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# Unmanned aerial vehicle trajectory planning based on enhanced sparrow search algorithm

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***Abstract*—In order to solve the problems of the original sparrow search algorithm (SSA) in the unmanned aerial vehicle (UAV) trajectory planning, such as low optimization accuracy and slow convergence speed, an enhanced sparrow search algorithm (ESSA) was proposed. Firstly, Halton sequence was used to initialize the population to increase the diversity of the population and improve the subsequent search accuracy of the algorithm. Secondly, the quasi-reflection learning mechanism is introduced to improve the individual quality of the algorithm after each iteration, and improve the optimization accuracy and convergence speed of the algorithm. The improved algorithm is applied to the trajectory planning of the UAV, the results show that the flight cost of the UAV trajectory found by ESSA is lower and the convergence speed is faster.**

***Keywords*-Sparrow search algorithm; Unmanned aerial vehicle; Trajectory planning; Halton sequence; Quasi-reflection learning;**

## I. Introduction

UAV [1] trajectory planning is a hot issue in the field of UAVs today, and ensuring that UAVs autonomously plan a reasonable and feasible flight path is the pursuit goal of UAV intelligence. However, when facing complex environments such as mountainous areas, urban areas and no-fly zones, due to uncertainties and constraints of numerous parameters, the trajectory planning still suffers from slow planning speed and unreasonable trajectories, so that UAVs face high flight costs and need to find new solutions.

The population intelligence optimization algorithm has been developed rapidly in recent years, and its excellent characteristics can help UAVs plan a reasonable and safe navigation route with low flight cost quickly. For example, Fu Xingwu et al [2] used an improved particle swarm optimization algorithm to achieve a good trajectory planning effect for UAVs in 3D. Wu Kun et al [3] used the improved whale optimization algorithm to obtain a flight cost and good feasibility of the trajectory, and AJEIL et al [4] combined particle swarm and bat optimization algorithms to solve a relatively short distance and good smoothness of the UAV trajectory.

In 2020, XUE J K et al. proposed a new population intelligent optimization algorithm-sparrow search algorithm [5] (SSA), which is significantly better than other population intelligent optimization algorithms in terms of the search accuracy and the ability to escape from the local optimum, and is more suitable for the complex optimization problem of UAV trajectory planning. To further improve the algorithm performance, Xin Lu et al [6] improved the global search capability and search accuracy of the algorithm by introducing Tent chaotic sequences and Gaussian variants. Qing-Hua Mao [7] et al. integrated the Coasean variation and the backward learning strategy to coordinate the algorithm's ability of global and local search and help the algorithm to jump out of the local optimum. Andi Tang et al [8] combined the sine cosine algorithm to improve the algorithm development and exploration capabilities. These improved algorithms have improved the performance of the sparrow algorithm for finding the optimum to some extent, but the algorithm still has the following defects: the individuals in the population are not evenly distributed and prone to overlap, which leads to incomplete subsequent search of the algorithm; the algorithm converges slowly, and the quality of individuals cannot change significantly after each iteration, and it cannot approach the optimal solution quickly. Due to these two major defects, the optimization accuracy and convergence speed of the sparrow algorithm in the UAV trajectory planning problem are not satisfactory.

In order to improve the above-mentioned algorithm defects, an Enhanced Sparrow Search Algorithm (ESSA) is proposed in this paper. Firstly, the sparrow population is initialized by Halton sequence [9], so that the population diversity is improved and the coverage of the population in the solution space is enhanced, and secondly, the quality of individuals after each iteration cycle is improved by using the quasi-reflective learning [10] mechanism. Simulation experiments show that ESSA can find a navigation route for UAVs with less flight cost, better robustness, faster convergence and better feasibility.

## II. Improvement of the sparrow search algorithm

### A. Sparrow search algorithm

Sparrow search algorithm (SSA) and Particle Swarm Optimization (PSO) [11], Whale Optimization Algorithm (WOA) [12], etc. are all population intelligence optimization algorithms. SSA simulates the predatory and anti-predatory behaviors of sparrow populations to continuously update individual positions to find the optimal food source. In the algorithm, there are three types of sparrows: discoverers, joiners and vigilantes. The parameters set the proportion of both discoverers and vigilantes to 10%-20%, and the proportion of both discoverers and joiners is



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kept constant; when the identity of a discoverer changes, there is always a joiner whose identity will also change. The discoverers guide the foraging area and direction of the population, the joiners follow the discoverers with a certain probability, and the vigilantes are mainly responsible for the vigilance and monitoring around the food source area.

### *B. The improvement method of sparrow search algorithm*

*1) Halton sequence to initialize populations:* The original sparrow search algorithm initializes the population positions in a random distribution, which leads to uneven distribution of individuals in the solution space, reduced population diversity and aggregation among individuals, making the algorithm fall into a local optimum. the Halton sequence can effectively improve this situation.

Select n mutually prime numbers and keep slicing them to form some non-repeating and uniform points, each with coordinates between [0,1]. The algorithm is as follows:

$$w=\sum_{i=0}^{m} b_i p_n^i = b_m p_n^m + \cdots + b_1 p_n^1 + b_0 \tag{1}$$

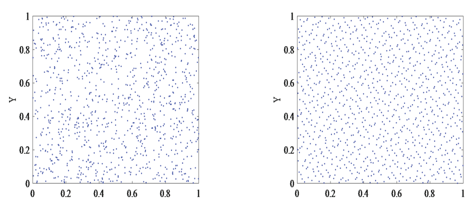
where $p_n \geq 2$, w is any integer greater than 1, $b_i \in \{0,1,\cdots p_n-1\}\,(i=0,1,\cdots m)$. Next, knowing $b_i$ and $p_n$, define the basic inverse (radical-inverse) function as

$$\varphi_n(w) = b_0 p_n^{-1} + b_1 p_n^{-2} + \cdots + b_m p_n^{-m-1} \tag{2}$$

The n-dimensional Halton sequence can be composed of n different and mutually prime bases p:

$$H(w)=\{\varphi_1(w),\varphi_2(w),\cdots,\varphi_n(w)\} \tag{3}$$

The two-dimensional sparrow population is selected and the location distribution maps of the random initialized population and the Halton sequence initialized population are compared, and the simulation plots are as follows:




(a) Random distribution (b) Halton sequence distribution

Figure 2: Population location distribution map

From the comparison of the Figure 2, it can be seen that the population, after initialized by Halton sequence, has a higher coverage in the solution space and is more uniformly distributed without population aggregation, which provides a good basis for the subsequent iterative optimization search.

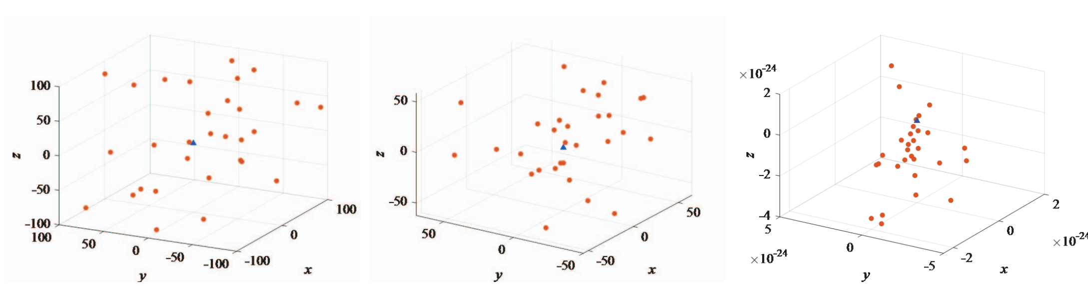
*2) Quasi-reflective learning:* The reverse learning mechanism [13] is to reverse the candidate solution represented by the population position to obtain a reverse solution, and then select a new population with higher quality according to the actual fitness ranking, which improves the probability of the algorithm to find the optimal solution. The quasi-reflective learning mechanism is a newly proposed concept based on reverse learning, which has improved the accuracy of finding the optimal solution and the convergence speed compared to the traditional reverse learning. The pseudo-code of the quasi-reflective learning mechanism is as follows:

**Algorithm 1** Quasi-reflective learning pseudo-code

**input:** $P_0=\{X_{i,j}\}, i=1,2,\cdots,N; j=1,2,\cdots,D$
**output:** $P=\left\{X_{i,j}^Q\right\}, i=1,2,\cdots,N; j=1,2,\cdots,D$

the number of populations be N, the dimension be D, the upper and lower bounds of the solution space be ub and lb respectively, and r be a random number between (0,1).
**for** $i=1:N$ **do**
    **for** $j=1:D$ **do**
        $M_j=(ub_j+lb_j)/2$
        **if** $X_{i,j}<M_j$ **then**
            $X_{i,j}^Q=X_{i,j}+(M_j-X_{i,j})\times r$
        **else**
            $X_{i,j}^Q=M_j+(X_{i,j}-M_j)\times r$
        **end if**
    **end for**
**end for**
Merge the populations $\{P_0, P\}$ and sort them from best to worst according to the fitness value
Select the first N individuals with better fitness values to form a new population

Thirty individual sparrows were selected for the quasi-reflex learning experiment. The upper and lower bounds of the three-dimensional solution space are taken as 100 and -100, respectively, with red dots indicating individual sparrows and blue triangles indicating the global optimal




(a) without Quasi-reflection learning (b) 10 times Quasi-reflection learning (c) 50 times Quasi-reflection learning

Figure 1: Population location distribution map

positions. The optimal object function is:

$$f(x)=\sum_{i=1}^{n} x_i^2 \tag{4}$$

Observing Figure 1, we can see that after the quasi-reflection learning, as the number of iterations of the algorithm increases, the individual sparrow will be infinitely close to the global optimal position. Thus, it can be seen that the quasi-reflection learning mechanism can help the sparrow algorithm to improve the search accuracy, increase the probability of individual sparrow searching for the optimal solution, and the convergence speed will be greatly improved.

### C. Algorithm flow of ESSA

1) Initialize the parameters, including the number of individuals of various classes of sparrows, alert threshold and safety threshold, etc.
2) Initialize the population locations using Halton sequence.
3) Calculate the fitness value of each sparrow location and find the individuals with the best and worst fitness values and their locations.
4) Perform the update of the discoverer's position.
5) Perform the update of joiner's position.
6) Update the position of the alerters.
7) Perform quasi-reflective learning of the locations of the updated sparrow population and select the N individuals with better fitness values to form a new population of sparrows.
8) Compare the fitness value of the new population with the fitness value of the original population and perform the update of the global optimal position.
9) Determine whether the iteration termination condition is met, if so, proceed to the next step, otherwise, skip to step 3.
10) The algorithm operation ends, output and record the optimal result.

## III. Experimentation

### A. Flight cost function

To ensure that the intelligent optimization algorithm finds the optimal solution and optimal trajectory, the UAV will have the lowest flight cost and the safest path. The experiments will combine the flight distance cost, flight altitude cost, flight turn angle cost and flight threat cost as the cost function [14], i.e., the fitness function of the algorithm to find the optimum, to constrain the flight trajectory of the UAV.

*1) Flight distance cost:* The closer the flight distance from the starting point to the end point, the more energy-efficient and efficient the UAV is for efficiency and energy considerations. The flight distance cost is expressed as

$$f_1=\sum_{i=1}^{n}\sqrt{\Delta x^2+\Delta y^2+\Delta z^2} \tag{5}$$

where $\Delta \mathrm{x}, \Delta \mathrm{y}, \Delta \mathrm{z}$ are the distances of two adjacent nodes on the trajectory in $x, y, z$, respectively. $i = 1, 2, \cdots n$ represents the two adjacent nodes of the ith group.

*2) Flight altitude cost:* In order to make the UAV perform the task at a relatively safe altitude, there will be a relative altitude range, and the altitude difference should not be too large when flying. This will help the UAV fly smoothly, reduce unnecessary lift operations and also save energy. The flight altitude cost is expressed as

$$f_2=\sqrt{\sum_{i=1}^{n}(h_i-h_a)^2} \tag{6}$$

where $h_i$ is the height of the nodes on the trajectory, $h_a$ represents the average height of all nodes, and $i = 1, 2, \cdots n$ represents the i-th node.

*3) Flight turn angle cost:* The flight turn angle represents the change in angle of the UAV as it passes two nodes on the trajectory, which can cause damage to the UAV if the turn angle is too large. The turn angle change of the UAV needs to be constrained, and the flight turn angle cost is expressed as:

$$f\_3=\sum\nolimits_{i=1}^{n}(\left|arccos(\frac{r_i^T r_{i+1}}{||r_i||\cdot||r_{i+1}||}\right|) \tag{7}$$

$$r_i=(x_{i+1}-x_i, y_{i+1}-y_i, z_{i+1}-z_i)^T \tag{8}$$

where $r_i$ denotes the transpose of the coordinate difference between the ith node and the i+1 node on the trajectory.

*4) Flight threat cost:* In order to make the UAV avoid mountain peaks and no-fly zones as much as possible and ensure flight safety, the flight threat cost is introduced, and for mountain peaks, it is expressed as:

$$f_s=\begin{cases}0, mz_i\geq z_2\left(x_i, y_i\right)\\ \infty, z_i<z_2\left(x_i, y_i\right)\end{cases} \tag{9}$$

where $(x_i, y_i)$ are the horizontal and vertical coordinates of the nodes on the trajectory, $z_i$ denotes the height of the nodes on the trajectory, and $z_2$ is the peak function model. For the no-fly zone, the flight threat cost is expressed as:

$$f_j=\begin{cases}0, d_i\geq d_j\\ \infty, d_i<d_j\end{cases} \tag{10}$$

where $d_i$ represents the distance of the node on the trajectory from the center of each no-fly zone, and $d_j$ represents the radius of each no-fly zone. So the total flight threat cost expression is:

$$f_4=f_s\cup f_j \tag{11}$$

Therefore, the total flight cost function, i.e., the algorithm seeking fitness function, can be expressed as:

$$F=\lambda_1 f_1+\lambda_2 f_2+\lambda_3 f_3+\lambda_4 f_4 \tag{12}$$

Where $\lambda\in(0,1)$ denotes the weighting coefficients, the contribution of each flight cost function to the trajectory is different, and for the consideration of UAV safety, optimal altitude and distance, four weighting coefficients are set in order: 0.5, 0.5, 0.3 and 0.2.

Table I: Terrain parameter setting

| Terrain type | Height(m) | Horizontal coordinate(km) | Vertical coordinate(km) | Horizontal slope/radius(km) | Vertical slope/radius(km) |
|---|---|---|---|---|---|
| Mountain 1 | 60 | 60 | 60 | 10 | 10 |
| Mountain 2 | 80 | 100 | 105 | 12 | 12 |
| Mountain 3 | 100 | 150 | 160 | 15 | 15 |
| No-Fly Zone 1 | 50 | 50 | 100 | 10 | 10 |
| No-Fly Zone 2 | 50 | 80 | 150 | 20 | 20 |
| No-Fly Zone 3 | 50 | 160 | 70 | 20 | 20 |
| No-Fly Zone 4 | 50 | 115 | 45 | 15 | 15 |

### B. Creation of terrain environment

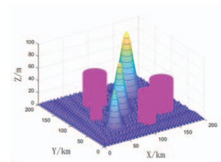
In order to simulate the relatively uneven ground in a realistic environment, the study uses a more commonly used geomorphic function model [15], as follows:

$$z_1 = sin(y+a) + bsin(x) + ccos(d\sqrt{x^2+y^2}) + ecos(y) + fsin(f\sqrt{x^2+y^2}) + gcos(y) \tag{13}$$

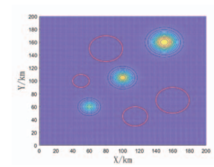
Where the six parameters, a, b, c, d, e, f, and g, can be used to adjust the degree of curvature roughness of the ground surface, and all six parameters are set to 1 in the study. In order to simulate the flight obstacle, the mountainous area and no-fly zone are added to the experiment, where the function model of the mountain peak is:

$$z_2 = \sum_{i=1}^{n} h_i \cdot exp\left[-\frac{(x-x_i)^2}{a_{xi}^2} - \frac{(y-y_i)^2}{b_{yi}^2}\right] \tag{14}$$

where i denotes the ith peak, n is the number of mountains, $h_i$ denotes the altitude of the mountain, $(x_i, y_i)$ is the coordinate of the highest point of the mountain, and $(a_{xi}, b_{yi})$ is the parameter of the slope of the mountain. The red cylinder is the no-fly zone. The parameters of the mountain peaks and the no-fly zone are set as shown in Table 1, and the resulting 3D topographic and aerial views are shown in Figure 4.




(a) 3D topographic



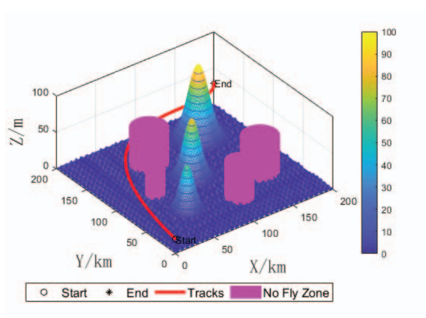

(b) Aerial view

Figure 4: topographic map

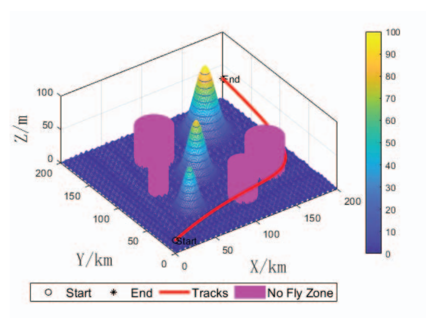
### C. UAV trajectory finding test

The ESSA, PSO, WOA and SSA algorithms are used to find the optimal trajectory in the 3D topographic map, and the starting point is set to [0,0,20] and the ending point is set to [200,200,30]. The number of algorithm populations is set to 30 and the number of iterations is 500.Compare the effect of merit search.

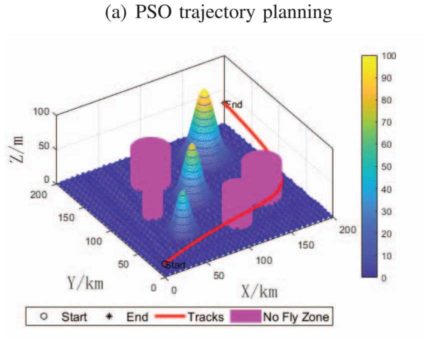
As can be seen from the track finding results in Figure 3, the ESSA algorithm plans the shortest track length,



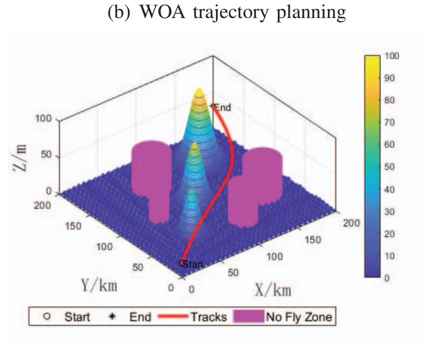

(a) PSO trajectory planning




(b) WOA trajectory planning




(c) SSA trajectory planning




(d) ESSA trajectory planning

Figure 3: UAV trajectory planning diagram

the smoothest track and has a better obstacle avoidance capability. The other algorithms fail to find the most ideal path, and the UAV faces a high flight cost.

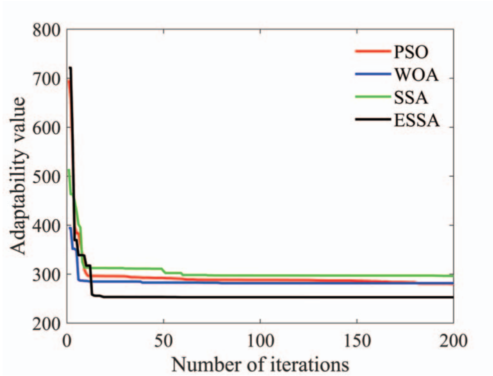



Figure 5: Population location distribution map

From the convergence graph in Figure 5, it can be seen that the ESSA algorithm has the smallest fitness value, i.e., the flight cost of the planned trajectory is the smallest. And the convergence is completed in 20 iterations. In order to prevent the chance of the experiment, each algorithm was done 30 times of the trajectory finding experiment.

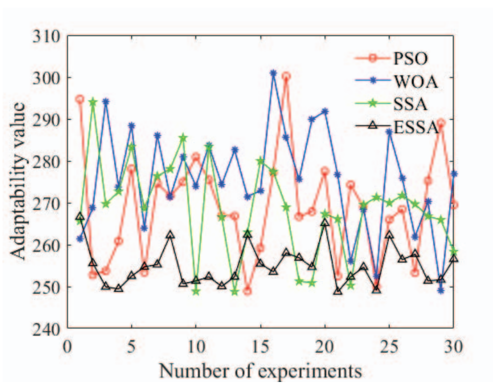



Figure 6: Optimal fitness value variation diagram

Table II: Optimize data statistics

| Algorithm | Optimal fitness | Average fitness | success |
|---|---|---|---|
| PSO | 248.91 | 269.00 | 18 |
| WOA | 249.13 | 275.54 | 15 |
| SSA | 248.78 | 268.67 | 21 |
| ESSA | 248.73 | 254.98 | 26 |

It can be visualized from Figure 6 and Table 2 that the average fitness value after ESSA seeking is the smallest, i.e., the UAV has the lowest flight cost. the seeking result of ESSA is less volatile and more stable than the remaining three algorithms, and its success rate of trajectory planning is higher, the trajectory is complete and can successfully avoid obstacles, which has stronger practical application than the remaining algorithms.

## IV. Conclusion

In this paper, the enhanced sparrow algorithm ESSA is applied to optimize the UAV trajectory planning problem. The Halton sequence and quasi-reflective learning strategy are introduced in turn, which improves the optimization accuracy and convergence speed compared with SSA, and is significantly better than other optimization algorithms. Through the experiments of UAV trajectory planning, it can be found that the trajectory planned by ESSA is safer and faster to converge, and the average flight cost is the lowest, which can better meet the UAV trajectory planning requirements.

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