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Research Article

Research on Combat Mission Configuration of Unmanned Aerial Vehicle Maritime Reconnaissance Based on Particle Swarm Optimization Algorithm

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In recent years, in the classic battles and armed conflicts around the world, battlefield environment reconnaissance and the collection and processing of operational information play an increasingly critical role in the victory and defeat of the battlefield. Unmanned equipment, especially UAV equipment, is used by more and more countries in the field of combat reconnaissance. Meanwhile, the types of UAV are gradually diversified with the change of operational requirements. UAVs adapted to different combat environments shine brightly on the battlefield. In terms of naval battle field, due to the limitations and deficiencies of reconnaissance methods such as surface radar, UAVs play a more prominent role in combat reconnaissance. There are more scenarios for UAVs to be used in combat reconnaissance in naval battle field and higher requirements for UAVs' combat effectiveness. Therefore, this paper takes UAVs' naval battle reconnaissance missions as the research object. By using PSO as the research method, this paper studies the combat reconnaissance task configuration of UAVs, hoping to contribute to the improvement of UAVs' combat reconnaissance capability and combat effectiveness.

1. Introduction

In recent years, the international situation in some parts of the world has become increasingly complex, with armed conflicts occurring in some sensitive areas. The use of unmanned equipment in modern warfare has become increasingly widespread, especially in battlefield environment reconnaissance, enemy action monitoring, force firepower guidance, and precise target strikes. The concealment of unmanned equipment both safety and functionality make it demonstrate impressive results and outstanding role in the battlefield [1]. In recent years, in the classic battles and armed conflicts that have occurred globally, battlefield environment reconnaissance and the collection and processing of combat information have played an increasingly crucial role in the victory or defeat of the battlefield. In terms of combat reconnaissance, unmanned equipment, especially drone equipment, is being increasingly used by more and more countries [2]. At the same time, with the changing needs of combat, the types of drones are gradually becoming more diverse, and drones adapted to different combat environments are shining brightly on the battlefield [3]. In terms of naval battlefield, due to the limitations and shortcomings of reconnaissance methods such as surface radar, the role of drones in combat reconnaissance is more prominent [4]. UAV maritime reconnaissance refers to the use of wireless sensing and electromagnetic spectrum management methods by UAV equipment, integrating a series of information technology means such as intelligence, big data, and satellites, to complete tasks such as reconnaissance and detection of enemy targets at sea [5]. There are many application scenarios for UAVs in combat reconnaissance on the sea battlefield, and the requirements for the effectiveness of UAV combat are higher [6]. Therefore, this article takes UAV sea battlefield reconnaissance combat tasks as the research object, uses particle swarm optimization algorithm to efficiently optimize the operation of nonlinear constraint problems, and completes different types or characteristics of UAV equipment for different sea combat reconnaissance tasks to achieve optimal task configuration efficiency, and I hope to contribute to the improvement of drone combat reconnaissance capabilities and drone battlefield combat effectiveness [7].

The main contributions of this paper are summarized as follows: [8]

(1) It solves the different characteristics of different combat reconnaissance missions under complex naval battle environment, and the established particle swarm optimization model is compatible with the research and calculation of the multimission in different complex environments and the configuration of UAV combat reconnaissance missions with more complex constraints [9].

(2) Considering the differences of different UAV models and different UAV equipment of the same model, through the consideration of the differences of reconnaissance combat forces, the ability and effectiveness of different UAV combat forces to complete different combat reconnaissance tasks are further analyzed, and the mission configuration model is established on this basis [10]. It can effectively improve the task allocation efficiency of UAV combat forces in carrying out complex combat tasks in sea battle field and ensure the maximum combat effectiveness of each UAV combat force [11].

(3) On the basis of the above research content, the particle swarm optimization algorithm model is established to analyze and study the simulation data of the deployment of combat missions of UAVs in naval battle fields [12]. Based on the simulation results, the effectiveness, scientificity, and convergence of the algorithm model proposed in this paper are analyzed [13].

The rest of this paper is organized as follows: Section 3 introduces the unmanned aerial vehicle maritime reconnaissance combat task assignment model [14]. In Section 4, the particle swarm optimal task assignment scheme is described in detail. In Section 5, the validity of the designed algorithm model is verified by the simulation analysis of the simulation data. Finally, the analysis conclusions and research results of this paper are discussed in Section 6 [15].

2. Literature Review

UAV operation is one of the important topics in modern air operations. UAV has been widely studied by scholars in various fields because of its significant safety, agility, and battlefield role. Ren Yaning, Liu Dapeng, and others from the Unmanned Systems Center of the Ninth Research Institute of China Aerospace Science and Technology Corporation Limited took anti-UAV warfare as a research topic. In their research paper, they summarized the current situation of anti-UAV warfare in some countries and proposed the future development situation of anti-UAV warfare according to the role and performance of anti-UAV equipment in combat. Xiao Peng, Xie Feng, and others from the School of Aeronautics of Northwestern Polytechnical University and Chengdu Aircraft Design Institute of Aviation Industry Corporation of China proposed an optimization method of task assignment and path planning for multi-UAV cooperative reconnaissance missions with the single-parent genetic algorithm as the main research method, which contributed to the improvement of multi-UAV cooperative combat effectiveness. Hu Jiawei, Jia Zequn, Sun Yantao, and others from the School of Computer and Information Technology of Beijing Jiaotong University and the Beijing Key Laboratory of Traffic Data Analysis and Mining took the problem of multi-UAV collaborative task planning under multiconstraint conditions as the research object. They established a general task planning model for UAV collaborative task and conducted in-depth research and analysis based on this model. In this paper, the cooperative task planning of multiple UAVs is studied and prospected, which provides an important reference for the application and development of UAVs. Zhang Yaozhong, Zhao Xuefang, and others from the School of Electronic Information of Northwestern Polytechnical University took the improved leapfrog algorithm as the main research method to study the task assignment problem of multiple UAVs. In this paper, they established an improved random leapfrog algorithm based on Levy for flight. The research of this algorithm provides a more effective reference and help for improving the efficiency of UAV task assignment problem.

PSO has been accepted by scholars in various fields and applied to all aspects of academic research due to its strong robustness, wide scope of application, and accuracy. Li Xiaojun, Zhao Xiaolei, and others from the School of Computer Science and Technology and the School of Architecture and Urban Planning of Shandong Jianzhu University designed an improved particle swarm optimization algorithm to study the traffic assignment problem. According to the characteristics of the problem studied, they adopted a simplified particle swarm optimization algorithm which controlled the particle evolution direction only by the position term. The problem of slow convergence speed and low precision of traditional particle swarm optimization algorithm is solved. Fang Ce, Mu Qifeng, and Feng Xiaolei from the Airport School of Civil Aviation Flight University of China believe that the multiobjective particle swarm optimization algorithm has a good effect on solving the location problem of flight service station. In this paper, they set up a multiobjective particle swarm operation model based on actual work and introduced a ridge distribution curve to describe the gradual coverage function in the model. The validity of the model is verified by simulation analysis. In his master's thesis, Zhai Zeyu from Dalian Ocean University discussed the basic characteristics and principle of particle PSO. By improving PSO, he conducted in-depth research on the target assignment problem of ship formation, and his research results contributed to the improvement of ship formation sailing efficiency. It provides a good solution to the problem of path planning of unmanned ship. Fang

Wenxiong, Hou Yuting, and CAI Xuan from the School of Automotive and Transportation, Chengdu University of Technology, took the train route search problem at station as the research object and established a particle swarm optimization algorithm model that conforms to the characteristics of the research object. In this paper, they verified the effectiveness and scientificity of the particle swarm optimization model for train route search at station through simulation analysis of the algorithm model. It provides important reference for solving related problems.

The above research results can help solve the problem of UAVs carrying out combat reconnaissance to a certain extent in the study of various task allocation problems [16]. However, most of these studies have not considered the complexity of the naval battlefield environment, and different combat reconnaissance tasks have different characteristics and properties. At the same time, the ability and effectiveness of different UAVs to carry out different tasks may be quite different, which is more important for the complex and changeable naval battle field [17]. Therefore, on the basis of the research on the task configuration of UAVs carrying out combat reconnaissance tasks in naval battlefields by using the particle swarm optimization algorithm, this paper fully considers the differences between different UAVs' equipment, the differences between different naval battlefields' combat reconnaissance tasks, and the differences between different UAVs carrying out different naval battlefields' combat reconnaissance tasks of different nature [18]. Through the research on such issues, it can effectively improve the efficiency and effectiveness of UAVs in carrying out combat reconnaissance tasks in the complex naval battle environment [19].

3. Unmanned Aerial Vehicle Maritime Reconnaissance Combat Task Assignment Model

In the marine battlefield environment, the enemy threat may come from any aspect, so the marine battlefield environmental reconnaissance plays a more important role in the victory and defeat of the battle. Meanwhile, affected by the limitations of ocean clutter and surface radar itself, conventional enemy reconnaissance means may not be able to play a more obvious role, so for the marine combat forces, it is very important for UAV to carry out long reconnaissance operations [20].

In this paper, it is assumed that there are m reconnaissance UAVs in the naval battlefield environment, F_i is the combat unit number of the i reconnaissance UAVs, and the overall set of UAVs is expressed as $F = \{F_1, F_2, F_3, \ldots, F_m\}$. At the same time, there are n reconnaissance tasks to be completed, R_j is the task unit number of the j reconnaissance task, and the overall set of reconnaissance tasks is expressed as $R = \{R_1, R_2, R_3, \ldots, R_n\}$; At the same time, different UAVs F_i may be affected by factors such as UAV type and mechanical state, and the content, difficulty, and battlefield environment of R_j of different battlefield reconnaissance tasks will also be different. Therefore, different UAV's ability to complete different battlefield reconnaissance tasks in naval battlefields will also be different. Accordingly, the combat effectiveness obtained by different UAVs when they complete different battlefield reconnaissance tasks is also different [21]. Therefore, assuming that the reconnaissance and combat effectiveness obtained by UAVs F_i when they complete battlefield reconnaissance task R_j is E_{ij}, combining UAVs $F = \{F_1, F_2, F_3, \ldots, F_m\}$ and combat reconnaissance task $R = \{R_1, R_2, R_3, \ldots, R_n\}$, the combat effectiveness matrix of UAVs in naval battlefields can be obtained as follows:

$$E = \begin{bmatrix} E_{11} & E_{12} & E_{13} & \cdots & E_{1n} \\ E_{21} & & & & E_{2n} \\ E_{31} & & \cdots & & E_{3n} \\ \cdots & & & & \cdots \\ E_{m1} & E_{m2} & E_{m3} & \cdots & E_{mn} \end{bmatrix}. \quad (1)$$

At the same time, the importance of different reconnaissance operations in the naval battle field is different, so the weight set of reconnaissance operations importance can be established as follows: $W = \{W_1, W_2, W_3, \ldots, W_n\}$.

From the above content, it can be seen that the effectiveness formula of the mission configuration scheme of unmanned aerial vehicle combat reconnaissance in the naval battle field can be established as follows.

Suppose that the decision variable $X_{ij} = 1$ represents that the i naval battlefield reconnaissance UAV is assigned to complete the j reconnaissance combat task, and the decision variable $X_{ij} = 0$ represents that the i naval battlefield reconnaissance UAV is assigned to complete the j reconnaissance combat task.

Therefore, the mission configuration scheme effectiveness formula of UAV combat reconnaissance in naval battle field is as follows:

$$S = \sum_{j=1}^{j=n} \sum_{i=1}^{i=m} \left(E_{ij} \cdot X_{ij}\right) W_j. \quad (2)$$

To sum up, in order to obtain the optimal efficiency scheme for the combat reconnaissance mission configuration of UAVs in naval battlefields, the mission configuration scheme model established above is a multiconstrained and nonlinear integer programming problem, and the solution of the problem model needs to use high-performance optimization algorithms such as particle swarm optimization algorithm to solve the optimal efficiency scheme for the combat reconnaissance mission configuration of UAVs in naval battlefields [22].

4. Particle Swarm Optimal Task Assignment Algorithm Design

Particle swarm algorithm, also known as the bird swarm algorithm, is an algorithm model formed by simulating the foraging activities of birds [23]. The algorithm simulates the solved problem as the activity space of particle swarm and then finds the optimal solution to the solved problem through the activity of particles in the space. The specific content of particle swarm optimization is as follows: assume that a certain population contains a total of m particles (the number of particles determines the operation scale that the algorithm can perform each operation in solving), and the elements contained in each population particle have two parts: position x_i and speed v_i. In the process of algorithm operation, suppose that the particle swarm moves to a certain time t, At this time, the position information and velocity information of a certain particle i in the group at this time t are, respectively, $x_i^t = (x_{i1}^t, x_{i2}^t, x_{i3}^t, \ldots, x_{in}^t)$ and $v_i^t = (v_{i1}^t, v_{i2}^t, v_{i3}^t, \ldots, v_{in}^t)$. With the passage of time t, the position information and velocity information of particle i will constantly change. In the process of change, the algorithm calculates the historical optimal location $id_i^t = (id_{i1}^t, id_{i2}^t, id_{i3}^t, \ldots, id_{in}^t)$ of individual particles and the historical optimal location $g_i^t = (g_1^t, g_2^t, g_3^t, \ldots, g_n^t)$ of particle swarm population according to the changes of the position information and velocity information of particle i. The position information and velocity information of individual particles in the population can be calculated based on the above historical optimal location of individual particles and the historical optimal location of particle swarm population. The formula for calculating its position and velocity is as follows [24]:

$$v_{id}^{t+1} = \omega \cdot v_{id}^t + C_1 \cdot r_1 \cdot \left(id - x_{id}^t\right) + C_2 \cdot r_2 \cdot \left(gd - x_{id}^t\right), \tag{3}$$

$$x_{id}^{t+1} = x_{id}^t + v_{id}^t. \tag{4}$$

The flow chart of the particle swarm algorithm is shown in Figure 1:

The specific steps of particle swarm optimization are as follows [25]:

(1) According to the content and characteristics of the unmanned aerial vehicle maritime reconnaissance combat task assignment model, we establish the initial particle population of the particle swarm optimization algorithm and set the algorithm parameters, the calculation function (fitness function) of the model target, and the termination conditions of the particle swarm optimization algorithm

(2) Calculate the fitness value of each particle in the particle swarm according to the calculation function (fitness function) of the model target and determine whether the termination condition is met

(3) Update the velocity and position information of particle swarm according to formulae (3) and (4) above

(4) Similar to Step (2) calculate the fitness value of the particle individual of the updated particle swarm and compare this fitness value with the fitness value corresponding to the historical best position and update the historical best position and the best fitness value of the particle according to the comparison result

(5) Similar to Step (4), the best historical position and best fitness value of each particle are compared with the best historical position and best fitness value of particle swarm, and the best historical position and best fitness value of particle swarm are updated according to the comparison result

(6) Determine whether the operation result meets the termination condition at this time. If yes, terminate the algorithm iteration and output the best historical position and the best fitness value, and otherwise, return to Step (3) for iterative calculation

5. Algorithm Simulation

In order to verify the effectiveness of the established task allocation model of UAV maritime reconnaissance operation and the particle swarm optimization task allocation scheme algorithm for solving the problem of UAV maritime reconnaissance operation task allocation, this paper adopts the method of simulation data to simulate and analyze the related model algorithm. In this paper, four different combat situations are set up for simulation. The effectiveness of the model and algorithm established in this paper is verified by simulation in different combat situations [26].

(1) Assume that there are m reconnaissance combat UAVs in the naval battlefield, and there are m combat reconnaissance tasks to be completed at the same time, each reconnaissance UAV can only complete one combat reconnaissance task, and each combat reconnaissance task is completed by reconnaissance combat UAVs. The value of m in this simulation analysis is 10.

Firstly, the UAV reconnaissance operational effectiveness matrix of the first type of the naval battlefield combat environment is established as follows:

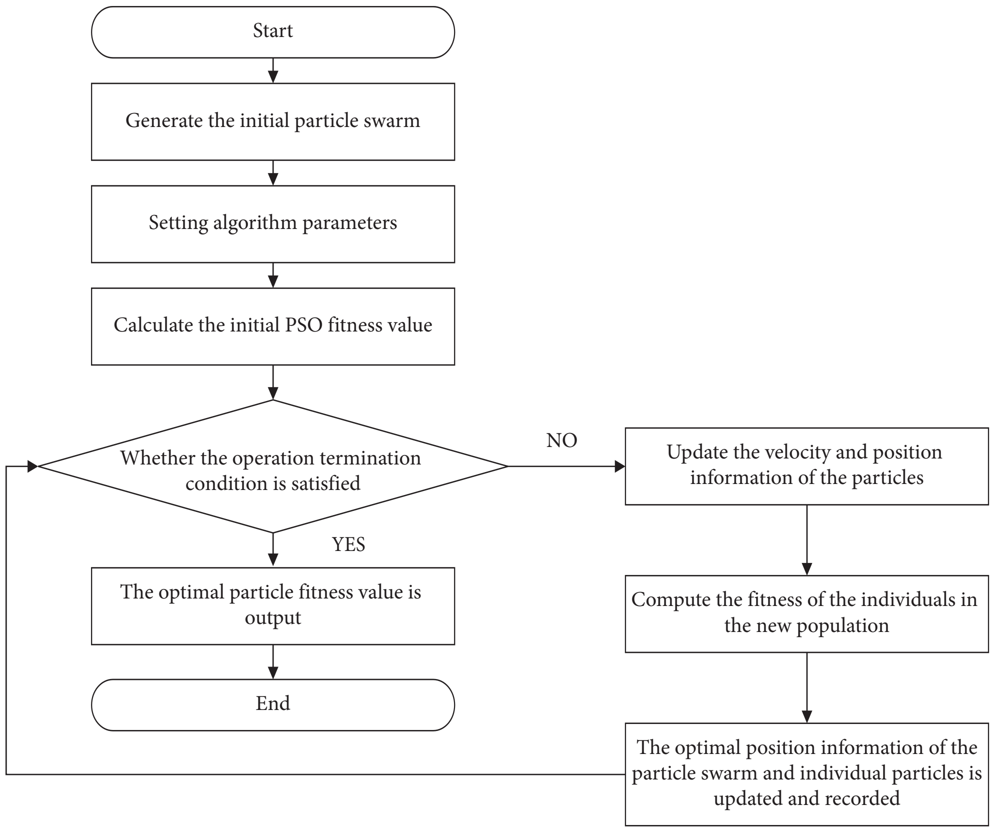

Figure 1: Flow chart of particle swarm optimization.

$$E = \begin{bmatrix} 0.93 & 0.71 & 0.12 & 0.63 & 0.70 & 0.11 & 0.94 & 0.89 & 0.73 & 0.70 \\ 0.78 & 0.96 & 0.69 & 1.00 & 0.89 & 0.81 & 0.33 & 0.71 & 0.48 & 0.75 \\ 0.29 & 0.55 & 0.59 & 0.82 & 0.17 & 0.88 & 0.75 & 0.86 & 0.15 & 0.76 \\ 0.18 & 0.02 & 0.75 & 0.76 & 0.04 & 0.36 & 0.54 & 0.75 & 0.60 & 0.68 \\ 0.87 & 0.02 & 0.81 & 0.57 & 0.98 & 0.92 & 0.24 & 0.88 & 0.18 & 0.96 \\ 0.14 & 0.66 & 0.32 & 0.65 & 0.97 & 0.82 & 0.29 & 0.28 & 0.66 & 0.38 \\ 0.92 & 0.94 & 0.08 & 0.58 & 0.85 & 0.79 & 0.83 & 0.93 & 0.02 & 0.44 \\ 0.16 & 0.76 & 0.16 & 0.84 & 0.90 & 0.82 & 0.54 & 0.70 & 0.11 & 0.91 \\ 0.24 & 0.76 & 0.24 & 0.76 & 0.89 & 1.00 & 0.68 & 0.73 & 0.97 & 0.38 \\ 0.45 & 0.28 & 0.48 & 0.01 & 0.41 & 0.28 & 0.60 & 0.10 & 0.64 & 0.11 \end{bmatrix}. \tag{5}$$

The importance weight set of reconnaissance operational tasks is established as follows:

$$W = \{0.47 \;\; 0.36 \;\; 0.41 \;\; 0.70 \;\; 0.16 \;\; 0.75 \;\; 0.70 \;\; 0.28 \;\; 0.25 \;\; 0.89\}, \tag{6}$$

Through the simulation operation of the particle swarm algorithm, the task allocation matrix of UAV maritime reconnaissance operation is obtained as Figure 2.

At this time, the overall operational effectiveness of the UAV maritime reconnaissance combat mission is $S = 4.3875$. The convergence level of the adaptive value of the established particle swarm optimization algorithm is shown in Figure 3 below.

(2) Assume that there are m reconnaissance combat UAVs in the naval battlefield, and there are m combat reconnaissance tasks to be completed. Different combat reconnaissance tasks can be completed by the same reconnaissance combat UAV, and each combat reconnaissance task is completed by reconnaissance combat UAV. The value of m in this simulation analysis is 10.

In this simulation operation, the effectiveness matrix of UAV reconnaissance operation and the importance weight set of reconnaissance operation task in the sea battlefield combat environment are combined with operation 1. The same content in.

Through the simulation operation of the particle swarm algorithm, the task allocation matrix of UAV maritime reconnaissance operation is obtained as Figure 4.

At this time, the overall operational effectiveness of the UAV maritime reconnaissance combat mission is $S = 4.1031$. The convergence level of the adaptive value of the established particle swarm optimization algorithm is shown in Figure 5.

(3) Assume that there are m reconnaissance combat UAVs in the sea battlefield, and n combat reconnaissance tasks need to be completed. Each reconnaissance combat UAV can complete multiple combat reconnaissance tasks, and each combat reconnaissance task is completed by reconnaissance combat UAVs. In this simulation analysis, the value of m is 8 and the value of n is 10.

Firstly, the UAV reconnaissance operational effectiveness matrix of the first type of the naval battlefield combat environment is established as follows:

$$E = \begin{bmatrix} 0.89 & 0.68 & 0.89 & 0.25 & 0.76 & 0.19 & 0.14 & 0.21 & 0.43 & 0.81 \\ 0.13 & 0.24 & 0.24 & 0.12 & 0.82 & 0.80 & 0.39 & 0.14 & 0.01 & 0.52 \\ 0.56 & 0.24 & 0.29 & 0.78 & 0.97 & 0.44 & 0.28 & 1.00 & 0.70 & 0.63 \\ 0.02 & 0.78 & 0.60 & 0.44 & 0.39 & 0.86 & 0.99 & 0.76 & 0.37 & 0.99 \\ 0.82 & 0.60 & 0.12 & 0.35 & 0.49 & 0.70 & 0.11 & 0.01 & 0.51 & 017 \\ 0.90 & 0.62 & 0.92 & 0.37 & 0.74 & 0.99 & 0.28 & 0.92 & 0.03 & 0.26 \\ 0.77 & 0.80 & 0.76 & 0.94 & 0.77 & 0.54 & 0.90 & 0.98 & 0.39 & 0.77 \\ 0.04 & 0.64 & 0.98 & 0.30 & 0.69 & 0.09 & 0.72 & 0.01 & 0.29 & 0.02 \end{bmatrix}, \tag{7}$$

The importance weight set of reconnaissance operational tasks is established as follows:

$$W = \{0.14 \;\; 0.67 \;\; 0.42 \;\; 0.97 \;\; 0.33 \;\; 0.72 \;\; 0.69 \;\; 0.42 \;\; 0.95 \;\; 0.56\}, \tag{8}$$

Through the simulation operation of the particle swarm algorithm, the task allocation matrix of UAV maritime reconnaissance operation is obtained as Figure 6.

At this time, the overall operational effectiveness of the UAV maritime reconnaissance combat mission is $S = 4.5255$. The convergence level of the adaptive value of the established particle swarm optimization algorithm is shown in Figure 7.

(4) Assume that there are m reconnaissance combat UAVs in the sea battlefield, and n combat reconnaissance tasks need to be completed. Each reconnaissance combat UAV can complete multiple combat reconnaissance tasks, and each combat

	Tasks 1	Tasks 2	Tasks 3	Tasks 4	Tasks 5	Tasks 6	Tasks 7	Tasks 8	Tasks 9	Tasks 10
Drone 1	0	0	0	1	0	0	0	0	0	0
Drone 2	0	0	0	0	0	0	0	0	1	0
Drone 3	0	0	1	0	0	0	0	0	0	0
Drone 4	0	0	0	0	0	1	0	0	0	0
Drone 5	0	0	0	0	0	0	0	0	0	1
Drone 6	0	0	0	0	0	0	1	0	0	0
Drone 7	0	0	0	0	1	0	0	0	0	0
Drone 8	0	1	0	0	0	0	0	0	0	0
Drone 9	0	0	0	0	0	0	0	1	0	0
Drone 10	1	0	0	0	0	0	0	0	0	0

FIGURE 2: The first type of combat task allocation matrix.

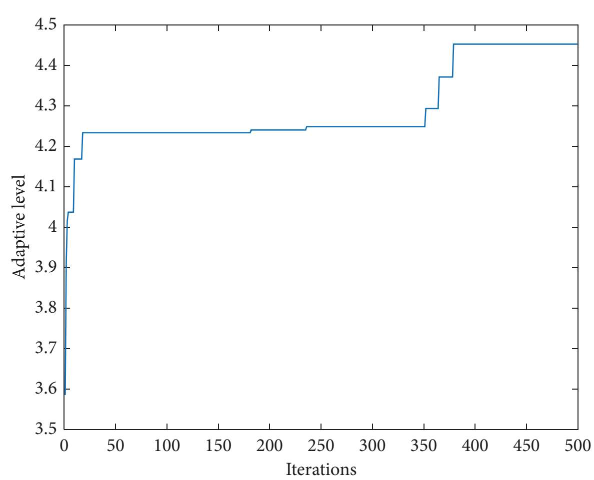

FIGURE 3: Variation of the adaptive value of PSO for the first type of combat task.

	Tasks 1	Tasks 2	Tasks 3	Tasks 4	Tasks 5	Tasks 6	Tasks 7	Tasks 8	Tasks 9	Tasks 10
Drone 1	0	0	0	1	1	0	1	0	0	0
Drone 2	0	0	0	0	0	0	0	0	1	0
Drone 3	0	0	0	0	0	1	0	0	0	0
Drone 4	0	0	0	0	0	0	0	0	0	0
Drone 5	0	0	0	0	0	0	0	0	0	1
Drone 6	0	0	0	0	0	0	0	0	0	0
Drone 7	0	0	0	0	0	0	0	0	0	0
Drone 8	0	1	0	0	0	0	0	0	0	0
Drone 9	0	0	0	0	0	0	0	1	0	0
Drone 10	1	0	1	0	0	0	0	0	0	0

Figure 4: The second type of combat task allocation matrix.

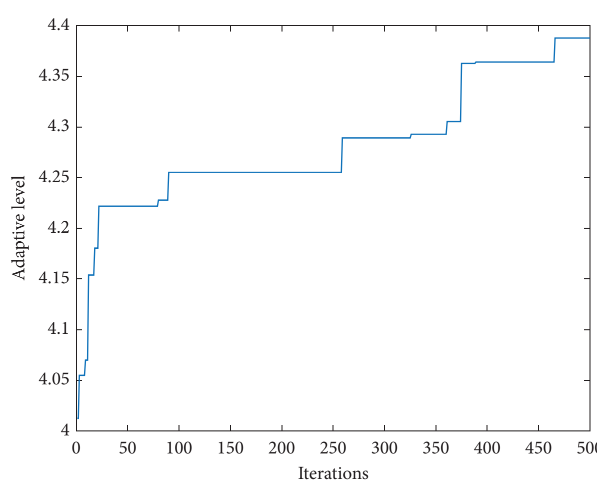

Figure 5: Variation of the adaptive value of PSO for the second type of combat task.

	Tasks 1	Tasks 2	Tasks 3	Tasks 4	Tasks 5	Tasks 6	Tasks 7	Tasks 8	Tasks 9	Tasks 10
Drone1	0	0	0	0	0	0	1	0	1	0
Drone2	1	0	0	0	0	0	0	0	0	0
Drone3	0	0	0	1	1	0	0	0	0	0
Drone4	0	0	0	0	0	0	0	0	0	0
Drone5	0	0	0	0	0	0	0	0	0	0
Drone6	0	1	1	0	0	0	0	0	0	1
Drone7	0	0	0	0	0	1	0	0	0	0
Drone8	0	0	0	0	0	0	0	1	0	0

Figure 6: The third type of combat task allocation matrix.

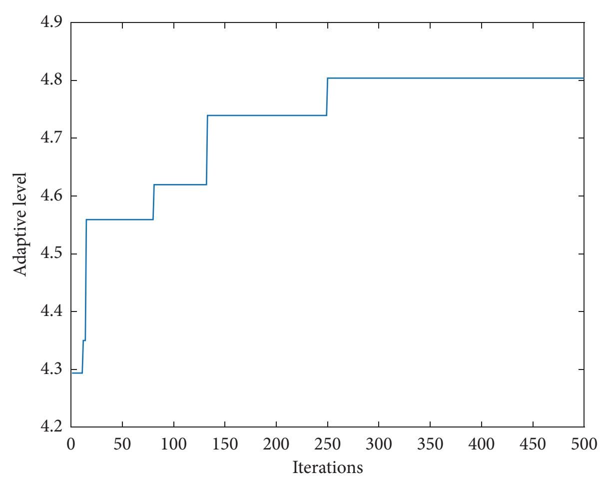

Figure 7: Variation of the adaptive value of PSO for the third type of combat task.

	Tasks 1	Tasks 2	Tasks 3	Tasks 4	Tasks 5	Tasks 6	Tasks 7	Tasks 8
Drone1	1	0	0	1	0	0	0	0
Drone2	0	0	0	0	0	0	0	0
Drone3	0	0	0	0	0	0	0	0
Drone4	0	0	0	0	0	0	0	0
Drone5	0	0	0	0	1	1	0	0
Drone6	0	0	0	0	0	0	0	0
Drone7	0	0	0	0	0	0	0	0
Drone8	0	0	0	0	0	0	1	0
Drone9	0	1	0	0	0	0	0	1
Drone10	0	0	1	0	0	0	0	0

FIGURE 8: The fourth type of combat task allocation matrix.

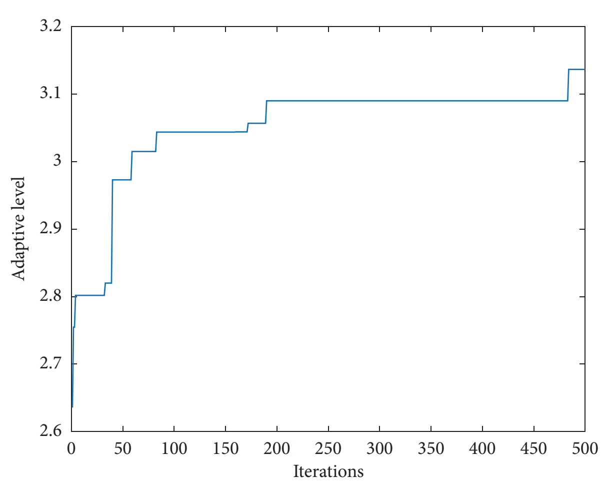

FIGURE 9: Variation of the adaptive value of PSO for the fourth type of combat task.

reconnaissance task is completed by reconnaissance combat UAVs. In this simulation analysis, the value of m is 10 and the value of n is 8.

Firstly, the UAV reconnaissance operational effectiveness matrix of the first type of naval battlefield combat environment is established as follows:

$$E = \begin{bmatrix} 0.99 & 0.48 & 0.59 & 0.97 & 0.53 & 0.47 & 0.43 & 0.09 \\ 0.40 & 0.11 & 0.83 & 0.52 & 0.48 & 0.17 & 0.14 & 0.49 \\ 0.14 & 0.29 & 0.25 & 0.01 & 0.18 & 0.04 & 0.60 & 0.41 \\ 0.32 & 0.74 & 0.43 & 0.04 & 0.23 & 0.89 & 0.35 & 0.77 \\ 0.28 & 0.59 & 0.24 & 0.74 & 0.96 & 0.91 & 0.64 & 0.28 \\ 0.49 & 0.73 & 0.03 & 0.83 & 0.93 & 0.12 & 0.24 & 0.84 \\ 0.56 & 0.41 & 0.19 & 0.03 & 0.40 & 0.52 & 0.77 & 0.85 \\ 0.72 & 0.46 & 0.78 & 0.40 & 0.66 & 0.85 & 0.72 & 0.10 \\ 0.32 & 0.84 & 0.11 & 0.82 & 0.10 & 0.90 & 0.69 & 0.97 \\ 0.04 & 0.52 & 0.94 & 0.26 & 0.88 & 0.37 & 0.07 & 0.82 \end{bmatrix}. \quad (9)$$

The importance weight set of reconnaissance operational tasks is established as follows:

$$W = \{0.66 \ \ 0.35 \ \ 0.53 \ \ 0.42 \ \ 0.15 \ \ 0.34 \ \ 0.64 \ \ 0.36\}, \quad (10)$$

Through the simulation operation of the particle swarm algorithm, the task allocation matrix of UAV maritime reconnaissance operation is obtained as Figure 8.

At this time, the overall operational effectiveness of the UAV maritime reconnaissance combat mission is $S = 3.1164$. The convergence level of the adaptive value of the established particle swarm optimization algorithm is shown in Figure 9.

Through the above simulation analysis of the above four different UAV reconnaissance operations in the sea battlefield, it is verified that the UAV maritime reconnaissance operational task allocation model and the particle swarm optimal task allocation scheme algorithm established in this paper are effective to solve the UAV maritime reconnaissance operational task allocation problem. At the same time, by observing the change of the adaptive value of the particle swarm algorithm during the operation period, the particle swarm optimization algorithm is used to solve the UAV maritime reconnaissance operational task allocation problem. The convergence and effectiveness of the particle swarm optimization algorithm in solving the UAV maritime reconnaissance operational task configuration problem are reflected. The algorithm model established in this paper can provide an efficient and effective solution for the UAV maritime reconnaissance operational task configuration problem.

6. Conclusion

In modern naval battlefields, the use of unmanned equipment has greatly improved the level of combat effectiveness [27]. This article takes the configuration of unmanned aerial vehicle reconnaissance combat tasks in naval battlefields as the research object and establishes an unmanned aerial vehicle sea reconnaissance combat task allocation model and a particle swarm optimization task allocation scheme algorithm [28]. Through simulation of four different types of combat environments in naval battlefields, the effectiveness and scientificity of the established model and algorithm for the research object were verified [29]. At the same time, by observing and analyzing the adaptive value changes of the particle swarm algorithm during the operation period, the convergence and effectiveness of the problem research model and particle swarm algorithm established in this paper in solving the problem of UAV sea reconnaissance combat task configuration were demonstrated [30]. It is hoped that this can provide assistance and contribution to the improvement of UAV combat effectiveness in the sea battlefield.

Data Availability

Data are available on request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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