Genetic Algorithm 3D Trajectory Planning Based on Digital Map Pre-processing for Tilt-rotor Aircraft

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Abstract. Tilt-rotor aircraft is a new type of aircraft which can take off and land vertically and cruise at high speed. It can be used to perform specific tasks by special departments such as public security or fire rescue. The terrain environment and threat types of tasks are complex and changeable. In order to ensure flight safety, the flight trajectory should be planned in advance. As a global optimization algorithm simulating biological evolution process, genetic algorithm is mostly used in two-dimensional flight path planning. In this paper, the three-dimensional digital map is preprocessed according to the actual mission environment and constraints of the tilt-rotor aircraft. The related genetic operators and individual evaluation function of the genetic algorithm are improved to reduce the calculation of the trajectory planning and effectively avoid the partial optimal solution. The simulation results show that after preprocessing the 3D digital map, a 3D mission trajectory with the best cost in the complex mission environment can be successfully planned by the improved genetic algorithm.

1. Introduction
With the development of space technology, varied aircrafts are more and more widely used in military and civil fields. Tilt-rotor aircraft is a new type of aircraft that can take off and land vertically and cruise at high speed [1]. It can be used to perform specific tasks by special departments such as public security and fire protection. The terrain environment and threat types of tasks are complex, which may cover mountains, basins, hills, plains, and there are various kinds of threats in the tasks, including no-fly zone, radar detection area, electromagnetic interference area, etc. Therefore, it is very important for the aircraft safety to plan the off-line trajectory of the mission area before the aircraft take-off [2-4].

Many scholars at home and abroad have carried out research on trajectory planning of aircrafts. Hart et al. proposed A* algorithm for global path search, which combined the advantages of Dijkstra algorithm and the best priority search algorithm, and it was a heuristic and efficient search algorithm [5]. Wei Xiaolong et al. improved the basic ant colony algorithm, which adopted the height level guidance factor and carried out UAV based on the segmentation method improving the quality of path planning [6]. Multi colony ant colony algorithm is used in the planning process to avoid the premature
convergence of single population ant colony optimization algorithm and realize the obstacle avoidance path planning of UAV in [7].

Genetic algorithm (GA) is a stochastic optimization algorithm, which was first proposed by Professor J. Holland in 1975 [8]. Genetic algorithm is a process of population optimization. In order to get the minimum (large) value of the objective function, it does not start from an initial value but from a group of initial values. This set of initial values is like a biological population, and the process of optimization is the process of reproduction, competition, inheritance and variation of this population. The parallelism and global optimization of genetic algorithm are especially suitable for solving multi-objective planning problems such as track planning. At present, many scholars have studied a variety of improved genetic algorithms to achieve the flight path planning for different needs. Optimal route planning for avoiding threat sources is researched by using improved ant colony algorithm in [9].

However, the above research mainly focuses on two-dimensional flight path planning of aircraft, which can be effectively completed in the environment of high altitude and less threat. The mission environment of the tilt-rotor aircraft is complex and changeable. It is often necessary to fly along the terrain as much as possible to avoid the threat of radar detection or electromagnetic interference. The flight altitude changes greatly. It is essential to judge whether to cross the lower obstacles while ensuring the track length. Therefore, it is important to perform the 3D trajectory planning in advance to achieve the mission safely and effectively. A 3D trajectory planning method based on digital map preprocessing is proposed in this paper. Firstly, the mission area is modeled by a digital map, and the digital map is preprocessed with the climbing performance and vertical turning limitation of the tilt-rotor aircraft. Then, the genetic algorithm with improved genetic operators and individual evaluation function is used to plan the trajectory in the mission area. The algorithm can successfully plan a three-dimensional mission trajectory with the best cost in a short time.

The rest of the article is organized as follows: In the next section, the digital environment modelling and aircraft performance constraints is established to simulate the aircraft mission environment. In section 3, the genetic algorithm used in trajectory planning is introduced and improved. The numerical simulations as well as their results are conducted and analysed in section 4. Finally, the conclusion are drawn in section 5.

2. Digital map modeling and optimization

2.1. Digital map modeling

The trajectory planning problem is closely related to the real geographical environment of aircraft flight. In the actual flight, the flight path of the aircraft needs to meet two requirements: the following of the actual flight terrain and the avoidance of the threat obstacles. Therefore, before the flight, it is necessary to model the mission area with digital map and describe the basic terrain, mountain peaks, threats and other information reasonably for the aircraft to carry out offline trajectory planning on the basis of the integrated digital map.

2.1.1. Base terrain modeling. When considering the terrain information of UAV mission, not only the obvious mountain topography should be considered, but also the undulation of the whole terrain should be considered. When the altitude of the UAV is lower than a certain value, the accuracy and precision of the UAV's flight environment will directly affect the quality of the route planned by the algorithm [10]. In this paper, the base terrain of mountain landform is represented as the following:

\[
    z_i(x, y) = \sin(y + a) + b \cdot \sin(x) + c \cdot \cos(d \cdot \sqrt{x^2 + y^2}) \\
    + e \cdot \cos(y) + f \cdot \sin(g \cdot \sqrt{x^2 + y^2})
\]  

(1)
Where \( x \) and \( y \) are the points coordinate of the model projected on the horizontal plane, \( z_i \) is the elevation value corresponding to the horizontal point. And \( a, b, c, d, e, f, g \) are constant coefficients, which can control the relief of datum terrain model in digital map. According to the actual scene, different parameters can be set to simulate different terrain features, which can be used as the reference terrain information of the aircraft.

2.1.2. Mountain terrain modelling. During the flight, the aircraft will encounter more prominent mountains. The higher and distinguishable mountain environment can be represented by exponential function, and its model can be described as:

\[
z_i(x, y) = \sum_{i=1}^{n} h_i \exp \left[ -\left( \frac{x-x_i}{x_a} \right)^2 - \left( \frac{y-y_i}{y_a} \right)^2 \right]
\]

(2)

Where \( z_i(x, y) \) is elevation value of this point in digital map, \( (x_i, y_i) \) represents central coordinate position of the \( i \)th mountain peak, \( h_i \) is terrain parameter, which can control the height of the mountain peak. \( x_a \) and \( y_a \) represent the attenuation along the \( x \) axis and \( y \) axis of the \( i \)th mountain peak, which can control the slope of the mountain peak. \( n \) is the number of peaks. Through the actual environment, these parameters are simulated to represent the terrain information of the mountain.

2.1.3. Threat information modelling. During the flight, the processing of threat information is particularly important for the aircraft since a little carelessness maybe lead to serious problems. Some researches show that different threats in flight environment can be described quantitatively by function. In this paper, the model of distance threat is rational and smooth, and its function step-by-step model can be expressed as follows:

\[
z_3(x, y) = f_i(x, y) = \frac{a_i}{(b_i + c_i(x-x_i)^2 + d_i(y-y_i)^2)^{3/4}}
\]

(3)

Where \( (x_i, y_i), i = 1, 2, 3, ..., M \) is the coordinate of threat center. \( f_i(x, y) \) is the spatial distribution of threat degree. \( (x, y) \) represents plane coordinates. \( a_i, b_i, c_i, d_i \) are all positive.

The above different kinds of terrain information can be integrated to equivalent digital map, and the integrated digital map model is as follows:

\[
z(x, y) = \max(z_1(x, y), z_2(x, y), z_3(x, y))
\]

(4)

Where \( z_i(x, y) \) is used to describe the height in the base terrain model. \( z_2(x, y) \) is the height of the mountain peak. \( z_3(x, y) \) is the altitude of radar threat. The elevation 3D digital map after the fusion of these environment models can be described in Fig.1.
2.2. Digital map optimization based on tilt-rotor aircraft performance

In the actual flight, the aircraft not only needs to meet the requirements of the flight mission, but also needs to consider some physical performance constraints of the aircraft such as minimum flight altitude, climbing performance and etc. According to the limitation of the aircraft, pre-processing the digital map can ensure that every point on the digital map is a feasible point for the aircraft, which can reduce the infeasible situation of generating the track and greatly reduce the calculation amount of the trajectory planning [11].

2.2.1. Minimum flight altitude of aircraft. During the flight, the aircraft cannot fly below the minimum flight altitude. Therefore, the digital map can be lifted to ensure that the height of each point of the map meets the minimum flight height limit, which can ensure that the aircraft can perform specific tasks in a safe flight height.

Assuming that the minimum flight altitude of the track segment of the $i$th segment is $H_i$, and the minimum flight altitude allowed by the aircraft in the whole flight process is expressed as $H_{\text{min}}$, the minimum flight altitude constraint of the aircraft is as follows:

$$H_i \geq H_{\text{min}} \quad (i = 1, \ldots, n)$$

(5)
2.2.2. **Aircraft climbing performance.** The tilt rotor aircraft can take off and land vertically, and there is no maximum climb angle in theory. However, most of the aircrafts are in the cruise state of fixed wing model during the flight, and its forward flight speed is not zero. Therefore, considering the flight safety and energy consumption of the aircraft, the maximum climb angle of the aircraft is limited to 20°, which is shown as the following:

$$\frac{|z_1 - z_2|}{d} < \tan \theta_{\text{max}}$$

Where $\theta_{\text{max}}$ is the maximum climb angle of aircraft. $z_1$ and $z_2$ are the height of two adjacent points on the map. $d$ is the horizontal distance between two points. The fusion digital map established above is scanned and compared the height difference of adjacent nodes with the maximum angle set. If the nodes do not meet the above formula, they should be raised.

2.2.3. **Aircraft Vertical turning performance.** When performing flight tasks, aircraft often need to track terrain. Although tilt rotor aircraft can take off and land vertically, there is no maximum vertical flight curvature in theory, but most of them are in the cruise state of fixed wing mode during the flight process. When there is a deep trough, the UAV cannot fly close to the ground due to the limitation of its vertical turning radius. Therefore, considering the flight safety and energy consumption, the maximum normal overload is set as 2g, the vertical flight curvature is shown as the following:

$$\rho = \frac{n - g}{v^2}$$

Where $\rho$ is the vertical flight curvature. $n$ is the vertical overload. $v$ is the flight speed.

The flight speed of the tiltrotor aircraft in cruise state is 35 $m/s$, and the maximum vertical flight curvature is $\rho_{\text{max}} = 0.008$. When the curvature between the adjacent three points on the digital map is greater than the set maximum curvature, the middle node should be raised to meet the vertical flight curvature limit.

3. **Genetic Algorithm Trajectory Planning for Tilt-rotor Aircraft**

3.1. **The basic principle of genetic algorithm**

Genetic algorithm is a global optimal probability search algorithm generated in the process of simulating the continuous genetic and evolution of organisms in the natural environment [12]. It simulates the reproduction, hybridization and mutation in the process of natural selection and natural genetic. It mainly adopted gene coding, three genetic operators of selection, cross-over and mutation, and selection strategy based on fitness function to get optimal solution.
The evolutionary process of genetic algorithm is to select a certain number of individuals with high fitness to form a breeding population for start genetic evolution according to the size of the initial population. This selection can ensure the following individuals with better genetic evolution [13]. The individuals in the breeding population cross each other, and there are operations such as mutation process, which change and optimize the individuals in the population and generate a new generation of individuals. These individuals can be sorted by fitness, and the size of fitness and the number of groups are selected and eliminated by controlling [14]. Finally, the overall evolution process will be completed, the total process is shown in Fig. 2.

Genetic algorithm is not limited by space constraints and has no special requirements for the cost function, so it is very suitable for solving the practical obstacle avoidance path planning problem.

3.2. Aircraft range constraint
It is necessary to consider the constraints of various factors, including various aspects of its own performance and operational requirements in flight path planning, otherwise the planned flight path will not be executed by the UAV. Therefore, it is necessary to plan the flight path under the basic constraints of flight path, which includes performance constraints and threat constraints.

3.2.1. Aircraft performance constraint. (1) Flight range limit: Due to the limited fuel and distance of the aircraft, the flight range of the aircraft must be limited to ensure the completion of the designated
task in the case of limited fuel [15]. In this paper, the distance between the starting point and the end point is 1.5 times.

Assuming that the flight path segment of the aircraft is composed of \( \{ L_i | i = 1, 2, \ldots, n \} \) and the maximum range of the aircraft can be represented by \( L_{\text{max}} \), the maximum range constraint of the aircraft can be described as follows:

\[
\sum_{i=1}^{n} \| L_i \| \leq L_{\text{max}} \tag{8}
\]

Where \( L_i = \sqrt{(x_{i+1} - x_i)^2 + (y_{i+1} - y_i)^2 + (z_{i+1} - z_i)^2} \) (\( i = 1, \ldots, n \))

(2) Minimum flight path length constraint: Considering the limitation of aircraft performance and actual navigation, when the aircraft needs to maintain a minimum flight distance before changing its attitude, the minimum flight distance is the minimum aircraft path length constraint. Suppose that the flight path segment of the aircraft mainly consists of \( \{ L_i | i = 1, 2, \ldots, n \} \) and the minimum flight path segment length of the aircraft is expressed as \( L_{\text{min}} \), then the constraint conditions of the flight path segment can be described as follows:

\[
L_i \geq L_{\text{min}} \quad (i = 1, \ldots, n) \tag{9}
\]

Where \( L_i = \sqrt{(x_{i+1} - x_i)^2 + (y_{i+1} - y_i)^2 + (z_{i+1} - z_i)^2} \) (\( i = 1, \ldots, n \))

(3) Maximum aircraft turning angle and climbing angle: For the aircraft, the yaw angle is not infinite, and its maximum yaw angle limit is to turn from the current path point to the next track point horizontally. When the maximum angle that the aircraft can bear is less than or equal to the maximum yaw angle, the aircraft can fly safely and smoothly [16]. The turning angle constraint can also be understood as a constraint of the minimum turning radius. The smaller the radius is, the more stable the aircraft can fly. According to the actual situation of the aircraft, this paper selects the maximum turning angle of 15°.

If the horizontal projection of the \( i \)th segment is \( a_i = (x_i - x_{i-1}, y_i - y_{i-1}) \), the maximum turning angle allowed by the aircraft is expressed as \( \varphi \), then the constraints of the maximum yaw angle and pitch angle can be described as follows:

\[
\cos \varphi \leq \frac{a_i^T a_{i+1}}{\| a_i \| \| a_{i+1} \|}, \quad i = 2, \ldots, n - 1 \tag{10}
\]

(4) Threat constraint: The threats encountered by aircraft in flight mainly include: terrain threats such as mountains and valleys, weapons threats such as enemy radar, air defense missiles, electromagnetic interference, etc. Generally, the aircraft will choose to bypass the threat area as much as possible. When the cost of passing through the threat area quickly is very small, the aircraft will also choose to penetrate through. These threats have been modeled in digital maps.

3.3. The design of genetic algorithm

In the design of genetic algorithm, the main steps are as follows: (1) gene coding design; (2) individual fitness function design; (3) genetic operator design; (4) population initialization; (5) trajectory planning algorithm procedure.

The real gene coding is used to transform the trajectory planning problem into solving the chromosome problem in the genetic algorithm. By analyzing the constraints of the aircraft and
selecting the appropriate individual fitness function and genetic operators, the genetic algorithm are carried out to continuously evolve. Finally, under the decoding operation, the optimal planning path can be obtained to complete the entire the process of trajectory planning solved by the genetic calculation method.

3.3.1. Gene Coding design. Before solving the problem, it is important to code the space of the solution and determine the gene coding method, then it is necessary to establish a one-to-one mapping relationship between the problem and genetic algorithm [17].

The real coding, usually represented by using real or floating-point numbers within a certain range, can directly decode the solution space without high-frequency operation and reduce the amount of calculation. The real coding method can improve the search efficiency of the algorithm, and it is more convenient to design genetic operators for multi constraint scenarios in the high complexity scene. Therefore, this article chooses the real coding as gene coding. The procedure of real coding is represented in Fig.3.

![Gene coding diagram](image)

Where \(X_n\) and \(Y_n\) represent the horizontal position coordinate on the digital map, \(Z_n\) stands for height of selected digital map.

3.3.2. The individual fitness function design. In this paper, the penalty function is used to design a fitness function. According to the feasibility analysis of trajectory, the priority can be given to the judgment logic [18]:

![Judgment logic](image)

The core of three-dimensional obstacle avoidance path planning is to design a path that meets the constraints and achieves the shortest and safest range. The cost function of each path feasibility is set as follows:

\[
F = w_f \times f_f + w_h \times f_h + w_d \times f_d
\]

Where \(f_f = \sum_{i=0}^{N-1} d_{i,j+1}\) is the cost of the voyage, which means the sum of the distances between two adjacent path segments. Set the starting point \(O\) as the 0th track point, the target \(G\) as the nth track point, and \(d_{i,j+1}\) as the distance between the two adjacent track points.

Where \(f_h = \sum_{i=0}^{N} h_i\) is the elevation cost, which is the sum of the elevations of each track point. \(h_i\) is the height of the track point \(i\).
Where \( f_d = \sum_{i=1}^{N} \sum_{j=1}^{m} f_{d(i,j)} \) is the cost of integrated threat, and 
\[
 f_{d(i,j)} = \begin{cases} 
 0, & d_{i,j} \leq R_j \\
 K_j \left( \frac{1}{d_{i,j}^2} \right), & d_{i,j} > R_j 
\end{cases}
\]
represents the distance between the \( i \)th track point and the \( j \)th threat point. \( m \) represents the number of threat points. \( K_j \) and \( R_j \) represent the strength and radius of action corresponding to the \( j \)th threat.

Where \( w_l, w_h, w_d \) represent the weight of each coefficient in the fitness function, and their satisfaction relationship is as follows:
\[
w_l + w_h + w_d = 1
\]

For the cost function, its sub cost functions are quite different. In order to make the sub cost have the same sensitivity to the total cost, the above sub cost functions need to be normalized. So the above \( f_l, f_h, f_d \) can be normalized as follows:
\[
\overline{f_k}(R') = \frac{f_k(R') - \min(f_k(R'))}{\max(f_k(R')) - \min(f_k(R'))}
\]

After normalization, \( f_k(k = l, h, d) \) is normalized to \( \overline{f_k}(k = l, h, d) \). Where \( R \) is the collection of all feasible paths, and \( \overline{f_k}(R') \) is the \( k \)th normalized sub cost of the \( i \)th path in \( R \).

The fitness function in this paper is improved. The modified nonlinear fitness function has the advantages of dynamic adjustment with evolution algebra. The functions are as follows:
\[
F^* = \frac{[\sqrt{n}]}{F}
\]
\[
\overline{F} = w_l \times \overline{f_l}(R') + w_h \times \overline{f_h}(R') + w_d \times \overline{f_d}(R')
\]

Where \( F^* \) is the non-linear fitness function, \( \overline{F} \) is the cost function after normalization, \( \lceil \sqrt{n} \rceil \) is the integer value less than or equal to \( \sqrt{n} \), \( m = 1 + \ln N \), \( N \) is the largest evolution algebra in genetic evolution, which indicates the current evolution algebra. It can ensure the diversity of the subsequent population and improve the competitiveness of each individual and the convergence of the algorithm.

3.3.3 Initial population design. In genetic algorithm, initial population will affect the result of algebra and optimal solution of trajectory planning. Therefore, in order to maintain the diversity and randomness of population, some individuals with excellent genes can directly participate in the initial population. In this paper, two kinds of initial population are used. [10].

(1) The linear trajectory: The linear path is the most simple and optimal path length index, which is the most similar to the final path. Therefore, it needs to be introduced into the initial population according to the proportion during initialization.

(2) The random trajectory: During the population initialization, the randomness and diversity of the population also should be considered. Therefore, it is necessary to add part of random trajectories to the initial population so that the initial population be as diverse as possible, but this kind of random path cannot be generated at will, otherwise, the trajectory may have different density before and after
the path point or the trajectory may go backward, which makes the algorithm unable to converge or get the optimal path. The generation method of random trajectory is described as follows:

Suppose $O$ is the starting point of the path, $G$ is the destination point of the path, and $K_i$ is current point of the path. Then, the next path point needs to be closer to $G$. Take $GK_i$ as the radius to form a circular range, and the next path point should be generated within this restricted area, and conditions that the next path point needs to meet are shown as follows:

$$
X_{i+1} = (X_G - R) + R b \cdots (R < X_G) \\
X_{i+1} = X_G \times b \cdots (R > X_G)
$$

(16)

Where $X_{i+1}$ represents the abscissa of the next point. $X_G$ represents the abscissa value of the end point. $R$ represents the distance between the current path point and the $G$. While $b$ belongs to a random value in the interval $[0, 1]$.

$$
\begin{align*}
Y_b &= Y_G - \sqrt{R^2 - (X_{i+1} - X_G)^2} \\
Y_t &= \max[Y_G, Y_b] \\
Y_{i+1} &= Y_t + (Y_G - Y_t) \times b
\end{align*}
$$

(17)

Where $Y_{i+1}$ is the ordinate of the next path point. $Y_G$ is the ordinate of the end point, and $Y_b$ is the ordinate of the start point.

For the selection of random function, it is also important in random trajectory generation. The random value belongs to $[0, 1]$. Considering the actual mission environment, the next path point should be close to the destination point. Therefore, the Gaussian distribution random functions are selected in this paper to generate the random value $a, b$:
In the Gaussian distribution, the path step size can be adjusted by adjusting the parameters of the Gaussian distribution function, which can make the distribution more uniform and reasonable. The resulting random path is shown in Fig. 6:

\[
\begin{align*}
\begin{cases}
  a - N(0, \sigma^2) &= \frac{1}{\sigma \sqrt{2\pi}} e^{-\frac{x^2}{2\sigma^2}} \\
  b - N(0, \sigma^2) &= \frac{1}{\sigma \sqrt{2\pi}} e^{-\frac{y^2}{2\sigma^2}}
\end{cases}
\end{align*}
\]  

(18)

3.3.4. Genetic operator design. The design of genetic operators is the key point of genetic algorithm. After the initial population is generated, the survival of the fittest will be realized by different genetic operators and the population evolution process will be completed. In this paper, four genetic operators are designed and used including mutation operator, repulsion operator, cross-over operator and insertion operator. [20].

Repulsion operator: In the later stage of the algorithm, the excellent individuals are almost the same, which causes the algorithm may fall into the situation of local optimization. Therefore, several unique individuals among the better individuals are reserved for reproduction and variation to produce new individuals in the process of genetic operation. The rejection factor is calculated as follows:

\[
r_j = \sum_{i \neq j} \left[ (x_j - x_i)^2 + (y_j - y_i)^2 \right]
\]  

(19)

Where \( n \) is number of excellent individuals selected in the population. \( x \) and \( y \) are the horizontal position coordinates of track points.

(2) Cross-over operator: The crossover operator simulates the chromosome crossover operation in nature and randomly selects a position on the two track chromosomes, from which the two are interchanged. In the nature, usually excellent individuals have greater reproductive rights. In order to reduce the amount of computation, the algorithm selects \( n \) individuals with larger rejection factor to cross operate so as to avoid the algorithm falling into local optimum.

Figure 6. Random trajectory
(3) Mutation operator: There is a certain probability of gene mutation in the track chromosome, and the probability of mutation changes with the individual evaluation function. In order to reduce the calculation amount of the algorithm, low mutation probability is given to the individuals with poor adaptability and high mutation probability is given to the individuals with better adaptability.

(4) Insertion operator: A task track is composed of multiple track points, and the calculation amount of the algorithm increases exponentially with the increase of the number of track points. In order to reduce the calculation of the algorithm, this paper adopts the hierarchical planning method. Firstly, the whole mission map is planned to get the long track with less track points, and then the genetic algorithm is used to interpolate the far track points to get the final track.

3.3.5. Trajectory planning algorithm procedure. (1) Initialization, including terrain, constraints, fitness function and selection of algorithm control parameters. 2) Population generation, generating the initial population as described in section 3.3. 3) Calculate the individual fitness value and judge the iteration termination condition. If the condition is met, it ends; if not, it enters. 4) The better n individuals were selected for crossover and mutation. 5) The new sub individuals generated. Evaluate the fitness of new individuals. Replace the individuals with the worst adaptability in the population, keep the population size and enter 3). 6) After the initial trajectory planning, the insertion operator is used to make the final trajectory planning, and the final trajectory is obtained.

The flow chart of genetic algorithm applied in trajectory planning is shown as follows:

![Figure 7. Genetic algorithm flow chart](image)

4. Simulation and Result Analysis
The digital map model method in section 2 is used to model the mission area digital map. The basic terrain parameters and the mountain terrain parameters are described in Table 1 and Table 2 respectively. After modelling and pre-processing, the final digital map is shown in Fig. 8
Table 1. Basic terrain simulation parameters

| a  | b    | c    | d    | e    | f    | g    |
|----|------|------|------|------|------|------|
| 10 | 0.6  | 0.1  | 0.05 | 0.06 | 0.1  | 0.1  |

Table 2. Mountain terrain simulation parameters

| No. | x_i  | y_i  | x_{si} | y_{si} | h_i (km) |
|-----|------|------|--------|--------|----------|
| 1   | 135  | 101  | 0.15   | 0.15   | 1        |
| 2   | 151  | 40   | 0.31   | 0.15   | 0.7      |
| 3   | 181  | 62   | 0.23   | 0.34   | 1.1      |
| 4   | 42   | 155  | 0.27   | 0.12   | 1.3      |
| 5   | 70   | 101  | 0.19   | 0.16   | 0.6      |
| 6   | 101  | 181  | 0.12   | 0.23   | 1.2      |

Figure 8. Digital map optimization based on tilt-rotor aircraft performance

The starting position of the mission is (0, 0, 0), and the ending point of the mission is (200, 200, 0). Based on the actual environment of the mission, the initial simulation parameters of genetic algorithm are set as follows:

Table 3. The situation of simulation

| name                                        | value |
|---------------------------------------------|-------|
| Population number                          | 100   |
| Initialize line trace                      | 10    |
| Initialize random trace                    | 70    |
| Number of long path points                 | 10    |
| Large step evolutionary algebra            | 100   |
| Number of insertion factors                | 5     |
| Number of excellent individuals in each generation | 10 |
| Number of offspring                        | 42    |
| Elimination rate                           | 10%   |

After 100 generations of population evolution, the algorithm first obtains the result of long stride track and then interpolates the segment with long distance between adjacent track points to obtain the final mission track. The simulation results are shown as follows. The track planning result of 3D map is shown in Fig.10a, the track planning result of 2D elevation map is shown as Fig.10b. The red track
is the large step track planning result, and the blue track is the final task track after interpolation. It can be seen that the interpolated final track avoids all kinds of threats better. Fig.10 shows the change curve of the evaluation function value of the optimal individual in each generation. The evaluation function value tends to converge with the evolution of the population, and the individual with the smallest evaluation function is also the closest to the optimal trajectory. Therefore, the algorithm can plan the mission trajectory with short range, low altitude and avoiding all kinds of threats for the aircraft, so that it can complete the mission successfully.

5. Conclusion
In order to ensure the flight safety, this paper proposes a genetic algorithm trajectory planning method combined with digital map pre-processing, which can plan the flight trajectory in advance. First of all, the 3D digital map is modelled and pre-processed according to the actual mission environment and constraints of the tilt-rotor aircraft. Then, the genetic algorithm is designed, and the related genetic operators and individual evaluation functions are improved, so that the calculation and storage of the algorithm are reduced, the convergence speed and optimization accuracy are accelerated, and the local optimal solution is avoided. The simulation results show that after pre-processing the 3D digital map, the improved genetic algorithm can successfully plan a 3D mission trajectory with the lowest overall cost and the best route in the complex mission environment.
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