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Research on UAV Regional Reconnaissance Coverage Path Planning for Mountain Environments

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Abstract: To address the problems of poor coverage quality and low reconnaissance efficiency in UAV regional reconnaissance tasks under complex mountain environments, an efficient regional coverage path planning method is proposed. Firstly, a 3D coverage and occlusion model is constructed, and a viewpoint generation method based on the greedy strategy is adopted to screen the optimal viewpoint set. Secondly, the Adaptive Chaotic Dung Beetle Optimization Algorithm (ACDBO) is proposed to solve the optimal order of path points. Through chaotic mapping initialization, nonlinear boundary convergence factor and parameter adaptive adjustment strategy, the global optimization ability and convergence speed of the algorithm are improved, and the optimization objectives comprehensively consider indicators such as path length and deflection angle. Simulation experiments show that the proposed method is superior to traditional methods in terms of the number of viewpoints and path length; compared with the original Dung Beetle Optimization Algorithm and other comparison algorithms, the ACDBO algorithm has better convergence performance and higher planned track quality, and can effectively complete the UAV regional reconnaissance coverage task under mountain environments.

Keywords: UAV; Path Planning; Dung Beetle Optimization Algorithm; Mountain Reconnaissance.

1. Introduction

With its advantages of high maneuverability, low cost and high safety, Unmanned Aerial Vehicles (UAVs) have been widely applied in fields such as battlefield reconnaissance, disaster rescue and geological exploration [1-3]. Its characteristic of not needing to consider the physiological limitations of personnel makes it a key technology for performing complex tasks. As a core link in UAVs' autonomous execution of regional reconnaissance, coverage path planning needs to generate efficient flight paths that meet dynamic constraints, and its planning effect directly affects task efficiency and coverage quality[4-5].

Most existing relevant studies focus on simple and large-scale environments, where researchers achieve path optimization through methods such as block strategy, combination of convex decomposition and ant colony algorithm, and design of collision-avoidance flight modes. In terms of path planning algorithms, grid-based algorithms such as A* algorithm [6], genetic algorithm [7] and ant colony algorithm [8] are often used for path planning in 2D scenarios, but these methods are difficult to adapt to 3D complex airspace environments.

For the problem of 3D coverage path planning, some existing studies combine K-means clustering [9] with hybrid ant colony algorithm to solve viewpoint paths, and others optimize viewpoint access sequences through tilted scanning modeling and sparrow search algorithm. However, in complex mountain environments, terrain undulation and occlusion still seriously restrict coverage effect and path economy.

Therefore, it is urgent to develop a 3D coverage path planning method with strong adaptability, which takes into account both viewpoint optimization and global path efficiency, so as to improve the reconnaissance efficiency of UAVs in mountain environments.

2. Path Planning Model

2.1. Spatial Model for Path Planning of Regional Reconnaissance Tasks

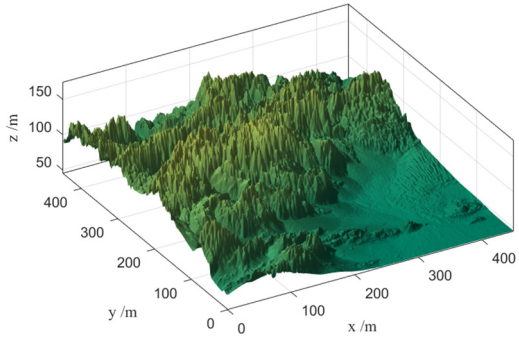


Fig 1. 3D Terrain Map of the Target Area

When UAVs perform regional coverage reconnaissance tasks, environmental modeling is a core prerequisite. Its core lies in abstracting actual elements such as terrain features, UAV positions and coverage efficiency into mathematical

models that can be processed by computers, providing an accurate foundation for path planning. A reasonable environmental modeling method can directly affect the efficiency and reliability of path planning, and it is a key link to ensure the effect of task execution. For the spatial expression of the task scenario, it is necessary to perform grid discrete processing on the ground area and the UAV flight space. Among them, the ground data can be characterized by a Digital Elevation Model (DEM), which is constructed through Geographic Information System (GIS) and remote sensing technology, and records surface elevation information in the form of discrete lattices (as shown in the figure 1). The DEM map can finely depict the undulating characteristics and geomorphological details of the terrain, and is especially suitable for the modeling needs of complex mountain environments. Therefore, this study selects it as the main expression form of ground data to support the accurate design and optimization of subsequent path planning algorithms.

2.2. UAV Regional Reconnaissance Coverage Mode

The detection capability of a sensor ω is usually characterized by its maximum detection distance. When a UAV performs tasks at a fixed altitude, it is necessary to accurately determine its effective coverage range. Firstly, based on the height difference between the viewpoint and the ground grid as well as the sensor detection elevation angle, the initial projection range of the viewpoint on the horizontal plane is calculated. However, due to actual terrain undulation, some points within the projection area may exceed the detection threshold. To this end, it is necessary to verify each point within the initial coverage range one by one: select any point, calculate the 3D Euclidean distance between it and the viewpoint, and derive the vertical height difference combined with the elevation angle. If the height difference does not exceed the sensor detection capability threshold, the point is determined to be within the effective detection range. Through traversal verification, the precise detection range set $\omega_\alpha$of the current viewpoint is finally determined.

$$\Delta h_i = H - z_i$$

$$R_{\text{pre}} = \Delta h_i \tan(\alpha/2)$$

$$d_\alpha = \sqrt{\left(x_j - x_{Oi}\right)^2 + \left(y_j - y_{Oi}\right)^2 + \left(z_j - H\right)^2}$$

$$d_{\text{vertical}} = \mid z_j - H \mid \cos(\alpha/2)$$

$$w_{Oi} = \{P_j \in R_{\text{pre}} | d_{\text{vertical}}(P_j) \leq R_{\text{pre}}\}$$

Where: H is the viewpoint height, h is the height of the ground-level grid, Δh_i is the difference between the viewpoint height and the ground-level grid height, R_{pre} is the actual detection range of the viewpoint on the plane where the current ground point is located, α/2 is the detection elevation angle, d_{Oi} is the Euclidean distance between the viewpoint and the point, d_{vertical} vertical is the vertical distance between the ground point and the perpendicular line of the viewpoint.

2.3. Objective Function

For the problem of generating regional reconnaissance coverage paths, it is necessary to construct a path objective function that conforms to the application scenario. In this study, coverage rate is taken as a rigid constraint to ensure no omission in the mission area. Meanwhile, a cost function is constructed with path length and path smoothness as optimization objectives, and their weighted sum forms the path objective function. Serving as a quantitative evaluation index for path quality, the smaller the value of this function, the better the comprehensive performance of the path and the more it meets the mission requirements. Specifically, path length directly affects mission timeliness and UAV energy consumption efficiency, which should be constrained by the shortest distance index. Path smoothness is related to flight safety and the dynamic response capability of UAVs. Indicators such as curvature change rate are used to suppress sharp turns and abrupt trajectories, so that the path has good executability and stability.

$$F_{\text{Distance}}(X_i) = \sum_{i=1}^{n-1} l_i$$

$$F_{\text{Curve}}(X_i) = \omega_1 \sum_{j}^{n-1} \varphi_i$$

$$F = \mu_1 F_{\text{Distance}} + \mu_2 F_{\text{Curve}}$$

Where: l_i denotes the distance between adjacent waypoints, ω_1 represents the deflection cost coefficient,φ_i is the deflection angle, $\mu_1$and μ_2 represent the weights of the distance cost and the smoothness cost, respectively.

3. Improved Dung Beetle Optimization Algorithm

3.1. Dung Beetle Optimization Algorithm

The Dung Beetle Optimizer (DBO) is a swarm intelligence optimization algorithm. Its design is inspired by the behaviors of ball rolling, dancing, spawning, foraging, and stealing of dung beetles. Compared with other similar swarm intelligence algorithms, DBO has the advantages of fast iteration speed and strong global search ability, and is suitable for solving complex optimization problems. Therefore, DBO is adopted in this study to optimize the waypoint access sequence.

In the DBO algorithm, ball rolling is one of the core mechanisms. To avoid competition and move the dung ball efficiently, dung beetles navigate by perceiving celestial light sources such as the moon and starlight. Their moving direction is jointly affected by the light source position and navigation error. This behavior is abstracted as the position update formula:

$$\begin{aligned} x_i^{t+1} &= x_i^t + \alpha \times k \times x_i^{t-1} + b \times \Delta x \\ \Delta x &= |(x_i^t - X^w)| \end{aligned}$$

Where:x_i^t denotes the position of the i-th dung beetle at the t-th iteration, the deflection coefficient k∈(0,0.2],b is a random value within the range (0,1),α takes the value of −1 or 1,X^w represents the global worst position,Δx is the light intensity change coefficient.

When encountering an obstacle, dung beetles will rotate and stop through dancing behavior to adjust their forward direction, and the tangent function is used to mimic the new rolling direction. The position update formula for ball-rolling dung beetles is as follows:

$$x_i^{t+1} = x_i^t + \tan(\theta)|x_i^t - x_i^{t-1}|$$

Where:$\theta \in [0,\pi]$ denotes the deflection angle.

Before reproduction, the egg-laying dung beetles select suitable oviposition sites, and a boundary selection strategy is employed to simulate their oviposition area, which is defined as:

$$Lb^* = max[X^* \times (1-R), Lb]$$
$$Ub^* = min[X^* \times (1+R), Ub]$$

Where:Lb^* and Ub^*represent the lower and upper bounds of the region, respectively, Lb and Ub represent the lower and upper limits of the optimization problem, respectively,X^* is the current local optimal position.

3.2. Circle Chaotic Map

In DBO, the random population initialization method can easily lead to problems such as uneven population distribution and reduced diversity, which in turn affect the convergence speed of the algorithm. To address this issue, the AC-DBO algorithm proposed in this study adopts a chaotic mapping method to optimize the generation of the initial population. The randomness, non-repetitiveness, and ergodicity of chaotic mapping are utilized to make the population distribution more uniform.

The Circle chaotic map is widely used in many studies due to its high stability and high coverage rate of chaotic values. However, its values are relatively dense in the interval [0.2, 0.6]. Therefore, the parameters of its mapping formula are improved to achieve a more uniform distribution:

$$x_{n+1} = \mathrm{mod}\left[3.85x_n + 0.4 - \frac{0.7}{3.85}\pi\sin(3.85\pi x_n), 1\right]$$

3.3. Nonlinear Boundary Convergence Factor

Faced with complex rules in population setting, behavior definition and other aspects of swarm intelligence algorithms, the linearly decreasing strategy of DBO limits the global search and local exploitation capabilities of the algorithm. This study expects the algorithm to conduct extensive global search in the early stage and accelerate the convergence speed in the later stage to obtain the optimal solution of local search more quickly. Therefore, the expression of the boundary convergence factor is set as follows:

$$R = \frac{1}{2} + \frac{1}{2}\sin\left(\frac{\pi}{2} + \pi\frac{t}{T_{\max}}\right)$$

4. Simulation Aanlysis

The regional coverage task of UAVs in mountainous environments requires the UAV to fully cover the selected area while avoiding collisions. To verify the effectiveness of the coverage path planning method proposed in this paper, these actual terrains utilized authentic DEM maps obtained via LiDAR sensors the Christmas Island, Australia, while Map spanned 450 × 450 × Z m. The experimental environment used MATLAB R2023b on a computer equipped with an Intel Core i5-13500H processor and 16GB RAM.

To verify the stability of the ACDBO algorithm, it is compared with the DBO algorithm and the ACO algorithm. They are run 30 times in total, and the optimal value, worst value, and variance of the objective function are counted. The results are shown in Table 1.

Table 1. Algorithm Stability Comparison

Algorithm	ACO	DBO	ACDBO
Optimal value	84 500	71 900	70 800
Worst value	89 200	73 100	71 500
Variance	10 800	1 950	260

Figure 2 shows the optimal solutions obtained by using the original DBO algorithm and the ACDBO algorithm for regional coverage path planning, respectively. The parameters used by both algorithms are exactly the same. It can be observed that the ACDBO algorithm yields a shorter path with fewer sharp turns, leading to superior path planning performance.

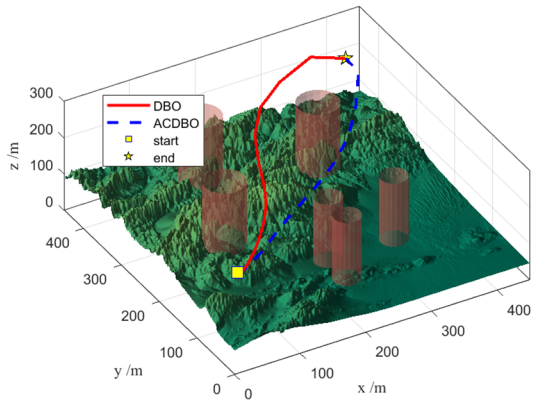


Fig 2. UAV path planning results

To evaluate the performance of the ACDBO algorithm, this study compares the ACDBO algorithm with the original DBO algorithm and the ACO algorithm on the current model dataset.

As shown in Figure 3, with the same population size and number of iterations, the ACDBO algorithm exhibits superior population initialization and employs a more rational random distribution strategy for population position updates. Consequently, it achieves a significantly faster convergence speed than both the ACO and DBO algorithms, while yielding a lower final objective function value.

5. Conclusion

This paper focuses on the coverage path planning problem for UAV regional reconnaissance in mountainous environments. First, the target area data is preprocessed via

gridding, and the viewpoint set and coverage point set are constructed according to the mission requirements. Second, a coverage model and an occlusion model are established respectively. Then, the optimal viewpoint selection is realized based on a greedy algorithm with viewpoint spacing and coverage rate constraints. Finally, a mathematical model is formulated with the objective of minimizing the weighted sum of UAV path length and number of turns, and the ACDBO algorithm is employed to solve this model. Simulation results demonstrate that the proposed method can effectively reduce energy consumption and achieve superior path planning outcomes.

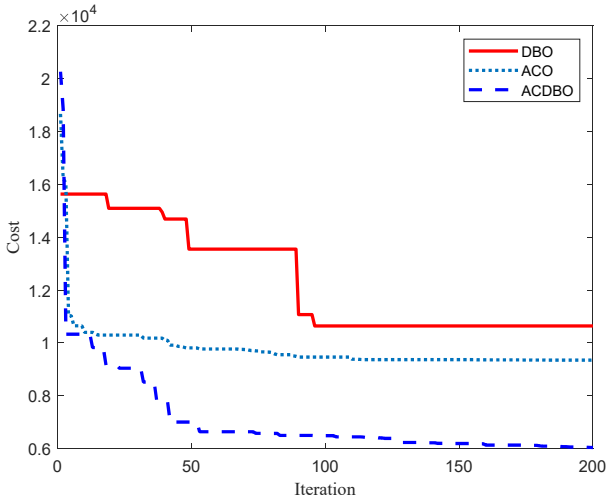


Fig 3. Fitness curve

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