International Journal of Computer Science and Information Technology
ISSN: 3005-9682 (Print), ISSN: 3005-7140 (Online) | Volume 2, Number 1, Year 2024
DOI: 4https://doi.org/10.62051/ijcsit.v2n1.18
Journal homepage: https://wepub.org/index.php/IJCSIT/index

UAV Track Planning Based on Improved Marine Predator Algorithm

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ABSTRACT

Aiming at the optimization problem in the field of automatic control of unmanned aerial vehicles (UAVs) for track planning, this paper proposes an optimization method of UAV track planning based on improved Marine predator algorithm, adopts uniform distribution space and pseudo-reverse learning strategy to improve population initialization, and uses T distribution as disturbance factor to update position. The objective function of the improved Marine predator algorithm considering the cost of track length, terrain and flight height is established, and the simulation test is carried out on MATLAB software. The simulation results show that an optimal path to avoid obstacles and threat areas can be obtained with particle swarm optimization and snake optimization, indicating that this method has stronger robustness and feasibility in UAV path planning.

KEYWORDS

UAV; Marine predator algorithm; OBL; Path planning

1. INTRODUCTION

UAV is a kind of aerial robot, which has the characteristics of fast flight speed and strong mobility, and has broad application prospects in unmanned distribution, unmanned inspection, surveying and mapping, military and other related fields [1]. In the actual execution of the task, the UAV needs to plan the path, that is, select the path according to some optimization criteria, such as the minimum energy cost, the shortest walking route and the shortest walking time, and find an optimal path from the starting position to the target position and avoid obstacles in the working space [2]。At present, there have been researches on UAV path planning, and the main algorithms include particle swarm optimization algorithm, gray Wolf algorithm, sparrow algorithm and snake optimization algorithm[3-5], the simulation has been verified to have better planning effect. Marine Predators Algorithm (MPA) was a new heuristic intelligent optimization algorithm proposed by S.Mirjalili in 2022[6], inspired by the predators strategies and predation behaviors of Marine creatures such as sharks, large yellow croakers, salmon and swordfish. Compared with other algorithms such as particle swarm optimization, Marine Predator algorithm has the advantages of simple structure, fewer parameters and easy implementation. In this paper, the Marine predator algorithm is applied to the UAV track planning problem, and the UAV track model is simulated and analyzed to verify the superiority of the Marine predator algorithm in solving this kind of process.

2. MATHEMATICAL MODEL OF TRACK PLANNING

2.1. Total Cost

Establish an objective function that comprehensively considers UAV track length cost, terrain threat cost, route smoothing cost, flight height cost and route smoothing cost f, and its formula is shown as follows:

$$f = af_L + bf_T + cf_H + df_G \tag{1}$$

Where: f_L is the cost of the track length of the UAV flight; f_T is the cost of terrain threat of UAV flight; f_H is the altitude cost of drone flight; f_G is For the cost of UAV route smoothing; a, b, c and d are four weight coefficients.

2.2. Track length cost

The shorter the track length of the UAV flight, the less flight time and fuel it needs, the Euclidean distance between the two nodes is taken as the length distance of each segment, and the route length cost formula is shown as follows:

$$f_L = \sum_{i=1}^{n-1} \| \vec{P}_{ij}\vec{P}_{i,j+1} \| \tag{2}$$

Where, m is the set of all threatening obstacles, the obstacle model is a cylinder, j is number of nodes, $\vec{P}$ is node position.

2.3. Terrain threat cost

The shorter the length of the UAV flight track, the less flight time and fuel it needs. The Euclidean distance between the two nodes is taken as the length distance of each segment, and its route length cost formula is as follows:

$$\begin{cases} f_L = \sum_{j=1}^{n-1}\sum_{m=1}^{M} T_m(\vec{P}_{ij}\vec{P}_{ij+1}) \\ T_m(P_{ij}P_{ij+1}) = \begin{cases} 0, & if\, d_m > S + D + R_m \\ (S + D + R_m) - d_m, & if\, D + R_m < d_m \leqslant S + D + R_m \\ \infty, & if\, d_m \leqslant D + R_m \end{cases} \end{cases} \tag{3}$$

Where, m is the set of all threatening obstacles; The obstacle model is a cylinder, and its projection center is C_m; R_m is the radius of the obstacle; D is the diameter of the UAV, the vertical distance between the two adjacent path nodes and the origin is d_m, S is the dangerous area of the obstacle, the value of which depends on the positioning accuracy of the UAV and the flight environment.

2.4. Flight altitude cost

The higher the flying altitude of the UAV, the greater the unknown threats and risks it will encounter. The flight altitude cost description is adopted, and its formula is as follows:

$$f_H = \begin{cases} \left| h_{ij} - \dfrac{(h_{\max} + h_{\min})}{2} \right|, & if \;\; h_{\min} \le h_{ij} \le h_{\max} \\ \infty, otherwise \end{cases} \tag{4}$$

Where: $h_{\min}$ and $h_{\max}$ are the minimum flight altitude and maximum flight altitude respectively.

2.5. Smoothing cost consideration

The flight Angle control parameters of UAV mainly include horizontal steering Angle and vertical pitch Angle. φ_{ij} is the horizontal steering Angle of the Angle between two continuous path segments projected on the horizontal plane Oxy, as shown in formula (5); θ_{ij} is the vertical pitch Angle of the Angle between two continuous paths projected on the vertical axis, as shown in formula (6).

$$\varphi_{ij} = \arctan\left(\frac{\left\| \vec{P}'_{ij}\vec{P}'_{i,j+1} \times \vec{P}'_{i,j+1}\vec{P}'_{i,j+2} \right\|}{\vec{P}'_{ij}\vec{P}'_{ij+1} \cdot \vec{P}'_{i,j+1}\vec{P}'_{ij+2}} \right) \tag{5}$$

$$\theta_{ij} = \arctan\left(\frac{z_{i,j+1} - z_{ij}}{\left\| \vec{P}'_{ij}\vec{P}'_{i,j+1} \right\|} \right) \tag{6}$$

Then the smoothing cost is calculated as follows:

$$f_G = \sum_{j=1}^{n-2} \varphi_{ij} + \sum_{j=1}^{n-1} \left| \theta_{ij} - \theta_{i,j-1} \right| \tag{7}$$

3. OCEAN PREDATOR ALGORITHM

3.1. Exploration phase

MPA is an optimization algorithm that simulates the foraging prey movement strategy of predators in the ocean, and the predator divides the whole into three stages according to the alternating motions of Levy and Brown.

When $Iter < \frac{1}{3} Max\_Iter$

$$\begin{aligned}&\overrightarrow{stepsize}=\overrightarrow{R_B}\otimes(\overrightarrow{Elite}-\overrightarrow{R_B}\otimes\overrightarrow{\Pr ey_i}),\quad i=1,2\cdots,n\\&\overrightarrow{\Pr ey_i}=\overrightarrow{\Pr ey_i}+P\cdot\vec{R}\otimes\overrightarrow{stepsize}\end{aligned}\tag{8}$$

Where， $\Pr ey_i$ is represented as the current individual position vector, $Iter$ is indicates the current iteration times, Max_Iter is the maximum number of iterations of the algorithm, $stepsize$ is the moving step of the prey, $\overrightarrow{R_B}$ is Represents Brownian motion, and the vector follows a normal distribution of random vectors, P is a constant, usually P =0.5.

3.2. Exploration to development stage

In the MPA algorithm, the transition stage is also called the unit velocity ratio stage, which occurs in the third to two-thirds of the iterations. In this stage, the speed between prey and predator is equal, the predator and prey are each looking for their own prey, the predator follows the Brownian motion, the prey follows the Levi motion. Both exploration and development are very important at this stage, so the whole population is divided into two parts, one for exploration and the other for development. The mathematical model of this stage is shown in the following formula:

When $\frac{1}{3}Max\_Iter < Iter < \frac{2}{3}Max\_Iter$:

The position update of the first part of the population is as follows:

$$\begin{aligned}&\overrightarrow{stepsize}=\overrightarrow{R_L}\otimes(\overrightarrow{Elite}-\overrightarrow{R_L}\otimes\overrightarrow{\Pr ey_i}),\quad i=1,2\cdots,n\\&\overrightarrow{\Pr ey_i}=\overrightarrow{\Pr ey}+P\cdot\vec{R}\otimes\overrightarrow{stepsize}\end{aligned}\tag{9}$$

Where, $\overrightarrow{R_L}$ is expressed as Levi motion, and the value of this vector follows Levi distribution. $\overrightarrow{R_L}$ is the dot product between the prey is represented by simulating the prey performing Levi's motion.

The mode of location renewal for the latter half of the population can be shown in the following formula:

$$\begin{aligned}&\overrightarrow{stepsize}=\overrightarrow{R_B}\otimes(\overrightarrow{Elite}\otimes\overrightarrow{R_B}-\overrightarrow{\Pr ey_i}),\quad i=1,2\cdots,n\\&\overrightarrow{\Pr ey_i}=\overrightarrow{Elite}+P\cdot CF\otimes\overrightarrow{stepsize}\\&CF=\left(1-\frac{Iter}{Max\_Iter}\right)^{(\frac{2\cdot Iter}{Max\_Iter})}\end{aligned}\tag{10}$$

Where, CF is expressed as Levi motion, and the value of this vector follows Levi distribution. $\overrightarrow{R_B}$ is the dot product between the prey is represented by simulating the prey performing Levi's motion.

3.3. Development stage

In MPA algorithms, the development stage is also known as the low speed ratio stage, which occurs in the two thirds to the last third of the iterations. In this phase, the speed of the prey is slower than the speed of the predator compared to the speed of the prey. Therefore, the best strategy for predators to adopt at this stage is Levi movement, and the main purpose of this stage is to carry out local exploitation. Its mathematical model is shown in the following formula:

When $Iter > \frac{2}{3} Max\_Iter$:

$$
\begin{aligned}
&\overrightarrow{stepsize} = \overrightarrow{R_L} \otimes (\overrightarrow{Elite} \otimes \overrightarrow{R_L} - \overrightarrow{\Pr ey_i}), \quad i = 1,2 \cdots, n \\
&\overrightarrow{\Pr ey_i} = \overrightarrow{E\text{lite}} + P \cdot CF \otimes \overrightarrow{stepsize}
\end{aligned}
\tag{11}
$$

In the formula, $\overrightarrow{R_L}$ and the dot product between the predator and the predator is expressed as simulating the predator's Levi motion.

4. IMPROVE THE MARINE PREDATOR ALGORITHM

4.1. Population initialization based on uniform distribution space and pseudo-reverse learning strategy

For heuristic intelligent algorithms, whether the population initialization is uniform is an important factor to determine the convergence speed and accuracy of the algorithm. In the MPA algorithm, the population initialization adopts a random method. When solving multi-peak functions with this random initialization method, if the generated initialization is relatively concentrated in a certain area or some individuals are scattered far away from the optimal position, the algorithm is likely to fall into the local optimal in the optimization process. Therefore, in the selection of initial points, the information in the solution function is extracted to the maximum extent and the diversity of the initial population is maintained.

Based on the above, this paper applies a uniform distribution method and pseudo-reverse learning strategy to the initialization of the algorithm, and distributes the initial points evenly in the search space region. The formula is as follows:

$$
\begin{aligned}
&X_i^j = (RNUM_i - 1) \times \frac{(ub_j - lb_j)}{N} + rand(0, \frac{(ub_j - lb_j)}{N}) \\
&RNUM = randpcrm(NUM)
\end{aligned}
\tag{12}
$$

Where, X_i^j is the initial position of the predator randomly obtained by using the uniform distribution space method; $i = 1, 2, \cdots, N$ is the initial population size; $j = 1, 2, \cdots, \dim$ is the spatial dimension of the individual; $rand(a,b)$ is expressed as the generated random number; It is represented by randomly shuffling the order of elements in the array, NUM is an array composed of the number of populations; ub and lb are respectively the upper and lower limits of the search space.

The pseudo-reverse Learning strategy is an improvement of the standard Opposition based Learning strategy [7] (OBL). Although reverse learning can effectively expand the search range of the algorithm and improve the performance of the algorithm by calculating the pair dissociation of the current position, the effect of reverse learning will be weakened when the domain is symmetric. In order to solve this phenomenon and improve the ability of reverse learning, a pseudo-reverse strategy is proposed. The formula is as follows:

$$\tilde{X}_i^j = ub + lb - X_i^j,\ \ j = 1, 2, \cdots, d$$

$$\bar{X}_i^j = \begin{cases} rand(M_j, \tilde{X}_i^j),\ \ X_i^j \le M_j \\ rand(\tilde{X}_i^j, M_j),\ \ X_i^j > M_j \end{cases} \tag{13}$$

Where, $\tilde{X}_i^j$ is the predator position obtained through reverse learning. $\bar{X}_i^j$ is the predator position obtained by pseudo-reverse learning, $M_j = 0.5(ub - lb)$, $rand(M_j, \tilde{X}_i^j)$ Is a random number of $(M_j, \tilde{X}_i^j)$.

4.2. T-distribution disturbance and variation

In view of the high dependence of the traditional MPA algorithm on the top predators in the iteration, the population is easy to concentrate on the top predators, and it is easy to fall into the local optimal situation. Therefore, this paper introduces a new position update strategy based on the position update of the original algorithm. The standard T-distribution probability density expression is as follows:

$$T = \frac{X}{\sqrt{Y/n}},\ \ X \sim N(0,1),\ \ Y \sim \chi^2(n) \tag{14}$$

T-distribution combines the advantages of Cauchy distribution and Gaussian distribution. In this paper, the distribution mutation operator of freedom parameters distributed with the number of iterations is used to perturb the position of the solution, so that the algorithm has better global development ability in the early iteration stage and better local exploration ability in the later iteration stage, and the convergence speed of the algorithm is improved. The specific position update method is as follows:

$$\widetilde{\Pr ey_i} = \Pr ey_i \otimes (1 + C\_iter) \tag{15}$$

where： $\Pr ey_i$ is the current location, $\widetilde{\Pr ey_i}$ is the position after disturbance.

5. SIMULATED ANALYSIS

In order to verify the superiority of the improved Marine predator algorithm to solve the problem, the improved Marine predator algorithm is compared with three existing algorithms. Among them, algorithm 1 is the traditional particle swarm optimization algorithm, algorithm 2 is the snake optimization algorithm, algorithm 3 is the original Marine predator algorithm, and algorithm 4 is the improved algorithm in this paper. Running in the MATLAB software environment, the population size of the four algorithms is 100, and the maximum number of iterations is 500. The learning factor in PSO is 2, the weight is 0.95, the factor in SO is 2, and the FADs in MPA and IMPA are 0.2. The map size is 800km*800km*200km, and the simulation results are shown in Figure 1.

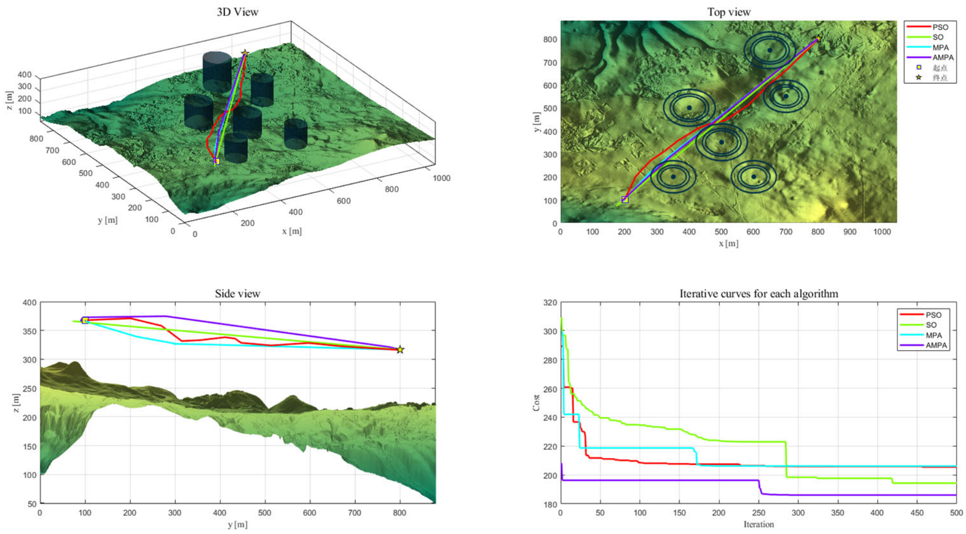

FIG. 1 Simulation results of UAV track planning

As can be seen from Figure 1, compared with other algorithms, the improved Marine predator algorithm has stronger global search performance and faster search speed. The optimal value searched by the algorithm is 183.5, which can effectively shorten the calculation time of flight path planning and avoid obstacles, and the obtained flight path can meet the flight safety requirements and meet the requirements of practical engineering applications.

6. SUMMARY

Compared with particle swarm optimization algorithm and snake optimization algorithm, the improved Marine predator algorithm has faster optimization speed and higher solving accuracy, which can shorten the calculation time of track planning, and obtain an optimal path to avoid obstacles and threat areas, indicating that the improved Marine predator algorithm has stronger robustness and feasibility in UAV path planning.

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