}^{N_c-1}\right) \tag{8}$$

where $X_{i0}^{N_c-1}$ is the position of the i th pigeon in the $N_c - 1$ th iteration, X_{gbest} is the position of the globally optimal pigeon.

In the optimization stage of landmark operator based on Cauchy mutation, Cauchy operator c_2 makes all pigeons gradually approach the global optimal solution. The appropriate Cauchy mutation operator c_2 can make the pigeons move efficiently at an appropriate speed and direction, and ensure the rapid and stable convergence of the algorithm.

2.3 ECM-PIO Process Including Path Smoothing

UAV cannot directly track the waypoint set obtained by ECM-PIO, and the flight path must be smoothed to meet the tracking conditions of UAV. In the course of path optimization of pigeon swarm algorithm, if the fitness of path without smoothing is calculated directly, the result often has large error. In order to meet the requirements of multi UAV cooperative path planning, the single path planning flow chart of pigeon swarm algorithm is shown in Fig. 1. The following describes the steps of single path planning of pigeon swarm intelligent algorithm:

The first step is to initialize the algorithm parameters, including pigeon swarm size, optimization space dimension, geomagnetic navigation operator, maximum iteration times $N_{c1\max}$ and $N_{c2\max}$ of the two optimization stages, weight coefficients of the first stage and the second stage, etc.

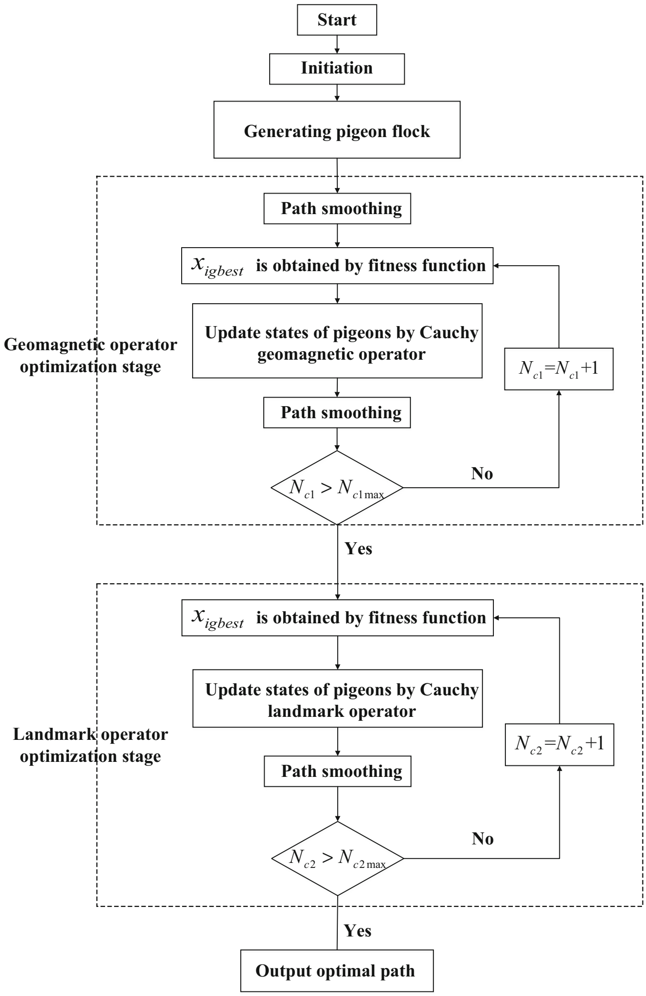


Fig. 1. Flow chart of single machine path planning based on ECM-PIO algorithm

The second step is to randomly find waypoints to form paths. Each pigeon with position and speed represents a path. The pigeon speed must be selected within the allowable speed range $[v_{\min}, v_{\max}]$, and all randomly generated paths shall be smoothed.

The third step is to find the optimal individual in the pigeon group through the fitness function x_{igbest}.

In the fourth step, the position and velocity of pigeons are updated by the geomagnetic operator based on Cauchy variation, and the paths are smoothed.

Step 5: compare the current iteration times and the maximum iteration times of the geomagnetic operator stage. If the current iteration is greater than the maximum iteration times, the operation will enter the landmark operator optimization stage, otherwise return to step 3.

In the sixth step, the pigeon group position is updated by the landmark operator based on Cauchy mutation, and the paths are smoothed.

Step 7: compare the current iteration number and the maximum iteration number of landmark operator stage. If the current iteration is greater than the maximum iteration number, the algorithm ends, otherwise return to step 6.

3 Selection Method of Cooperative Path in Complex Environment

The selection of multi UAV cooperative paths includes the following key contents: single path fitness evaluation, multi paths coordination evaluation and dynamic response ability in case of emergencies.

3.1 Single Path Evaluation Function

Firstly, the path needs to keep a distance from the environmental wind farm, and the safety distance is defined l_{wind_safe}. The scoring rules for the distance l_{wind_i} between the path and the wind field $wind_i$ are as follows:

$$f_{wind} = \sum_{i=1}^{n_w} F_{wind\_i}, \begin{cases} F_{wind\_i} = 0 & (l_{wind\_i} \geq l_{wind\_safe}) \\ F_{wind\_i} = \dfrac{1}{l_{wind\_i}} & (l_{wind\_i} < l_{wind\_safe}) \end{cases} \tag{9}$$

Similar to wind fields, UAVs are also required to stay away from buildings. The scoring rules are:

$$f_{solid} = \sum_{i=1}^{n_s} F_{solid\_i}, \begin{cases} F_{solid\_i} = 0 & (l_{solid\_i} \geq l_{solid\_safe}) \\ F_{solid\_i} = \dfrac{1}{l_{solid\_i}} & (l_{solid\_i} < l_{solid\_safe}) \end{cases} \tag{10}$$

From the perspective of economy, the shorter the total length $\sum l_i$ of the UAV path, the better. When the total length $\sum l_i$ of the route is greater than the maximum sailing distance of the UAV, it is necessary to give a great penalty to guide the intelligent algorithm to search in the correct direction and deny the path. Here, the cruise speed V_a of UAV will be obtained as follows, and the total route length score is expressed as:

$$f_{length} = F_{length}, \begin{cases} F_{length} = \dfrac{\sum l_i}{L_{\max}} & \left(\sum l_i \leq L_{\max}\right) \\ F_{length} = \sum l_i \ \ and \ \ \text{return} & \left(\sum l_i > L_{\max}\right) \end{cases} \tag{11}$$

To sum up, the evaluation function of a single UAV can be expressed as:

$$f_{single} = k_1 f_{solid} + k_2 f_{wind} + k_3 f_{length} \tag{12}$$

The smaller the value f_{single} of the single unmanned evaluation function, the higher the path fitness. For the weight, k_1, k_2 and k_3, the larger the value, the higher the importance of a certain attribute of the path. For example, when the range of the UAV required by the mission is close to the maximum range of the UAV, the commander pays more attention to whether the flight range of the UAV exceeds the maximum range and whether there is enough fuel margin. At this time, the flight range evaluation item f_{length} is highly valued, the corresponding weight value k_3 should be large. When the environmental wind field is complex and difficult to predict accurately, the commander is most concerned about keeping a safe distance from the wind field and leaving a large distance margin. At this time, the items of avoiding the wind field f_{wind} will receive higher attention, and the corresponding weight value k_1 should be large; For some tactical arrangements, the UAV is expected to keep a distance from the mountains, or in consideration of the safety of residents, the UAV is expected to keep a distance from urban buildings. Avoiding the evaluation items of urban buildings f_{solid} will receive higher attention, and the corresponding weight value k_2 should be large.

3.2 Multi UAV Cooperative Path Evaluation Method

The coordination of multi UAV paths is mainly reflected in meeting the requirements of UAV time consistency and inter aircraft collision avoidance.

In the single UAV path evaluation, the path length of UAV has been controlled. In the multi UAV cooperative path evaluation method, only the appropriate cruise speed needs to be selected for each UAV to meet the requirements of time consistency. Select the flight time of UAV as:

$$t_r = \frac{1}{2}\left(\frac{\max(\sum l_i)}{V_{a\_\max}} + \frac{\min(\sum l_i)}{V_{a\_\min}}\right) \tag{13}$$

where $i = 1, 2 \cdots n$, $\sum l_i$ is the length of the $path_i$. The expected cruise speed of UAV can be calculated according to the formula:

$$V_i = \frac{\sum l_i}{t_r} \tag{14}$$

Collision avoidance between aircraft can be realized by prohibiting path crossing. When $path_i$ and $path_{i+1}$ intersect with each other, compare their single path fitness. If the fitness of $path_{i+1}$ is low, replan $path_{i+1}$, and the specified waypoint of $path_{i+1}$ must be in the space between $path_i$ and $path_{i+2}$.

3.3 Dynamic Response Mechanism in Emergency

When the UAV formation performs its mission according to the planned cooperative paths, it often encounters emergencies, which makes one or more UAVs unable to continue flying according to the planned paths. For example, in an urban environment, when the UAV formation flies together, a leader inspects a certain area or a sudden fire becomes a no-fly zone, at this time, a dynamic response mechanism is needed to guide the UAV formation to respond timely and correctly in case of emergencies and complete the task successfully.

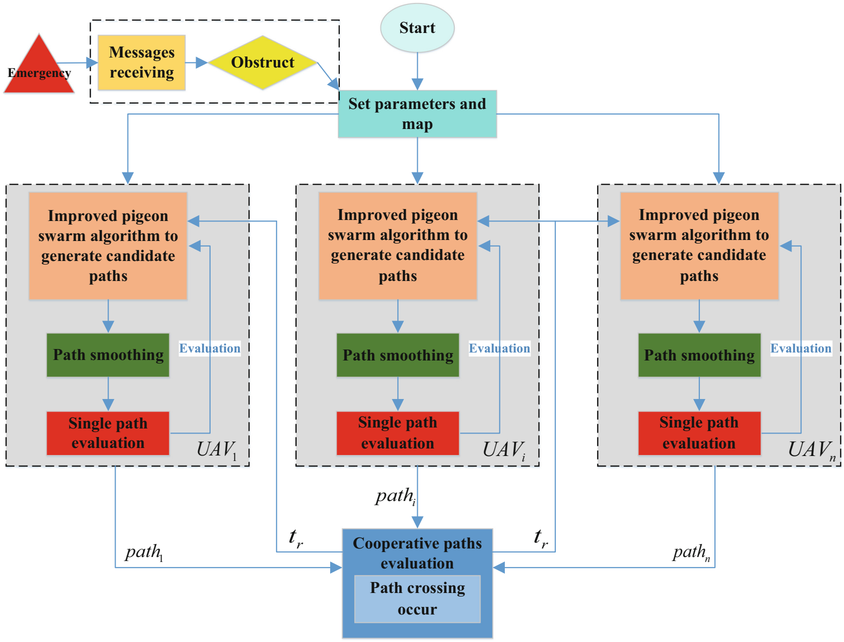


Fig. 2. Collaborative path planning process

The emergency response mechanism is triggered by the emergency. First, judge whether it interferes with the flight of UAV. If so, reset the flight map according to the emergency and restart the collaborative path planning process. Note that because the course of the UAV cannot change suddenly when flying in the air, when the collaborative path planning process is restarted, the starting point of the new path is set to the front of the current position of the UAV in the distance *R* (minimum turning radius) along the current course.

Based on the above three key contents of multi UAV cooperative path selection, the cooperative path planning process is shown in Fig. 2. In brief, firstly, the path planning method based on Cauchy mutation pigeon swarm intelligence algorithm plans each UAV path separately, and guides the algorithm optimization through the single path evaluation function; After the UAV obtains the optimal path, it carries out multi path coordination evaluation. When the route cannot meet the coordination requirements, it modifies the waypoint selection range and re-plans the paths; When an emergency occurs and the UAV cannot fly according to the preset paths, trigger the emergency response mechanism to re-plan the paths.

4 Simulation Results and Analysis

In order to test the performance of the multi UAV cooperative path planning method, simulation experiments are carried out in Matlab/2014a environment. There are three simulation tests. The first two tests respectively use the cooperative path planning method based on ECM-PIO proposed in this paper and the cooperative path planning method based on improved pigeon swarm algorithm (EPIO) proposed by scholar Li Xiaomeng [12]. The third test sets up emergencies during UAV guided flight. Three UAVs with the same parameters were used in the three tests to assemble from different positions (Table 1).

Table 1. Parameters of improved pigeon swarm intelligent optimization algorithm

Parameters	Symbol	Value
Maximum number of iterations in optimization phase I	$N_{c1\max}$	100
Maximum number of iterations in optimization phase II	$N_{c2\max}$	50
Number of pigeons	M	50
Spatial dimension	D	3
Pigeon position change speed range	$(v_{\min}, v_{\max})$	(–1.2, 1.2)

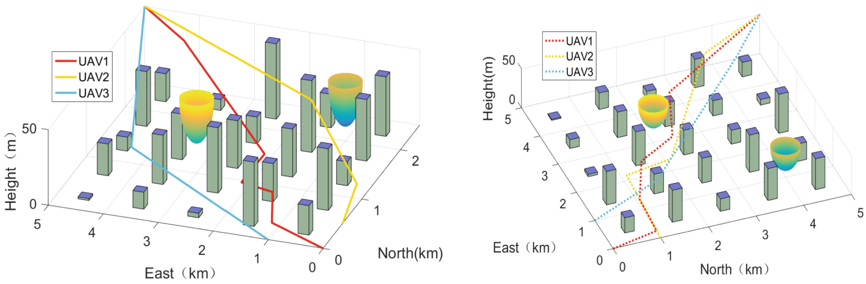
The coordinates of the starting point and target point are shown in Table 2.

Table 2. Coordinates of starting point and target point of UAV

	Start point	Target point	Unit
UAV1	(0, 0, 0)	(4900, 5000, 50)	m
UAV2	(0, 1000, 0)	(5000, 5000, 50)	m
UAV3	(1000, 0, 0)	(5000, 4900, 50)	m

The gap between buildings in urban terrain is extremely narrow, the height change of buildings is random and discontinuous, and the flight area of urban environment is small. These characteristics lead to UAV flight paths in urban environment with lots of sharp turns and short legs.

Figure 3a and Fig. 3b respectively show the path planning results of ECM-PIO based collaborative path planning method and EPIO based collaborative path planning method in urban environment. It can be seen from the figures that the paths of the cooperative path planning method based on EPIO are too dense, and there are great hidden dangers of inter aircraft collision when UAV performs program-controlled flight. The path distribution obtained by the cooperative path planning method based on ECM-PIO is loose and the safety factor is high; Table 3 lists the length of each path. It can be seen from Table 3 that although the length of the route output by the cooperative path planning method based on ECM-PIO is slightly longer, the gap between the lengths of each path is small, which is conducive to the time consistency requirements of UAV formation at the same time. To sum up, the path obtained by the cooperative path planning method proposed in this paper can better meet the task coordination requirements of UAV formation.



a. Based on ECM-PIO b. Based on EPIO

Fig. 3. Path planning results of cooperative path planning method

Table 3. Flight path length of UAV obtained by two cooperative path planning methods

	UAV1	UAV2	UAV3
The method in this paper	8.39 *km*	8.27 *km*	8.32 *km*
Other method	8.40 *km*	8.15 *km*	8.11 *km*

Emergencies are added in the third test, as shown in Fig. 4. In the 60th second of UAV guided flight, an emergency occurred, and a no-fly area appeared in the flight area. As shown in the figure, the black area is the no-fly area. The pink triangle in the figure is the current position of the UAV, the red, yellow and blue paths are the planned cooperative flight paths of UAVs. It can be seen that if the UAV formation continues to fly according to the original route, UAV1 and UAV2 will break into the no-fly area. At this time, the sudden no-fly area activates the emergency dynamic response mechanism of collaborative path planning. If the no-fly area conflicts with the original path, task re-planning will be triggered. The starting point of the coordinated planning paths is shown in the blue pentagram in the figure.

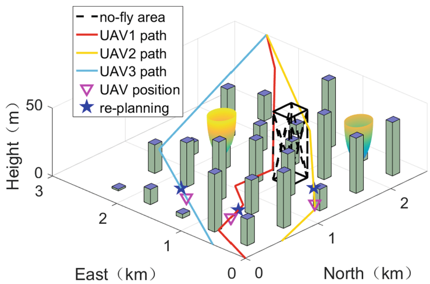


Fig. 4. Dynamic response mechanism of path planning triggered by emergencies

Figure 5 shows the results of path re-planning. The anti-collision judgment in the process of path re-planning ensures that the new path can avoid the no-fly area. The dotted line segment in Fig. 5 is the original flight path of UAV, and the solid line segment is the flight path after re-planning. As can be seen from Fig. 5, the new cooperative path not only avoids the no-fly area, but also meets other path evaluation indexes, which reflects that the cooperative path planning method proposed in this paper has the ability of dynamic re-planning in the face of emergencies.

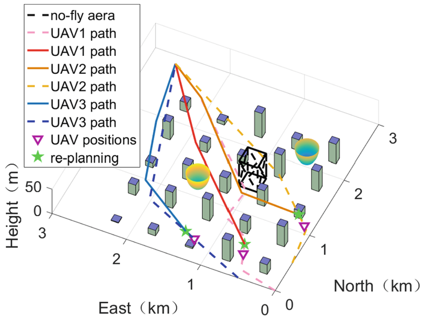


Fig. 5. Re-planning path after emergency response

5 Conclusion

This paper studies the cooperative path planning of multiple UAVs in urban environment, and proposes a cooperative path planning method based on ECM-PIO, including the following contents:

Firstly, the requirements of UAV cooperative paths in urban environment are proposed, including the requirement of obstacle avoidance, the requirement of rapidity of cooperative path planning algorithm, the constrains of kinetic ability of UAV, and the requirements of coordination of paths. Secondly, the selection method of cooperative paths in complex environment is proposed, including the ECM-PIO based algorithm for single path planning, fitness function of single path, coordination function of multi paths, and the dynamic response mechanism in case of emergencies. Thirdly, ECM-PIO intelligent optimization algorithm is proposed, by adding the Cauchy mutation to the process of traditional PIO. The error in the optimization process is avoided and the disadvantage that the traditional PIO is easy to fall into local optimization is overcome. Finally, the simulation experiments show the advanced of the presented ECM-PIO based cooperative path planning method in urban environment.

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