ULTRA-LOW-ALTITUDE PENETRATION PATH PLANNING FOR FIXED-WING AIRCRAFT BASED ON NMP ALGORITHM

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Abstract

Ultra-low altitude penetration of UAV is an important tactic. In order to enable UAV to plan flight path quickly during mission, an efficient path planning method based on NMPA algorithm is proposed in this paper. The NMP algorithm introduces adaptive parameters to control the predator's moving step, which can maintain the high exploration ability of the algorithm in the middle development stage and the whole optimization process. At the same time, nonlinear control parameters are introduced to balance the exploration and development stage of NMP algorithm. Finally, adaptive parameters are added to the eddy current forming model to make the NMP algorithm overcome the problem of premature convergence in the process of optimization. In order to verify the effectiveness of the ultra-low altitude penetration path planning algorithm of NMP fixed-wing UAV proposed in this paper, the path planning is carried out on the complex mountain map. It shows that the method proposed in this paper is more efficient in path planning, at the same time, the path is smooth, meets the kinematic constraints of fixed-wing aircraft, and meets the needs of ultra-low altitude penetration.

Keywords: Ultra-low-altitude Penetration, Path Planning, NMP Algorithm, Fixed-wing Aircraft.

1. Introduction

Aircraft penetration refers to the combat behavior that goes deep into the enemy's deep area and strategic hinterland, carries out strategic or tactical tasks, and eliminates its important political, economic and military targets[1-3]. In order for the aircraft to successfully project weapons, attack the target and approach the target in most cases, we must try to break through the enemy's air defense firepower. In the modern war with increasingly perfect air defense technology, low-altitude penetration can improve the operational effectiveness of aircraft and is an effective means to achieve precision strike. With the development of radar technology, low-altitude penetration technology has been unable to meet the demand, so it is necessary to further reduce the flight altitude and avoid air defense radar detection without reducing the flight speed. Therefore, the ultra-low altitude penetration technology is then developed, which is characterized by a low height, which is only 30-100m above the ground. It is easy to encounter obstacles when flying at ultra-low altitude. safe and efficient path planning is one of the key technologies of aircraft ultra-low altitude penetration. In order to improve the survival rate of aircraft, it is necessary to rely on terrain and threat information and comprehensively consider specific constraints. Plan an efficient flight path with the highest survival probability from the starting point to the target point.

Compared with the rotor aircraft, the fixed-wing aircraft has faster flight speed and longer range, and is more suitable for the implementation of long-distance ultra-low altitude penetration tactics. Therefore, the path planning of ultra-low altitude penetration of fixed-wing aircraft is studied in this paper. Before carrying on the ultra-low altitude penetration three-dimensional path planning, this paper first establishes the terrain constraint, threat model constraint, fixed-wing aircraft kinematics constraint. The mountain peak has the greatest influence in the terrain constraint, and the flight boundary and the maximum flight altitude need to be considered at the same time. The threat model mainly includes radar detection. The fixed-wing aircraft has many motion constraints, fast flight speed and large turning radius, so its smoothness needs to be considered in path planning.

To address the path planning problems, various methods have been investigated in literature, such as the potential field method[4], sampling-based method[5], A* algorithm[6], intelligent-algorithm-based planning[7-8], etc. These methods are usually only suitable for scenarios that are not sensitive to computational efficiency. As for the case of ultra-low-altitude penetration with complex three-dimensional terrain environment, the path planning algorithm is commonly required to generate feasible optimized flight paths in a limited period of time. The path cost model comprehensively weights terrain constraints, elevation costs, threat model constraints and fixed-wing aircraft kinematic constraints. therefore, the ultra-low altitude penetration path planning of fixed-wing aircraft is a complex multi-objective optimization problem. Marine predators algorithm is a meta-heuristic optimization algorithm proposed by Afshin Faramarzi et al in 2020[9]. It is inspired by the theory of marine survival of the fittest, the Levy and Brownian movements of marine predators, and the strategy of optimal encounter rate between predators and prey. However, it is easy to fall into the local optimal solution in the search. The NMP algorithm introduces adaptive parameters to control the predator's moving step, and the adaptive step is a linear parameter, which can maintain the high exploration ability of the algorithm in the middle development stage and the whole optimization process. At the same time, nonlinear control parameters are introduced to balance the exploration and development stage of NMP algorithm, and prey development based on Levy walking strategy and predator exploration based on Brownian walking strategy are updated. Finally, adaptive parameters are added to the eddy current forming model to make the NMP algorithm overcome the problem of premature convergence in the process of optimization[10]. In order to solve this complex multi-objective optimization problem, a path planning method for ultra-low altitude penetration of fixed-wing UAV based on nonlinear marine predators algorithm is proposed in this paper.

The structure of this paper is as follows, the second section introduces the problem description and modeling, the third section introduces the design of the path planning algorithm, the fourth section carries on the comparative simulation, and the fifth section is the conclusion of this paper.

2. Problem Formulation

The ultra-low altitude penetration process of the UAV is shown in the following figure. The core of the success of UAV ultra-low altitude penetration is to plan a collision-free path between the starting point and the end point of the mission to avoid the threat. Major threats include complex terrain and radar.

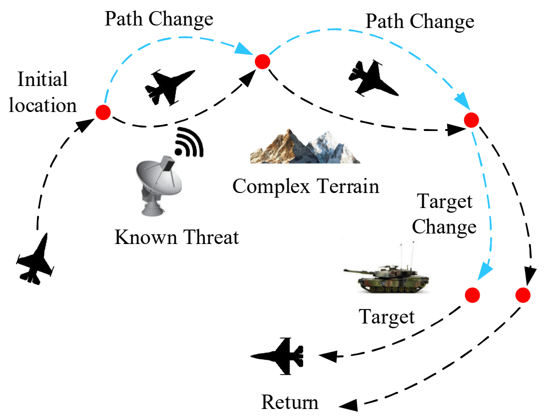


Figure 1 – Indication of the aircraft ultra-low-altitude penetration process.

2.1 Terrain Threat Modeling

When the flight altitude is low, the mountain peak becomes the main threat to the aircraft safety flight in the complex terrain area. a typical three-dimensional model for mountains can be described as:

$$z(x,y) = h_p * e^{\left(\frac{(x-x_0)^2}{m_1} - \frac{(y-y_0)^2}{m_2}\right)} \quad (1)$$

where (x,y) is the coordinate of the mountain envelope in the horizontal projection plane, (x_0, y_0) is the coordinates of the center of the mountain peak, h_p is the peak altitude, and m_1 and m_2 reflects the steepness. Again, we point out that several mountains overlap each other, in order to speed up the path search efficiency, we equivalent them to a hemispherical envelope model to reflect the large-scale characteristics of the terrain, and the results are as follows:

$$(x-x_0)+(y-y_0)+(h-h_c) = R_m^2 \,(h \ge 0) \quad (2)$$

2.2 Radar Threat Modeling

The other major threat at low altitudes is the radar. The geometric illustration for a typical bistatic radar is described as fowllows:

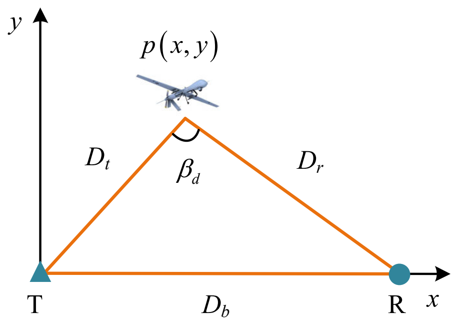


Figure 2 – Indication of the detection range of Bistatic radar.

In Figure 2, $p(x,y)$ is the aircraft position projected in the horizontal plane, T denotes the location of thetransmitter, while R denotes the location of the radar receiver. D_{b} is distance between the transmitter and the receiver, $\mathrm{D_t}$ is distance from the aircraft to transmitter, and $\mathrm{D_r}$ is distance from the aircraft to receiver, β_d denotes the dual-base angle. The maximum detection range of bistatic radar can be expressed as follows:

$$D_{\max} = \left[\frac{p_\tau \sigma \lambda_c^2 G}{(4\pi)^3 K T_0 L (S/N)}\right]^{1/4} \quad (3)$$

In this paper, we regard mountains and detection range of radar as obstacles to be avoided in path planning, the ultimate goal is to ensure that the search path is outside the detection range of radar, while maintaining max security margin with the mountains

3. Path Planning Algorithm Design

In this section, we first introduce the MPA (Marine Predator Algorithm) algorithm and then its non-linear version which the NMPA (Nonlinear Marine Predator Algorithm) algorithm.

3.1 Marine Predator Algorithm

MPA (Marine Predators Algorithm) is a new meta-heuristic optimization algorithm proposed by Afshin Faramarzi et al in 2020. Its inspiration comes from the theory of marine survival of the fittest. Marine predators choose the best foraging strategy between Lévy flight and Brownian motions.

3.2 MPA Mathematical model

The marine predators algorithm generates the initial solution through a set of random values uniformly distributed in the search space. The initial solution of the algorithm is shown in the following formula:

$$x_p = x_{\min} + rand * (x_{\max} - x_{\min}) \quad (4)$$

where $x_{\min}$ is the upper bound for solving the problem, $x_{\min}$ is the lower bound of solving the

problem.
$rand$ is a random number with a value of [0, 1].
The marine predator algorithm is inspired by the hunting strategies of predators in nature. According to the natural law of the jungle, the ability of top predators to capture food is often stronger than that of ordinary predators in nature. The algorithm considers the top predator to have the greatest search ability. Therefore, the matrix composed of top predators in the MPA algorithm is called an elite matrix. The elite matrix is expressed as follows:

$$Elite = \begin{bmatrix} X_{1,1}^I & X_{1,2}^I & \cdots & X_{1,d}^I \\ X_{2,1}^I & X_{2,2}^I & \cdots & X_{2,d}^I \\ \vdots & \vdots & \vdots & \vdots \\ X_{n,1}^I & X_{n,2}^I & \cdots & X_{n,d}^I \end{bmatrix}_{n \times d} \quad (5)$$

where $x_i = \left[x_{i,1} \ x_{i,2} \ \ldots \ x_{i,d} \right]$ is the top predator vector, copy it n copies to get the elite matrix. n is the number of populations, n is the dimension of solving the problem. In MPA algorithm, another matrix is called prey matrix. Keep the size of the two matrices the same in the MPA algorithm. The position of the predator is changed through the prey matrix. The prey matrix is represented as follows:

$$Prey = \begin{bmatrix} x_{1,1} & x_{1,2} & \cdots & x_{1,d} \\ x_{2,1} & x_{2,2} & \cdots & x_{2,d} \\ \vdots & \vdots & \vdots & \vdots \\ x_{n,1} & x_{n,2} & \cdots & x_{n,d} \end{bmatrix}_{n \times d} \quad (6)$$

Where n is the number of populations, n is the dimension of solving the problem.

3.3 MPA Optimization stage

Considering the different stages and modes of hunting among marine predators, as well as the influence of predator and prey speed on the simulation of this process, MPA algorithm consists of three main stages. These phases are defined as follows:

a. The first method is in the stage of higher velocity of prey and predator, in this update mode, the speed of prey is faster than that of predator.
b. In the second update mode, the velocity of prey and predator is similar, assuming that the two are unit speed ratio.
c. The third way is to assume that the velocity of the two is relatively low, and the speed of the predator is faster than that of the prey.

Since the nature of predator and prey movements in nature follows unique rules, and these rules are the main source of inspiration for the main stages of the development of the MPA algorithm, the number of iterations specified in MPA is assigned to these stage.

3.4 Exploration stage(high-velocity)

In this algorithm, the exploration phase is also called the high-speed ratio stage, in which the prey moves faster than the predator $(v \geq 10)$. At this time, the best predation strategy for predators is not to move at all. This occurs in the first 1/3 stages of the total number of iterations of the algorithm, when the mathematical model of this stage can be expressed by the following formula:

$$\begin{aligned} & While\ Iter < \frac{1}{3} Max\_Iter \\ & \overrightarrow{Stepsize_i} = \overrightarrow{R_B} \otimes \left(\overrightarrow{Elite_i} - \overrightarrow{R_B} \otimes \overrightarrow{Prey_i} \right) \quad i = 1, \ldots, n \\ & \overrightarrow{Prey_i} = \overrightarrow{Prey_i} + P \cdot \vec{R} \otimes \overrightarrow{Stepsize_i} \end{aligned} \quad (7)$$

Where $\overrightarrow{R_B}$ is Brownian motion, the vector is a random vector with normal distribution. The dot product of P and the prey matrix simulates the Brownian motion of the prey. In the above formula, P represents a constant and usually taking the value 0.5, $\vec{R}$ represents a random vector obeying the uniform distribution of [0, 1]. $Iter$ is the current number of iterations, Max_Iter is the maximum number of iterations.

3.5 Transition from exploration stage to development stage(unity-velocity)

In the algorithm, the transition from the exploration stage to the development stage is also called the unit speed ratio stage. In this stage, the prey speed and the predator speed are equal $(v=1)$.Predators and prey are looking for their own prey. This occurs between 1/3 and 2/3 of the number of iterations. Exploration and development are important at this stage, when the whole population is divided into two parts, one representing predators for exploration and the other for prey development. The mathematical model of this stage can be expressed by the following formula:

$$\begin{gathered} While\ \frac{1}{3}Max\_Iter<Iter<\frac{2}{3}Max\_Iter \\ \overrightarrow{Stepsize_i}=\overrightarrow{R_L}\otimes\left(\overrightarrow{Elite_i}-\overrightarrow{R_L}\otimes\overrightarrow{Prey_i}\right)\ \ i=1,\ldots,n/2 \\ \overrightarrow{Prey_i}=\overrightarrow{Prey_i}+P\cdot\overrightarrow{R}\otimes\overrightarrow{Stepsize_i} \end{gathered} \tag{8}$$

Where $\overrightarrow{R_L}$ represents the Lévy motion, and the value of the vector obeys the Lévy distribution. $\overrightarrow{R_L}$ multiplying the prey represents the Levi movement of the prey. It is essential highlighting that above formula is applied only for the first half of the MPA population. The position renewal mode of the latter half of the population can be expressed by the following formula:

$$\begin{gathered} \overrightarrow{Stepsize_i}=\overrightarrow{R_B}\otimes\left(\overrightarrow{R_B}\otimes\overrightarrow{Elite_i}-\overrightarrow{Prey_i}\right)\ \ i=1,\ldots,n/2 \\ \overrightarrow{Prey_i}=\overrightarrow{Elite_i}+P\cdot CF\otimes\overrightarrow{Stepsize_i},\ CF=\left(1-\frac{Iter}{Max\_Iter}\right)^{\left(2\frac{Iter}{Max\_Iter}\right)} \end{gathered} \tag{9}$$

In the above formula, CF is an adaptive parameter, which is used to control the moving step size of the predator. $\overrightarrow{R_B}$ multiplying the predator represents the Brownian motion of the predator. The location of prey is updated by the movement of predators.

3.6 Development stage (Low-velocity)

In the algorithm, the development stage is also known as the low speed ratio stage, in which the speed of the predator is faster than that of the prey $(v=0.1)$. At this time, the best predation strategy for predators is Lévy motion. This occurs at the last 1/3 of the number of iterations, which is primarily for local development. The mathematical model can be expressed as follows:

$$\begin{gathered} While\ Iter>\frac{2}{3}Max\_Iter \\ \overrightarrow{Stepsize_i}=\overrightarrow{R_L}\otimes\left(\overrightarrow{R_L}\otimes\overrightarrow{Elite_i}-\overrightarrow{Prey_i}\right)\ \ i=1,\ldots,n \\ \overrightarrow{Prey_i}=\overrightarrow{Elite_i}+P\cdot CF\otimes\overrightarrow{Stepsize_i} \end{gathered} \tag{10}$$

3.7 Eddy formation and FADs' effect

The change of environmental factors in marine ecology will also affect the predation strategy of organisms. The eddy current formation and the role of FADs are taken into account in the MPA algorithm. The mathematical model of these factors can be shown by the following formula:

$$\overrightarrow{Prey_i}=\begin{cases}\overrightarrow{Prey_i}+CF\left[\vec{x}_{\min}+\vec{R}\otimes\left(\vec{x}_{\max}-\vec{x}_{\min}\right)\right]\otimes\vec{U} & if\ \ r\le FADS \\ \overrightarrow{Prey_i}+\left[FADS(1-r)+r\right]\left(\overrightarrow{Prey_{r1}}-\overrightarrow{Prey_{r2}}\right) & if\ \ r>FADS\end{cases} \tag{11}$$

Where $FADS$ represents the probability of being affected by changes in the marine environment, and the value of $FADS$ is usually 0.2. $\vec{U}$ represents a binary vector, the vector is generated by randomly generating a set of numbers with values in [0, 1]. If the generated number is less than 0.2, it will be converted to 0, otherwise it will be converted to 1. r is a random number obeying the uniform distribution [0, 1]. r_1 and r_2 represent random indexes of the prey matrix.

3.8 Marine memory

Marine predators have excellent memories of where they have successfully hunted. This ability is simulated in the MPA algorithm through storage. Therefore, in the MPA algorithm, it is necessary to evaluate the merits of individual positions. If the current position is better, the previous position needs to be replaced with the current position.

3.9 Nonlinear Marine Predator Algorithm

The MPA algorithm simulates the motion of predators and prey according to the rules and key points of various studies and the actual behavior of nature. Although it has reasonable exploration and development speed, MPA still stagnates near the local optimal solution and can not achieve the global optimal solution. The main purpose of NMPA is to enhance the exploration and development of MPA by adjusting the size of the predator phase towards the prey and using the exploration and development phase of the introduced control parameter balancing algorithm. The second phase of MPA algorithm includes two stages: exploration and development. The changes in this step will improve the efficiency and effectiveness of the MPA algorithm. The update of MPA algorithm is as follows:

First of all, the NMPA algorithm controls the moving step of the predator through new adaptive parameters. This parameter is defined as follows:

$$CF_{New} = abs\left(2*\left(1-\left(\frac{Iter}{Max_{Iter}}\right)\right)-2\right) \tag{12}$$

Where CF is an adaptive parameter, and its value increases linearly in the interval [0, 2], which is mainly used to determine the step length of the predator to reach its prey. Another goal of this parameter is to maintain high exploratory ability during the development phase of the second phase of the algorithm and throughout the optimization process. Therefore, the chance that the algorithm will not fall into the local optimal solution increases.

Secondly, the exploration and development phase of NMPA is balanced by the nonlinear parameter w, which is defined as follows:

$$\omega = 2*\exp\left(-\left(6*\frac{Iter}{Max_{Iter}}\right)^{2}\right) \tag{13}$$

The value of ω decreases nonlinearly in the interval [2, 0]. The prey is developed based on the Lévy flight strategy and the updated formula explored by the predator based on the Brown motion strategy is improved as follows:

$$\begin{aligned}
&While\ \frac{1}{3}Max_Iter<Iter<\frac{2}{3}Max_Iter \\
&\overrightarrow{Stepsize_i} = \overrightarrow{R_L} \otimes \left(\overrightarrow{Elite_i} - \overrightarrow{R_L} \otimes \overrightarrow{Prey_i}\right) \quad i=1,\dots,n/2 \\
&\overrightarrow{Prey_i} = \omega * \overrightarrow{Prey_i} + P \cdot \vec{R} \otimes \overrightarrow{Stepsize_i} \\
&\overrightarrow{Stepsize_i} = \overrightarrow{R_B} \otimes \left(\overrightarrow{R_B} \otimes \overrightarrow{Elite_i} - \overrightarrow{Prey_i}\right) \quad i=n/2,\dots,n \\
&\overrightarrow{Prey_i} = \omega * \overrightarrow{Elite_i} + P \cdot CF_New \otimes \overrightarrow{Stepsize_i}
\end{aligned} \tag{14}$$

In addition, the third stage of the algorithm and the model of eddy current formation also use new adaptive parameters, which are updated as follows:

$$\begin{aligned}
&While\ Iter>\frac{2}{3}Max_Iter \\
&\overrightarrow{Stepsize_i} = \overrightarrow{R_L} \otimes \left(\overrightarrow{R_L} \otimes \overrightarrow{Elite_i} - \overrightarrow{Prey_i}\right) \quad i=1,\dots,n \\
&\overrightarrow{Prey_i} = \overrightarrow{Elite_i} + P \cdot CF_New \otimes \overrightarrow{Stepsize_i}
\end{aligned} \tag{15}$$

Finally, the formula of FADs effect is updated as follows:

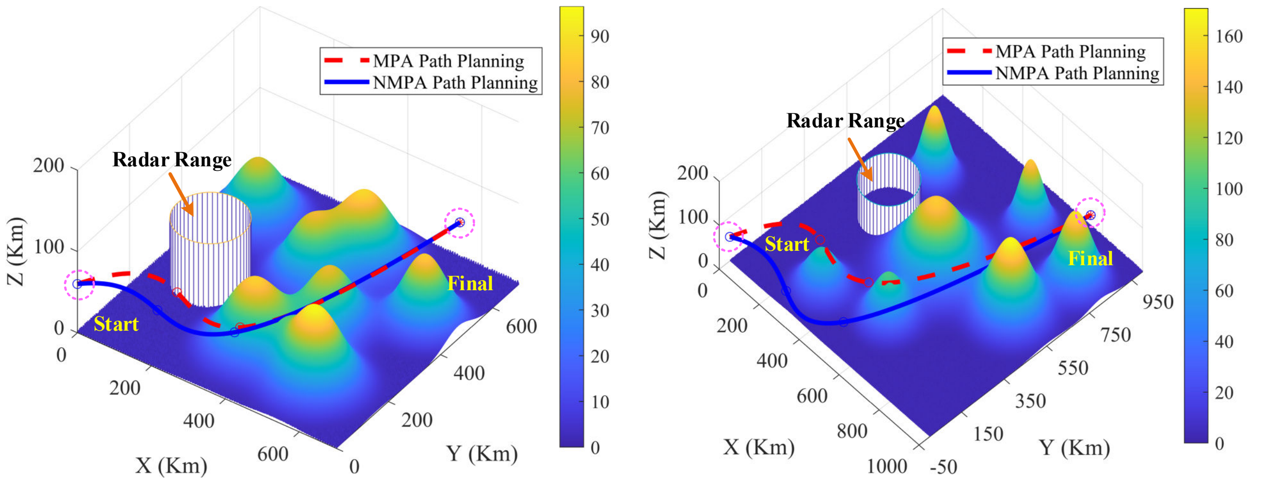
$$\overrightarrow{Prey_i} = \begin{cases} \overrightarrow{Prey_i} + CF\_New\left[\vec{x}_{\min} + \vec{R} \otimes \left(\vec{x}_{\max} - \vec{x}_{\min}\right)\right] \otimes \vec{U} & if \ r \le FADS \\ \overrightarrow{Prey_i} + \left[FADS(1-r) + r\right]\left(\overrightarrow{Prey_{r1}} - \overrightarrow{Prey_{r2}}\right) & if \ r > FADS \end{cases} \quad (16)$$

4. Simulation and discussion

In this section, we conduct simulation tests to validate the performance of the designed path planning algorithm. The simulation platform processor is AMD Ryzen 7 4800H 2.90 GHz. The simulation status is shown in the following table 1. Now, the goal is to plan a collision-free path through these obstacles which mountain and radar. We conduct comparative simulations of the marine predator algorithm and the nonlinear marine predator algorithm in the complex terrain environment.

Table 1 Simulation scene details

Scenario 1 (Km)		Scenario 2 (Km)	
Start Position	Final Position	Stat Position	Final Position
[0, 0, 60]	[567,663,60]	[0, 0, 55]	[780, 963, 55]
Mountain Position	Mountain Height	Mountain Position	Mountain Height
[180, 350]	85	[150, 300]	90
[153, 535]	95	[500, 500]	150
[569, 379]	85	[802, 875]	160
[550, 100]	75	[227, 548]	100
[450,310]	70	[750, 225]	160
[330,450]	75	[550, 820]	170
[466,610]	85	[850,600]	150
Radar Position	Detect Radius	Radar Position	Detect Radius
[142, 309, 0]	90	[234, 527, 0]	110



(a) Planning results in scenario 1 (b) Planning results in scenario 2
Figure 3 Comparison result of different planning algorithm in scenario 1 and scenario 2.

In scenario 1, the path length of MPA and NMPA are 1398.2m and 902.5m, respectively. In scenario 2, the path length of MPA and NMPA are 1980.5m and 1223.7m, respectively. In order to analyze in more detail the performance improvement of NMPA algorithm compared with MPA algorithm, 50 groups of comparative experiments are carried out in this paper. The test results are shown in Table 2. In terms of path planning length, NMPA algorithm is 14% higher than MPA algorithm. In terms of path planning time consumption, NMPA algorithm is 17% higher than MPA algorithm.

Table 2 Comparison of calculation results of different algorithms

	Average path length(m)	Minimum path length (m)	Planning Time (s)
MPA	1545.1	1374.6	4.5
NMPA	1323.4	1192.5	3.7

5. Conclusion

The NMP algorithm introduces adaptive parameters to control the predator's moving step, and the adaptive step is a linear parameter, which can maintain the high exploration ability of the algorithm in the middle development stage and the whole optimization process. At the same time, nonlinear control parameters are introduced to balance the exploration and development stage of NMP algorithm, and prey development based on Levy walking strategy and predator exploration based on Brownian walking strategy are updated. Finally, adaptive parameters are added to the eddy current forming model to make the NMP algorithm overcome the problem of premature convergence in the process of optimization. The above methods make the whole algorithm avoid falling into local optimization.When the fixed-wing aircraft is flying in the mountain area with dense obstacles, the feasible path can be quickly found through the planning method proposed in this paper to avoid the danger of obstacle collision. The NMPA algorithm path planning speed is improved by 17% and path planning length is reduced by 14% compared to the MPA algorithm.

6. Copyright Statement

References

[1] Yang Z, Yuan Z, Wang X, et al. Autonomous control of UAV trajectory based on RHC-Radau method in complex penetration combat environment[J]. Aerospace Science and Technology, Vol. 146, No. 108915, pp 1-11, 2024.

[2] Jie L, Chaofeng L, Cheng D, et al. Necessity analysis and scheme of constructing ultra-low-altitude defense system in megacities. IEEE Aerospace and Electronic Systems Magazine, Vol. 36, No. 1, pp 14-21, 2021.

[3] Zhu D, Wang S, Shen J, et al. A multi-strategy particle swarm algorithm with exponential noise and fitness-distance balance method for low-altitude penetration in secure space. Journal of Computational Science, Vol. 74, No. 102149, pp 17-25, 2023.

[4] Qu Y, Zhang Y, et al. A global path planning algorithm for fixed-wing UAVs. Journal of Intelligent & Robotic Systems, Vol. 91, No. 1, pp 691-707, 2018.

[5] Levin J M, Nahon M and Paranjape A. Real-time motion planning with a fixed-wing UAV using an agile maneuver space. Autonomous Robots, Vol. 43, No. 8, pp 2111-2130, 2019.

[6] Guruji A K, Agarwal H and Parsediya D K. Time-efficient A* algorithm for robot path planning. *Procedia Technology*, Vol. 23, No. 1, pp 144-149, 2016.

[7] He L, Aouf N, Song B. Explainable Deep Reinforcement Learning for UAV autonomous path planning. *Aerospace science and technology*, Vol. 118, No. 107052, pp 12-28, 2021.

[8] Yan C, Xiang X, et al. Towards real-time path planning through deep reinforcement learning for a UAV in dynamic environments. *Journal of Intelligent & Robotic Systems*, Vol. 98, No. 1, pp 297-309, 2020.

[9] Faramarzi A, Heidarinejad M, Mirjalili S, et al. Marine Predators Algorithm: A nature-inspired metaheuristic. *Expert systems with applications*, Vol. 152, No. 113377, pp 1-15, 2020.

[10]Sadiq A S, Dehkordi A A, Mirjalili S, et al. Nonlinear marine predator algorithm: A cost-effective optimizer for fair power allocation in NOMA-VLC-B5G networks. *Expert Systems with Applications*, Vol 203, No 117395, pp 1-17, 2022.