Three dimensional path planning of UAV based on adaptive particle swarm optimization algorithm

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Abstract: Aiming at the problem of falling easily into local optimal solution of conventional particle swarm optimization algorithm, an adaptive particle swarm optimization algorithm is proposed, which adaptively adjusts the values of inertial weight and two learning factors in the iterated search process. The environment model of path planning is built for unmanned aerial vehicle (UAV) to perform reconnaissance task in mountain environment. The self-constraint conditions of UAV are analyzed. The fitness degree function of adaptive particle swarm optimization algorithm and flow chart of path planning algorithm are designed. The simulation experiments of three dimensional path planning of UAV are carried out by adopting respectively the adaptive particle swarm optimization algorithm and the conventional particle swarm optimization algorithm. The contrast of simulation result shows that the proposed adaptive particle swarm optimization algorithm has higher global search ability and search precision than the conventional particle swarm optimization algorithm.

1. Introduction
In the past few years, great progress has been made in UAV technology, which can be seen from various types of UAVs successfully developed and their performance gradually improved. This technology has been successfully applied in many military and civil fields. It has become a research hotspot of military departments, research institutions and universities all over the world. As an important topic in the field of UAV technology, UAV path planning has received great attention from researchers at home and abroad [1]. Path planning is to plan the optimal or satisfactory flight path for UAV under the premise of considering the arrival time, energy consumption, threat and dynamic constraints of UAV, so as to ensure the successful completion of flight mission [2]. The task space of fixed wing UAV is a three-dimensional environment space, which spans a large range of space with a complex environment and many constraints. Therefore, the route planning algorithm needs to make a trade-off among computational complexity, search time and route cost so as to meet the actual task requirements. Track planning generally consists of the following parts: describing the planning environment space, selecting the track representation, analyzing the constraints, determine the cost function, selecting the track search algorithm and track smoothing. Among them, the selection of path search algorithm serves as the core part to solve the problem of path planning.

There are many kinds of route planning algorithms, each of which has its own advantages and disadvantages and scope of application. According to the planning decision, it can be divided into traditional classical algorithms and modern intelligent algorithms. The traditional classical algorithms commonly used in UAV path planning include Dijkstra algorithm [3], Simulated Annealing Algorithm [4], Dubins Curve Method [5], Artificial Potential Field Method [6], Fast Extended Random Tree and its improved algorithm [7]. Modern intelligent algorithms include: A * Algorithm [8], Genetic Algorithm...
GA) [9], Ant Colony Optimization (ACO) algorithm [10], Particle Swarm Optimization (PSO) algorithm [11], Pigeon Colony Algorithm [12], etc. Compared with traditional classical algorithms, modern intelligent algorithms are more widely used. Among them, particle swarm optimization algorithm has two significant characteristics: first, there is no “survival of the fittest” mechanism. All particles are always retained as members of the population in the iterative process; second, there is no crossover, mutation and other evolutionary operators. Each particle finds the global optimal value by following the current optimal value. The advantages of particle swarm optimization algorithm are strong robustness, low sensitivity to population size, with few design parameters and fast convergence in the early stage; the disadvantages lie in the slow convergence in the late stage, which results in easily falling into the local optimal solution prematurely.

In order to overcome the shortcomings of PSO algorithm, some researchers have explored in recent years and proposed several improved methods. In reference [13], an adaptive sensitivity decision operator is introduced into the PSO algorithm, which solve the problems that the PSO algorithm is easy to fall into local optimum and the convergence speed is slow in the later stage, and obtains better quality tracks. In reference [14], the spatial selective voting mechanism is introduced into PSO algorithm to find out the optimal position of each track point in the solution space, which overcomes the difficulty that PSO algorithm is easy to fall into local optimum prematurely. Reference [15] studies the path planning problem of UAV in the environment of dense obstacles. Artificial potential field is added to the particle swarm optimization algorithm to solve the local optimal solution problem and improve the convergence speed of the algorithm. In reference [16], the particle position updating method of PSO algorithm is improved by using simulated annealing jump probability strategy, which can increase the global search ability and reduce the track planning time. In reference [17], the PSO algorithm is used for 3D local dynamic path planning of UAV, and the layered random initialization and particle lazy exile strategy are used to improve the PSO algorithm to speed up the convergence efficiency. In reference [18], the route planning problem of unmanned aerial vehicle is studied. Quantum particle swarm optimization algorithm and artificial potential field method are used to solve the local optimal solution problem of PSO algorithm, and the convergence speed is fast. In reference [19], the pheromone of ant colony algorithm is introduced into PSO algorithm to speed up the convergence speed, and the input quantity of route planning is controlled by fuzzy processing to prevent the system from falling into local optimum. In reference [20], the piecewise inertia weight adjustment formula is designed to improve the PSO algorithm, which can ensure the search speed of the algorithm and improve the accuracy of the path planning solution.

Although previous studies on particle swarm optimization algorithm for UAV path planning have been carried out, there are still some problems to be further studied. Small fixed wing UAV has many and severe constraints, so its space environment will be more complex and dangerous in the future. It is necessary to further explore the path planning algorithm of UAV in combination with the constraints of UAV itself and the complex situation of task environment in practical engineering. Moreover, limited by economic factors such as manufacturing cost, the solution ability of airborne computer is limited; therefore, the route planning algorithm is required to be as simple and efficient as possible, with the advantages of small amount of calculation, high accuracy and large fault tolerance. In this paper, an adaptive particle swarm optimization algorithm is proposed. It only needs to adjust the inertia weight and learning factor adaptively, and does not need to add other algorithms. It can overcome the problems of local optimization and slow convergence in the later stage, and meet the requirements of simplicity and efficiency. It provides a reliable guarantee for fixed wing UAV to perform tasks in complex three-dimensional environment space.

2. Path Planning of UAV

2.1. 3D Route Planning Environment Modeling
Environment modeling is to transform all kinds of physical information in the environment into digital model that can be processed by computer algorithm, which is the premise and foundation of UAV
flight path planning. In this paper, the UAV in the mountain environment to carry out the task of natural disaster investigation is studied as an example. The mountain environment is threatened by mountain peaks, high-voltage power lines, trees, birds and wind shear. Taking the northeast sky coordinate system as the inertial reference coordinate system, the cone is used to simulate the towering peaks approximately, and the terrain height of mountain area can be simulated by the following algorithm [6].

\[ z_i(x, y) = z_0 + \sum_{i=1}^{I} h_i \exp \left[ -\left( \frac{x-x_{0i}}{x_{li}} \right)^2 - \left( \frac{y-y_{0i}}{y_{li}} \right)^2 \right] \]

(1)

In formula (1): \( z_0 \) is the local base terrain height; \( h_i \) is the peak height of the peak \( i \); \( I \) refers to the number of peaks; \( x_{0i} \) and \( y_{0i} \) are the horizontal and vertical coordinates of the top of the first peak in the horizontal plane; \( x_{li} \) and \( y_{li} \) are the transverse and longitudinal slope of the first peak. Each peak is a terrain threat in the flight environment.

The extreme weather such as wind shear usually exists in the area near the mountain peak, and these areas are also flight threat areas. We can use the ellipsoid approximation to simulate, and set the center coordinate of the ellipsoid threat area near the first peak as \((x_{ic}, y_{ic}, z_{ic})\), and the half axis length as \((r_{ix}, r_{iy}, r_{iz})\). For threats such as high-voltage wires and trees, UAV can avoid them through its own minimum flight height constraint. In other words, the minimum flight height of UAV should be a certain distance higher than the maximum height of high-voltage wires and trees. The flying birds are a sudden dynamic threat to the UAV, and the motion information of the flying birds or birds is complex. This paper will not study this sudden situation, which is the focus of the next step.

2.2 Self Constraints of UAV

The fixed wing UAV does not have the vertical take-off and landing, hovering in the air, flight flexibility and other performance of the rotor UAV, so the self-constraint conditions in flight are stricter than that of the rotor UAV. Compared with rotary wing UAV, fixed wing UAV has the advantages of fast flight speed, long range and low energy consumption, so it is more suitable for long-distance and large-scale space environment. We mainly consider the following constraints:

(1) Maximum Track Distance

Suppose the maximum range of UAV is \( L_{max} \), the planned track includes \( K \) segment track with a length of \( L_k \), \( k=1,2,L,K \). Then the maximum track distance constraint can be expressed as:

\[ \sum_{k=1}^{K} L_k \leq L_{max} \]

(2)

(2) Minimum Inertial Distance

The minimum inertial distance is the shortest distance that the UAV needs to fly in the original direction due to the inertial effect when it suddenly changes the flight direction. When the minimum inertial distance is set to \( L_{min} \), the minimum inertial distance constraint is expressed as:

\[ L_k \geq L_{min} \quad k=1, 2, \cdots, K \]

(3)

(3) Maximum Horizontal Turning Angle

Due to the limitation of its own hardware performance, the turning angle of UAV in horizontal direction cannot exceed the maximum horizontal turning angle \( \Delta \psi_{max} \). Suppose that the horizontal turning angle of track segment \( K \) is \( \Delta \psi_k \), as compared with the segment of \( k-1 \) then the horizontal
turning angle constraint can be expressed as:

$$|\Delta \psi_k| \leq \psi_{\text{max}} \quad k = 1, 2, \cdots, K \quad (4)$$

(4) Maximum Elevation Angle

The altitude angle refers to the angle of UAV climbing up or diving down. Due to performance limitations, the altitude angle of UAV in flight cannot exceed the maximum altitude angle $$\theta_{\text{max}}$$. Suppose that the angle between the first track segment and the horizontal plane is: $$\theta_k$$, the maximum altitude angle constraint is:

$$|\theta_k| \leq \theta_{\text{max}} \quad k = 1, 2, \cdots, K \quad (5)$$

(5) Maximum/Minimum Flight Altitude

The UAV needs to fly at low altitude to carry out the reconnaissance mission. If the maximum altitude of UAV from the ground is set as $$\Delta h_{\text{max}}$$, a track is composed of track points, the altitude of the track point $$d$$ ($$d=1,2,\cdots,D$$) is $$z_d$$, and the terrain altitude below the track point is $$z_1$$: (calculated by formula (1)), then the maximum flight altitude constraint is expressed as:

$$z_d \leq z_1 + \Delta h_{\text{max}} \quad d = 1, 2, \cdots, D \quad (6)$$

In addition, the flight height of UAV should be higher than the maximum height of high-voltage wires and trees. Suppose that the maximum height of high-voltage wires and trees is: $$h_t$$, and the safety distance is $$h_{\text{safe}}$$, the minimum flight height constraint is expressed as:

$$z_d \geq z_1 + h_t + h_{\text{safe}} \quad d = 1, 2, \cdots, D \quad (7)$$

3. Adaptive Particle Swarm Optimization Algorithm Design

3.1 Basic Principle of Algorithm

Particle Swarm Optimization (PSO) is a common method for UAV path planning. Its main defects are: slow convergence in the later stage, easy to fall into the local optimal solution. In order to overcome this defect, an adaptive particle swarm optimization (APSO) algorithm is proposed by adding an adaptive adjustment algorithm to the particle swarm optimization algorithm, adjusting the inertia weight and two learning factors at the same time.

In PSO, each individual in the population represents a solution of the optimization problem. In the process of solving the problem, we need to define the optimization function to calculate the fitness value of each particle. Suppose that the problem search space is D dimension, the total number of particles in the population is N. The position of the $$n^{\text{th}}$$ particle is represented by the vector $$S_n = (S_{n1}, S_{n2}, \cdots, S_{nD})$$, and the velocity is represented by the vector $$V_n = (V_{n1}, V_{n2}, \cdots, V_{nD})$$. In each iterative search, each particle updates its position and velocity according to two extremums. The first extremum is the optimal solution position found by the particle itself, which is called individual extremum $$P_b$$. The second extremum is the optimal position found by the whole population, which is called global extremum $$G_b$$. Through these two extremums, the particle continuously adjusts the search direction to move to the optimal solution position. In the $$t^{\text{th}}$$ iteration, the velocity update and position update formulas of the $$n^{\text{th}}$$ particle are as follows:

$$V_n(t + 1) = wV_n(t) + c_1r_1(P_b - S_n) + c_2r_2(G_b - S_n) \quad (8)$$

$$S_n(t + 1) = S_n(t) + V_n(t + 1) \quad (9)$$

In equations (8) and (9): w refers to the inertia weight; $$c_1$$ and $$c_2$$ are learning factors; $$r_1$$ and $$r_2$$ are random numbers in the range of [0,1]. In traditional particle swarm optimization algorithm, the design parameters w, $$c_1$$ and $$c_2$$ are taken as constants.
Next, we put forward the corresponding improvement strategy by analyzing the role of these parameters. \( w \) reflects the trend that particles maintain their previous motion speed. In case a larger value is taken, the search speed can be accelerated, but the search accuracy will be affected. \( c_1 \) reflects the cognitive ability of particles. Taking a larger value, it can improve the individual search speed and enhance the global search ability, but it affects the local search ability and search accuracy. \( c_2 \) reflects the social ability of particles. If the value is larger, it can enhance the local search ability and accelerate the convergence speed, but it is easy to fall into the local optimal solution prematurely. Based on the above analysis, dynamic adjustment of parameters can achieve the coordination of search speed and search accuracy, global search and local search, and overcome the local optimal solution.

The adaptive adjustment algorithm is designed as follows:

\[
\begin{align*}
    w &= w_{\text{max}} - t \left( w_{\text{max}} - w_{\text{min}} \right) / t_{\text{max}} \\
    c_1 &= c_{1\text{max}} - t \left( c_{1\text{max}} - c_{1\text{min}} \right) / t_{\text{max}} \\
    c_2 &= c_{2\text{min}} + t \left( c_{2\text{max}} - c_{2\text{min}} \right) / t_{\text{max}}
\end{align*}
\]

In formula (10) ~ (12): \( w_{\text{max}} \) and \( w_{\text{min}} \) are the maximum and minimum of \( w \); \( c_{1\text{max}} \) and \( c_{1\text{min}} \) are the maximum and minimum of \( c_1 \); \( c_{2\text{max}} \) and \( c_{2\text{min}} \) are the maximum and minimum of \( c_2 \); \( t \) the current number of iterations; and \( t_{\text{max}} \) is the maximum number of iterations.

The principle of this improved strategy is: in the early stage of the iteration, the values of \( w \) and \( c_1 \) are larger, while the values of \( c_2 \) are smaller; we can use the larger values of \( w \) and \( c_1 \) to speed up the search speed to enhance the global search ability; for the problem of poor search accuracy, we can make up for it in the late stage of the iteration; we can also use \( c_2 \) smaller to avoid premature into local optimal solution. For the problem of poor search accuracy, we can make up for it in the late stage of the iteration; we can also use the smaller value of \( c_2 \) to avoid premature into local optimal solution. At the end of the iteration, the values of \( w \) and \( c_1 \) are smaller, while the values of \( c_2 \) are larger; in the later stage, the particle swarm basically moves to the region near the optimal solution, and the search accuracy can be improved by slowing down the search speed. The local search ability can be improved by reducing the global search ability, so as to accelerate the convergence speed to the optimal solution; thus, the coordination of search speed and search accuracy, global search and local search can be realized.

### 3.2 Fitness Function Design

Fitness function is the optimization function of UAV path planning, which is the index function to measure the quality of a particle. Combined with the limitations of various environmental threats and UAV self-constraints analyzed above, the fitness function should include track length, environmental threats and constraints:

\[
\min Fit = w_L F_L + w_T F_T + w_S F_S \tag{13}
\]

In formula (13): \( F_L \) represents the cost of track length; \( F_T \) represents the cost of environmental threat; \( F_S \) represents the cost of constraint conditions; and \( w_L, w_T \) and \( w_S \) represent the weight of three costs respectively, \( w_L + w_T + w_S = 1 \).

For UAV three-dimensional path planning problem, a particle represents a path, and the path is composed of a group of three-dimensional path points. A track consists of D track points and a track segment of \( K (K = D - 1) \), the track length fitness function is:

\[
F_L = \sum_{k=1}^{K} L_k \tag{14}
\]

Environmental threats mainly include the threats from the mountain peak and wind shear area. The
location of mountain peak in flight environment and wind shear area nearby are known. Threats such as high-voltage wires and trees can be avoided by restricting the minimum flight altitude of UAV; moreover, according to the altitude constraint (7), the flight altitude of UAV must be higher than that of terrain including mountain. The mountain threat considered here is that the UAV track should be far away from the mountain at a certain height in the horizontal plane to improve the flight safety; it is not necessary to rely on increasing the flight height to avoid the mountain threat; if the UAV flies too high, it is not conducive to the investigation work. Suppose that the position coordinate of the $d^{th}$ ($d=1, 2, L, D$) track point on the $n^{th}$ track is $S_{nd} = (x_{nd}, y_{nd}, z_{nd})$. The mountain threat fitness function can be shown as:

$$F_{T1} = \sum_{i=1}^{I} \frac{f_{T1} I}{R_{li}}$$

$$R_{li} = \min_d \left[ \left( x_{nd} - x_{oi} \right)^2 + \left( y_{nd} - y_{oi} \right)^2 \right]^{0.5}$$

In equations (15) and (16); $f_{T1}$ represents the constant factor of threat cost of mountain peak; $R_{li}$ represents the minimum distance from all track points on the $n^{th}$ track to the center point of the $i^{th}$ mountain peak in the horizontal plane.

The wind shear area $R_{li} = \min_d \left[ \left( x_{nd} - x_{oi} \right)^2 + \left( y_{nd} - y_{oi} \right)^2 \right]^{0.5}$ is also a threat area, and the trajectory of UAV should be far away from the threat area by using ellipsoid approximation simulation. The number of threat zones is $I$, and the central coordinate of the $i^{th}$ threat zone is $(x_{ic}, y_{ic}, z_{ic})$. The fitness function is:

$$F_{T2} = \sum_{i=1}^{I} \frac{f_{T2} I}{R_{2li}}$$

$$R_{2li} = \min_d \left[ \left( x_{nd} - x_{ic} \right)^2 + \left( y_{nd} - y_{ic} \right)^2 + \left( z_{nd} - z_{ic} \right)^2 \right]^{0.5}$$

In formulas (17) and (18); $f_{T2}$ denote the threat cost constant factor in the wind shear area; $R_{2li}$ denote the minimum distance from all track points on the $n^{th}$ track to the center of the $n^{th}$ threat area.

To sum up, the environmental threat fitness function is:

$$F_T = F_{T1} + F_{T2}$$

Next, the cost function of constraint conditions is established. For the sake of simplicity, the penalty constant factor is used to describe the cost function [9]. If the penalty constant factor is $C_0$, it is better to take a larger positive number. The fitness function of the maximum track distance is as follows:

$$F_{SL} = \begin{cases} C_0, & \sum_{k=1}^{K} L_k > L_{max} \\ 0, & \sum_{k=1}^{K} L_k \leq L_{max} \end{cases}$$

The fitness function of other constraints is the same. If the constraints are not satisfied, the fitness value is $C_0$; if the constraints are satisfied, the fitness value is 0.

### 3.3 Route Planning Process

The three-dimensional path planning of UAV is carried out by using APSO algorithm, and the global extremum is the optimal reference path through the iterative search of particle swarm optimization. The planned track is a path from the starting point to the target point via $K$ track segments. The process of route planning is shown in Figure 1.
4. Simulation Analysis

MATLAB R2010b software is used to build the simulation model of UAV three-dimensional path planning, and the simulation experiment is carried out to verify the effectiveness of APSO algorithm. Assuming that the mountain environment is 100km * 100km * 4km, the starting point S of UAV is (0,0,0.06), the first task point \( T_1 \) is (43,81,1.1), and the second task point \( T_2 \) is (80,23,1.2). The UAV flies from the starting point to the sky of \( T_1 \) to carry out the investigation task of natural disasters (such as landslides, debris flows, etc.), then flies to the sky to investigate, and finally returns to the starting point. This paper focuses on the problem of track planning. For the sake of simplicity, the above-mentioned tracks are planned separately, that is, the first planned track is \( S \rightarrow T_1 \); the second planned track is \( T_1 \rightarrow T_2 \); the third planned track is \( T_2 \rightarrow S \). The UAV hovers over the point \( T_1 \) for a week to carry out the survey mission, complete the turn, and then fly to the point \( T_2 \) for survey; the survey work of hovering is not studied here.

Suppose that the base terrain height of the mountain area is set as \( z_0 = 0.05 \) km with 8 peaks and 8 wind shear ellipsoid areas, the parameters of peaks and the parameters of wind shear ellipsoid area can be seen in Table 1 and Table 2 respectively.

| Sequence No. | \( x_{0i} \) | \( y_{0i} \) | \( x_{si} \) | \( y_{si} \) | \( h_i \) |
|-------------|-------------|-------------|-------------|-------------|--------|

Fig1. flowchart of path planning
Tab.2 Parameters of the wind shear ellipsoid areas

| Sequence No. | $x_{ci}$ | $y_{ci}$ | $z_{ci}$ | $r_{xi}$ | $r_{yi}$ | $r_{zi}$ |
|--------------|----------|----------|----------|----------|----------|----------|
| 1            | 13       | 30       | 0.8      | 5.0      | 5.0      | 0.25     |
| 2            | 13       | 65       | 0.9      | 5.0      | 5.0      | 0.25     |
| 3            | 36       | 14       | 1.4      | 5.8      | 5.8      | 0.29     |
| 4            | 34       | 72       | 0.9      | 5.2      | 5.2      | 0.26     |
| 5            | 45       | 48       | 1.6      | 7.0      | 7.0      | 0.35     |
| 6            | 68       | 83       | 1.2      | 5.8      | 5.8      | 0.29     |
| 7            | 69       | 13       | 1.1      | 5.2      | 5.2      | 0.26     |
| 8            | 84       | 50       | 1.0      | 5.0      | 5.0      | 0.25     |

Then calculate the height of the mountain area by using the formula (1). The constraints of UAV are set as: $L_{\text{max}} = 500\, \text{km}$, $L_{\text{min}} = 1.0\, \text{km}$, $\Delta \varphi_{\text{max}} = 1\, \text{rad}$, $\theta_{\text{max}} = 0.8\, \text{rad}$, $\Delta h_{\text{max}} = 0.5\, \text{km}$, $h_{\text{t}} = 0.02\, \text{km}$, $h_{\text{safe}} = 0.05\, \text{km}$. In order to reduce the complexity of path planning and improve the planning efficiency, the path height is directly set, that is, according to the mountain terrain height and the maximum/minimum flight height constraint of UAV, the real-time path height of UAV is set to be 0.2km higher than the terrain height below, which meets the height constraint.

Using APSO algorithm for route planning is actually an iterative optimization of x and y coordinates of all route points. The simulation trial and error method can be used to make repeated attempts, and the algorithm parameters are determined as follows: $N=300$, $D=25$, $w_{\text{max}}=0.8$, $w_{\text{min}}=0.2$, $C_{1,\text{max}}=3.0$, $C_{1,\text{min}}=1.0$, $C_{2,\text{max}}=3.0$, $C_{2,\text{min}}=1.0$, $t_{\text{max}}=300$, $w_{l}=0.4$, $w_{r}=0.3$, $w_{s}=0.3$, $f_{1}=300$, $f_{2}=300$, $C_{0}=900$. In order to compare with the traditional PSO algorithm, the traditional PSO algorithm is also used for UAV path planning simulation experiment. In the traditional PSO algorithm, and are constant, their values are too large or too small will affect the effect of path planning, usually according to the design experience and simulation trial and error method. Without losing generality, it is selected as the average value between the maximum value and the minimum value of the previous APSO algorithm, that is $w=0.5$, $c_{1}=2.0$, $c_{2}=2.0$. The other parameters are the same as the APSO algorithm. A total of 50 simulations were carried out in the simulation experiment, and the average fitness values of each planned track segment were calculated. The comparison of fitness values of the two algorithms is shown in Table 3. It can be seen from Table 3 that the APSO algorithm proposed in this paper obtains smaller fitness values than the traditional PSO algorithm for three segments of planned tracks, which indicates that the algorithm proposed in this paper has higher global search ability and search accuracy.

Tab3 Contrast of fitness values of two algorithms

| Algorithm | Tracks 1 | Tracks 2 | Tracks 3 | The Sum |
|-----------|---------|---------|---------|---------|
| APSO      | 125.33  | 119.05  | 101.88  | 346.26  |
| PSO       | 130.23  | 123.17  | 107.81  | 361.21  |
The last simulation result is given below. The convergence curve of the optimal track and its fitness value based on APSO algorithm is shown in Figure 2. The convergence curve of the optimal track and its fitness value based on traditional PSO algorithm is shown in Figure 3.

Fig 2 UAV path planning based on the APSO algorithm

a) Three segments of paths of UAV

b) Fitness value of the first segment of path
c) Fitness value of the second segment of path
d) Fitness value of the third segment of path
5. Conclusion
In this paper, an adaptive particle swarm optimization algorithm is proposed to solve the path planning problem of fixed wing UAV in three-dimensional environment space. Taking the mountain area as an
example, the UAV flight environment is studied. On this basis, the fitness function and route planning algorithm flow of adaptive particle swarm optimization algorithm are designed. In order to test the effectiveness of APSO algorithm, three-dimensional path planning simulation experiments of UAV are carried out by using APSO algorithm and traditional PSO algorithm respectively. Simulation results show that the proposed APSO algorithm has higher global search ability and search accuracy than the traditional PSO algorithm. This paper mainly considers the static threat in the environment, and the next step is to study the path planning method of UAV to avoid the sudden dynamic threat.

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