Multi-UAV Task Assignment Based on the Improved Discrete Pigeon-Inspired Optimization Algorithm

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Abstract. Aiming at the multiple Unmanned Aerial Vehicle (multi-UAV) task assignment problems, a multi-UAV task assignment algorithm based on the improved discrete pigeon-inspired optimization (PIO) algorithm is proposed considering various fitness functions and constraints. And a correction algorithm is designed for the constraint overflow problem in the algorithm. First, a multi-UAV task fitness function problem model is established with various benefits, costs, and constraints. In addition, referring to the idea of the learning factor in the particle swarm optimization (PSO) algorithm, the PIO algorithm is improved to strengthen the learning ability of the pigeons for global and local optimal information. Then, the improved PIO algorithm is discretized to fit the discrete task assignment model. Finally, aiming at the constraint overflow problem, a constraint check correction algorithm is designed to correct the constraint overflow sequence. Simulation experiments show that the improved discrete PIO algorithm can effectively solve the multi-UAV task assignment problem.

Keywords: Multi-UAV task assignment · Discrete pigeon-inspired optimization algorithm · Constraint overflow correction

1 Introduction

The UAV systems have been an active area of research for several decades. The main application scenarios of the UAV systems include target reconnaissance, strike and damage assessment in the military field and environmental monitoring, regional logistics, and pesticide spraying in the civil field [1]. But there are some problems such as unbalanced resource allocation and unsatisfactory task execution effect when the cluster performs the task. To achieve the optimal execution effect under such circumstances, the collaborative control of the UAV cluster is crucial, whose key problem is the Multi-UAV Task

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Allocation Problem (MTAP) [2]. MTAP refers to assigning multiple UAVs to multiple targets to perform multiple tasks within the specified decision time. Through the internal coordination of the cluster, the best task execution effect is obtained [3]. Due to the priority problem that needs to consider various constraints and costs during allocation, this type of problem can be essentially classified as an NP-Hard problem [4].

Current research results on Multi-UAV task assignment can be summarized in a variety of classical task models [5]. Among them, are the Multiple Traveling Salesman Problem (MTSP) model [6], Vehicle Routing Problem (VRP) model [7], Network Flow Optimization model [8], Multiple Processors Resources Allocation model [9], etc. According to the task architecture, task allocation problems can be divided into centralized problems and distributed problems [10]. The optimization algorithm, heuristic algorithm, and distributed mixed-integer linear programming are used to solve task assignment problems [11], among which the heuristic algorithm is the most focused research direction. Heuristic algorithms mainly include genetic algorithm (GA) [12, 13], particle swarm optimization (PSO) algorithm [14–16], evolutionary algorithm (EA) [17], simulated annealing (SA) algorithm, etc. The pigeon-inspired optimization (PIO) is a new heuristic algorithm proposed by Professor Duan in 2014 [18]. It mainly imitates the behavior of homing pigeons using geographic information for guidance for fast optimization. Due to its high computational efficiency and fast convergence, it has been widely applied in various fields, such as low-altitude UAV target detection problem [19], spacecraft optimal formation reconstruction problem [20], etc. At the same time, some scholars have proposed many improved PIO algorithms to solve the problems arising in the application process. For example, the PIO algorithm combined with Cauchy variation, variable weight mutation PIO algorithm [21], quantum updating PIO algorithm [21], etc.

In this paper, the PIO algorithm is improved by the learning factors in the PSO, which improve the optimization efficiency of the algorithm and strengthen the global search ability of PIO in the first stage and the convergence ability of landmark information in the second stage. At the same time, the PIO algorithm is discretized to fit the discrete task assignment model. Aiming at the constraint overflow problem, a constraint check correction algorithm is designed to correct the constraint overflow sequence.

2 Multi-UAV Task Assignment Model

2.1 Description of Task Assignment Problem

There are N_u UAVs in a two-dimensional space divided into reconnaissance UAVs and attack UAVs, and N_t task target points in this space, whose number of tasks is N_m. These tasks are divided into two types: reconnaissance and strike tasks. Existing task requirements: The number of tasks performed by each UAV must not exceed its task constraint. The execution time of a single strike task is 10 s, and the reconnaissance task is 50 s. The strike mission must be performed after all the reconnaissance tasks have been carried out. The final assignment plan should have the highest profit and the lowest cost.

2.2 Multi-UAV Task Fitness Function Modeling

To balance various task constraints, benefits, and costs in the process of multi-UAV task assignment, a multi-UAV task assignment model is established. First, the mathematical models of the UAV and the task target are established based on their physical performance parameters. Ideally, the UAV is seen as a particle and travels at a constant speed V_u. Finally, the multi-UAV task fitness function model is established which consists of task profits, task costs, and task constraints. The modeling process is as follows:

The multi-task profits F_{profit} are divided into reconnaissance profits F_{r_profit} and strike profits F_{s_profit}. Both of them are determined by the UAV's performance characteristics and the reconnaissance or strike value of the target point corresponding to the UAV.

The multi-task costs F_{cost} are divided into distance costs $F_{distance}$ and time costs F_{time}. Both of them are determined by the location of the UAVs and the task target points. In addition, the time costs F_{cost} need to consider the task execution time.

The task constraints are divided into strike ammunition I_{ammo} constraints and tasks executed constraints I_{task}. I_{ammo} relates to the task ammunition. When the amount of ammunition carried by the task's corresponding UAV meets its ammunition task demand, record 1, otherwise record 0. I_{task} relates to the task number. When the number of its tasks meets its demand, record 1, otherwise record 0.

The expression of the overall function is as follows:

$$F_{total} = I_{ammo} \cdot I_{task} \cdot (t_{profit} \cdot F_{profit} + t_{cost} \cdot F_{cost}) \tag{1}$$

where t_{profit}, t_{cost} are the corresponding weighting factors. Since the optimization process is the process of finding the minimum value, the profit weight factor t_{profit} is negative.

3 Discrete Pigeon-Inspired Optimization Algorithm Combined with Learning Factors

3.1 Pigeon-Inspired Optimization Algorithm Combined with Learning Factors

The standard PIO algorithm mainly imitates the learning behavior of pigeons to geographical information when they return to the nest. Professor Duan referred to the behavior and proposed the Pigeon-inspired Optimization algorithm. PIO algorithm takes the position information $X(k)$ and velocity information $V(k)$ as the iterative target, and iterates the pigeons' information in two stages using the map and compass operator and landmark operator, so that it has a fast convergence speed and is applied to a variety of scenarios.

Learning factors in the particle swarm optimization (PSO) algorithm regulates the learning process of global information and local information which is used to enhance the global search ability and convergence ability of the PIO algorithm.

The first stage equation of the PIO algorithm combined with learning factors is as follows:

$$\begin{aligned} V(k+1) &= e^{-Rk} \cdot V(k) + C_1 \cdot rand_1 \cdot (X_{gbest}(k) - X(k)) \\ X(k+1) &= X(k) + V(k+1) \\ C_1(k+1) &= C_1(k) - e_1 \cdot \frac{k}{N_{k1max}} \end{aligned} \tag{2}$$

where k is the current iteration number, e^{-Rk} is the map and compass operator, X_{gbest} is the current global optimal solution, and $rand_1$ is a random value on the interval [0,1], controlling the learning of the algorithm to the current global optimal solution. C_1 is the global learning factor, where e_1 is the linear change factor, and N_{k1max} is the maximum number of iterations in the first stage. The C_1 has a large value in the early iterations of the stage so that the learning ability to the global information is strong. With the increase in the number of iterations, the value of the C_1 gradually decreases and the decreasing speed gradually accelerates. These indicate that the global search ability decreases gradually in the late iteration of the first stage.

Through (2) can get the current velocity information of the pigeons and update their location information, so that the pigeons can develop to the optimal pigeon.

The second stage equation of PIO combined with the learning factors is as follows:

$$\begin{gathered}
N_p(k+1) = \frac{N_p(k)}{2} \\
X_c(k) = \frac{\sum X_i(k) \cdot F_{total}(X_i(k))}{N_p(k) \sum F_{total}(X_i(k))} \\
X_i(k+1) = X_i(k) + C_2 \cdot rand_2(C_{X_c} \cdot (X_c(k) - X_i(k)) + C_{X_P} \cdot (X_{ipbest}(k) - X_i(k)) \\
C_2(k+1) = C_2(k) + e_2 \cdot \frac{k - N_{k1max}}{N_{k2max}}
\end{gathered} \tag{3}$$

The first equation of Eq. (3) represents the pigeons' elimination behavior, which means that half of the pigeons with high fitness values are eliminated in each iteration of the second stage. In the second equation, $X_c(k)$ is the central landmark of the pigeons, and then the location information of the pigeons is updated through the third equation. In the third equation, C_{XC} and C_{XP} are the landmark optimization weight factors, that are given at the beginning of algorithm iteration to regulate the learning of landmark information and local optimal information. C_2 is the local optimization learning factor, whose principle is contrary to C_1. The value of C_2 increases with the increase of the number of iterations, and the growth rate is gradually accelerated, which indicates that the local learning ability of the algorithm is gradually enhanced in the latter iteration, the optimization efficiency is high, and the convergence speed is fast.

3.2 Algorithm Discretization

Discrete Coding of Individual Pigeons

Because the task assignment problem model is a discrete model and the PIO is a continuous solution algorithm, the improved PIO algorithm should be discretized to solve this problem. The first step is the discrete coding of individual pigeons. Two sequences, UAV departure sequence ***vehicle***, and task target sequence ***target*** are employed to encode individual pigeons. In an individual coding sequence, a set of tasks is represented by an array composed of a UAV serial number and its corresponding task target point serial number. Its task execution order is represented by the position of the array in the individual coding sequence, and the coding example is shown in Table 1.

Table 1. Discrete coding example of pigeons

vehicle	1	2	3	1	3
target	8	9	6	7	3

PIO Algorithm Discretization

The discrete PIO algorithm is also divided into two stages, whose main idea is to iterate the sequences of the pigeons. According to this idea, the operators in the continuous algorithm are discretized into cross-learning operations of sequence information.

The result $C_1 \cdot rand_1$ in the first stage is a value on the interval [0,1], which represents the pigeon's learning degree of the global optimal value of the pigeons $X_{gbest}(k)$. Combined with the actual problem, the multiplication operation of two numbers is defined as the crossing operation with thresholds C_1 and probability $rand_1$ in a discrete problem. First, generate a random number $rand_1$ on [0,1] when iterating on the i$^{\text{th}}$ pigeon's $X_i(k)$ in the k$^{\text{th}}$ iteration. If $rand_1 < C_1$, generate two different random integers a and b ($a < b$, b-$a < 10 \cdot C_1$) in the interval [1, N_t]. Then, cross the information which is between the a$^{\text{th}}$ position and the b$^{\text{th}}$ position of the two sequences ***target*** and ***vehicle*** belong to the $X_i(k)$ and the information in the corresponding position of global optimal value $X_{gbest}(k)$. If $rand_1 \geq C_1$, no operation is performed. Through the above operations, the initial iteration position information $X_i{}^{mid}(k + 1)$ is obtained. The specific operation mode is shown in Fig. 1 (a).

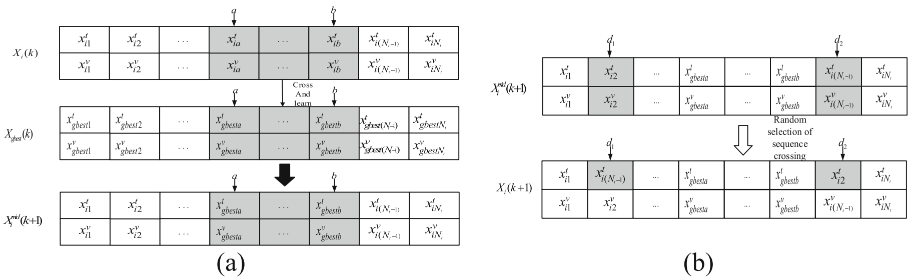

Fig. 1. (a) Operation of discrete PIO for the global optimal sequence in the first stage. (b) Operation 2 of discrete PIO for the global optimal sequence in the first stage

In e^{-Rk}, R is the map and compass factor. With the increase in the number of iterations, the pigeon's inertia will decrease and gradually converge to the local range. Combined with the actual problem, this operation is defined as an inheritance behavior with the thresholds e^{-Rk} and the probability $rand_R$. $rand_R$ is a random number on [0,1], and e^{-Rk} changes with the number of iterations. If $rand_R < e^{-Rk}$, generate two different random integers d_1 and d_2 on the interval [1, N_t]. Then, cross the information of the ***vehicle*** or ***target*** sequence which is in the $d_1$$^{\text{th}}$ position and the $d_2$$^{\text{th}}$ position. If $rand_R \geq e^{-Rk}$, no operation is performed. The position information of iteration $X_i(k + 1)$, $(k + 1 < N_{k1max})$ in the first stage is obtained through the above operations. The specific operation mode is shown in Fig. 1 (b).

According to Eq. (3), the iteration in the second stage of the PIO algorithm is mainly the fast convergence landmark information learning iteration. (Among which the pigeons' iteration k satisfies $N_{k1max} < k \leq N_{k2max}$) The current pigeons are sorted in descending order of fitness value from high to low, and the median value of the current population $N_{p\_}mid(k)$ and fitness value of individual pigeons $F_{total\_}mid(k)$ corresponding to this address are calculated at the same time. Then the pigeons whose fitness value is higher than the current median fitness value are eliminated. Then, the new generation of pigeons $N_p(k+1)$ is got. Then calculate the landmark information of the current pigeons and conduct local optimization. Combined with practical problems, the landmark center of the current pigeons is discretized, and its calculation equation is as follows:

$$X_c(k)\_j = \frac{\sum_{i=1}^{N_p(k)} X_i(k)\_j}{N_p(k)}, 1 \leq j \leq N_v \tag{4}$$

The idea of pigeons' iteration in the second stage is similar to the first stage. The operation is defined as a cross operation with the thresholds C_2 and probability $rand_2$. Perform the same cross operation as in the first stage for the $X_i(k)$ sequence and the $X_c(k)$ sequence to obtain the sequence $X_i(k+1)\_1$. Next, do the same operations between $X_i(k)$ and the local optimal value $X_{ipbest}(k)$ to obtain the sequence $X_i(k+1)\_2$. Finally, calculate and compare the fitness value of the two sequences: $X_i(k+1)\_1$ and $X_i(k+1)\_2$, output the lower value sequence as $X_i(k+1)$. If $rand_2 \geq C_2$, no operation is performed. The position information $X_i(k+1)$ of iteration in the second stage was obtained through the above operations.

3.3 Constraint Check Correction Algorithm

Due to the common random search process of heuristic algorithms, the sequence output by the discrete PIO algorithm may overflow constraints during searching iteration, which needs to be corrected. The correction algorithm is shown in Fig. 2.

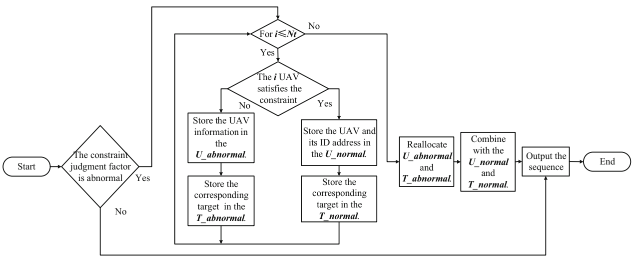

Fig. 2. Flow chart of constraint check correction algorithm

The main idea of the correction algorithm is to check the pigeon's sequence and store the normal information and abnormal information in the corresponding array. Then reallocate the abnormal array and combine it with the normal array.

4 Simulation

Based on the above algorithm design, simulation experiments are carried out in the simulation environment of matlab2021a software, Intel11 generation i5 processor, and 8GB processing memory.

In a multi-task environment of 50 km*50 km, there are 10 UAVs and 10 target points. The UAVS consist of 5 reconnaissance UAVs and 5 strike UAVs. Each target point must be carried out with a reconnaissance task and a strike task. Each UAV has its task number constraint. Each UAV flow at a speed of 50 m/s. Other UAV performance parameters are shown in Table 2.

Table 2. UAV performance parameters

Number	1	2	3	4	5	6	7	8	9	10
Location	1,10	1,20	1,30	1,40	1,50	10,1	20,1	30,1	40,1	50,1
Rec	10	10	10	10	10	0	0	0	0	0
Ammo	0	0	0	0	0	10	10	10	10	10
R-coefficient	0.9	0.85	0.80	0.75	0.70	0	0	0	0	0
S-coefficient	0.9	0.85	0.80	0.75	0.70	0.90	0.85	0.80	0.75	0.70
constraint	2	2	1	3	3	2	2	2	3	3

The performance parameters of the task target point are shown in Table 3.

Table 3. Performance parameters of the task target point

Number	1	2	3	4	5	6	7	8	9	10
Location	10,40	10,30	20,20	30,28	31,43	45,47	40,35	25,10	45,5	40,22
Rec demand	5	5	5	5	5	5	5	5	5	5
Strike demand	5	5	5	5	5	5	5	5	5	5
Rec profit	41.2	31.6	28.2	41.0	53.0	65.1	53.1	26.9	45.2	45.6
Strike profit	53.6	41.1	36.7	53.3	68.9	54.6	69.1	35.0	58.8	59.3

Algorithm internal parameter: $N_p = 400$, $N_k = 20$, $N_{k1max} = 12$, $N_{k2max} = 8$, $C_1(0) = 0.95$, $e_1 = 0.012$, $C_2(0) = 0.35$, $e_2 = 0.012$, $C_{XC} = C_{XP} = 0.5$, $t_{profit} = 0.6$, $t_{cost} = 0.4$.

The optimal task sequence output by the algorithm is shown in Table 4, and the simulation diagrams are shown in Fig. 3.

Table 4. Optimal task sequence

UAV	Task plan (target point, location, time point, task type)	Task time
1	[(1,10), 0] → [2 (10,30), 488.63, Rec]	1
2	[(1,15), 0] → [9 (45,5), 952.44, Rec] → [5 (31,43), 1812.40, Rec]	2
3	[(1,20), 0] → [7 (40,35), 885.70, Rec]	1
4	[(1,25), 0] → [1 (10,40), 399.85, Rec] → [3 (20,20), 897.07, Rec] → [4 (30,28), 1203.21, Rec]	3
5	[(1,30), 0] → [6 (45,47), 993.39, Rec] → [8 (25,10), 1884.61, Rec] → [10 (40,22), 2318.81, Rec]	3
6	[(10,1), 0] → [1 (10,40), 2790.12, Strike] → [2 (10,30), 3000.00, Strike]	2
7	[(15,1), 0] → [9 (45,5), 2615.31, Strike] → [8 (25,10), 3037.62, Strike]	2
8	[(20,1), 0] → [7 (40,35), 2798.91, Strike] → [5 (31,43), 3049.84, Strike]	2
9	[(25,1), 0] → [3 (20,20), 952.44, Strike] → [4 (31,43), 1812.40, Strike]	2
10	[(1,15), 0] → [6 (45,5), 2402.92, Strike] → [10 (30,28), 2669.12, Strike]	2

Table 4 shows the number of tasks performed by each UAV, the location information, time point information, and mission target point information when the tasks were performed. As can be seen from Table 4, all strike tasks are executed after all reconnaissance tasks have been completed. At the same time, the number of tasks performed by all UAVs did not exceed their task number constraints. Figure 3(b) shows that in the early stage of the algorithm, the fitness value decreases rapidly, and its global optimization effect is better in the first stage. The first stage ends at the 12th generation and transfers to the second stage. The fluctuation of the local optimization in the second stage is small, indicating that the algorithm has approached the optimal solution of the problem in the first stage, and the local search for a better situation in the second stage. The task execution sequence of the task point is shown in Fig. 3(c), and the simulation of the task environment is shown in Fig. 3(d). It can be seen from the figure that each task point has executed two tasks, and there is no time conflict between the two tasks, which conforms to the task point constraints.

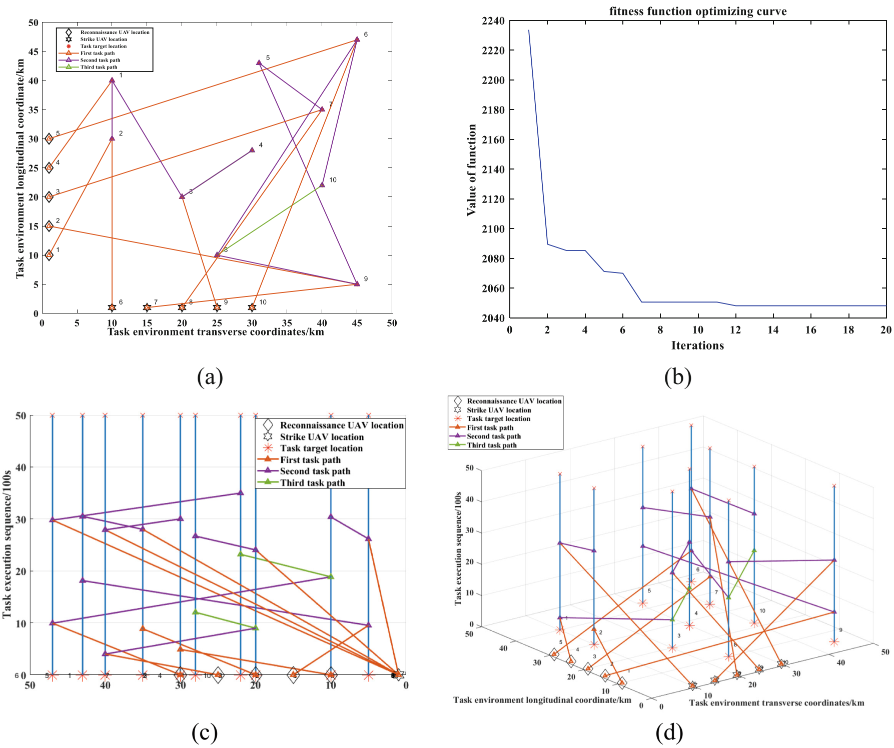

Fig. 3. (a) Two-dimensional environment simulation (b) fitness function optimizing curve (c) Task point Task execution sequence diagram (d) Multi-task environment simulation

The algorithm comparison results are shown in Fig. 4. The genetic algorithm(GA) and the PSO algorithm are chosen to compare with the improved PIO algorithm. The above algorithms are used to carry out comparative experiments on the task models with task numbers 20, 16, 12, and 8 respectively. The results show that the improved PIO algorithm has a faster optimization speed and better results.

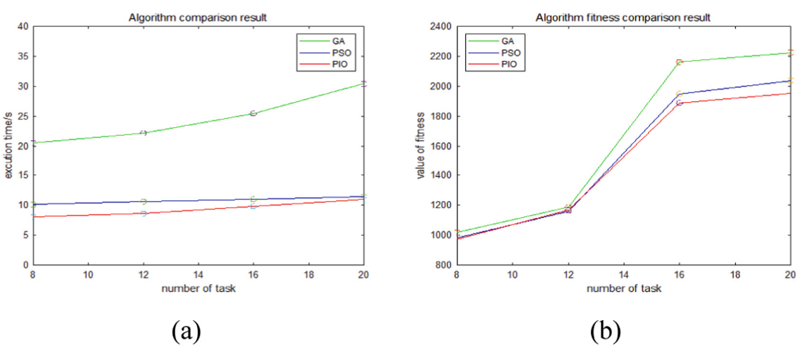

Fig. 4. (a) Algorithm time comparison result (b) Algorithm fitness comparison result

5 Conclusion

Aiming at the typical multi-UAV task assignment problem, considering various costs and constraints, a multi-task fitness function model is established. To enhance the global search ability of the algorithm, a discrete PIO algorithm combined with a learning factor is proposed, At the same time, a constraint check correction algorithm is designed to correct the constraint overflow problem of the heuristic algorithm. The simulation results show that the proposed algorithm has a good solution effect on this kind of task model, and at the same time meets the task constraints.

References

1. Yue, Y., Qu, G.: Research on distributed Multi UAV cooperative reconnaissance task allocation. J. Ordnance Equipment Eng. **82**(3), 57–61 (2018). [Chinese]
2. Qi, X., Li, B., Fan, H.: A survey of mission planning on UAV systems based on multiple constraints. CAAI transactions on intelligent systems **15**(2), 204–217 (2020). [Chinese]
3. Chen, Y., Yang, D., Yu, J.: Multi-UAV task assignment with parameter and time-sensitive uncertainties using modified two-part wolf pack search algorithm. IEEE Trans. Aerosp. Electron. Syst. **54**(6), 2853–2872 (2018)
4. Fan, H., Liu, W., Xu, Z.: Hybrid particle swarm optimization for solving VRPSPD problems with soft time windows. Computer Engineering and Applications **54**(19), 221–229(2018). [Chinese]
5. Beard, R., McLain, T., Goodrich, M.: Coordinated target assignment and intercept for unmanned air vehicles. IEEE Trans. Robot. Autom. **18**(6), 911–922 (2002)
6. Hu, X., Paolo, E.: A hybrid genetic algorithm for the traveling salesman problem. In: Nature Inspired Cooperative Strategies for Optimization 2007,NICSO, pp. 357-367. Springer, Berlin, Heidelberg (2008)
7. Dantzig, G., Ramser, J.: The truck dispatching problem. Manage. Sci. **6**(1), 80–91 (1959)
8. Lu, H.: A Study of Some New Problems Arising from the Field of Minimum cost Network Flows. Zhejiang University (2007). [Chinese]
9. Zheng, C.: Research on Route Planning for Air Vehicles. Huazhong University of Science and Technology (2003). [Chinese]
10. Ba, H.: Research on UAV Trajectory Planning. Northwestern Polytechnical (2006). [Chinese]
11. Edison, E., Shima, T.: Integrated task assignment and path optimization for cooperating uninhabited aerial vehicles using genetic algorithms. Comput. Oper. Res. **38**(1), 340–356 (2018)
12. Zhao, C., Liu, Y., Cen, L.: Research and development trend of multi-UAV path planning based on metaheuristic algorithm. Control and Decision **37**(5), 1102–1115 (2022). [Chinese]
13. Ye, Y., Min, C., Shen, L.: Hybrid genetic algorithm and constraint handling for multiple UCAV mission assigning. Control and Decision **21**(07), 781–786, (2006). [Chinese]
14. Zhang, R., Feng, Y., Yang, Y.: Hybrid particle swarm algorithm for multi-UAV cooperative task allocation. Acta Aeronautica et Astronautica Sinica,1–15 (2021). [Chinese]
15. Li, W., Zhang, W.: Method of tasks allocation of multi-UAVs based on particle swarm optimization. Control and Decision **25**(9), 1359–1363 (2010). [Chinese]
16. Han, Q.: Research on cooperate task allocation of multiple UAVs based on PSO algorithm. J. Ordnance Equipment Eng. **40**(11), 74–78 (2019). [Chinese]
17. Zou, D., Liu, H., Gao, L.: An improved differential evolution algorithm for the task assignment problem. Eng. Appl. Artif. Intell. **24**(4), 616–624 (2011)

18. Duan, H., Qiao, P.: Pigeon-inspired optimization: a new swarm intelligence optimizer for air robot path planning. Int. J. Intell. Comp. Cybernet. **7**(1), 24–37 (2014)
19. Li, C., Duan, H.: Target detection approach for UAVs via improved pigeon-inspired optimization and edge potential function. Aerosp. Sci. Technol. **39**, 352–360 (2014)
20. Zhang, S., Duan, H.: Gaussian pigeon-inspired optimization approach to orbital spacecraft formation reconfiguration. Chin. J. Aeronaut. **28**(1), 200–205 (2015)
21. Fei, L., Duan, H., Xu, X.: ADRC controller design for UAV based on variable weighted mutant pigeon inspired optimization. Acta Aeronautica et Astronautica Sinica **41**(1), 261–270 (2020). [Chinese]