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Multi-UAV Cooperative Trajectory Planning Based on Many-Objective Evolutionary Algorithm

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Abstract: The trajectory planning of multiple unmanned aerial vehicles (UAVs) is the core of efficient UAV mission execution. Existing studies have mainly transformed this problem into a single-objective optimization problem using a single metric to evaluate multi-UAV trajectory planning methods. However, multi-UAV trajectory planning evolves into a many-objective optimization problem due to the complexity of the demand and the environment. Therefore, a multi-UAV cooperative trajectory planning model based on many-objective optimization is proposed to optimize trajectory distance, trajectory time, trajectory threat, and trajectory coordination distance costs of UAVs. The NSGA-III algorithm, which overcomes the problems of traditional trajectory planning, is used to solve the model. This paper also designs a segmented crossover strategy and introduces dynamic crossover probability in the crossover operator to improve the solving efficiency of the model and accelerate the convergence speed of the algorithm. Experimental results prove the effectiveness of the multi-UAV cooperative trajectory planning algorithm, thereby addressing different actual needs.

Key words: multiple unmanned aerial vehicles (multi-UAV); coordinated trajectory planning; NSGA-III; many-objective optimization

1 Introduction

Unmanned aerial vehicles (UAVs) continue to play an increasingly vital role in numerous future combat missions due to their easy control, small size, and low cost. In practice, the working capacity of a single UAV and its working range will be restricted. For example, single UAVs can be damaged or underpowered during missions, as well as significant miss information during reconnaissance missions considering the trivial observation range. These issues can cause incalculable damage. UAVs currently need to perform increasingly difficult missions, and the flight environment of UAVs is becoming remarkably complex. Therefore, single UAVs are no longer partly sufficient for many missions. Most combat missions require the complete cooperation of multi-UAVs. Therefore, the cooperative mission of multiple UAVs has become a trend for future research.

UAV trajectory planning is an essential component of the UAV mission system. Single UAV trajectory planning intends to find a trajectory under its performance constraints. Nevertheless, multi-UAV cooperative trajectory planning focuses on finding multiple trajectories that satisfy the cooperative relationship based on single UAV trajectory planning. This task is not simply superimposing the trajectory of each UAV but requires considering numerous factors, including environmental, UAV performance, and space and time coordination. The UAV time coordination can be divided into three categories according to the needs of the UAV mission. The first category is the limited time period sequence restriction. In the limited time period, all UAVs follow a certain flight sequence to reach the mission target point sequentially. The second category is the limited time period without sequence restriction. All UAVs arrive at the target point in a certain period, and the order of arrival does not need to

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be considered. Finally, multi-UAVs simultaneously arrive at the target point. Space cooperation helps avoid the crashing of UAVs performing the mission with other UAVs and obstacles, thus ensuring the safe completion of the mission. The time and space cooperation of UAVs is currently the focus of multi-UAV trajectory research.

Multi-UAV cooperative trajectory planning is a multi-objective optimization problem (MOP). Among these existing studies, the length and threat of the trajectory are concerned with solving the UAV trajectory using a multi-objective evolutionary algorithm (MOEA). However, MOEA is ineffective in solving models with more than four objectives. With increasing objectives, non-dominated solutions comprise the majority of the candidate solutions in MOEA. The Pareto dominance relation cannot select well converged and diverse candidate solutions during this time. The selection mechanism of the Pareto dominance relation will fail in solving the MOP. Therefore, the many-objective trajectory cost model is constructed by considering the trajectory distance, trajectory time, trajectory threat, and trajectory cooperative distance costs and utilizing the many-objective evolutionary algorithm (MaOEA)[1, 2] is necessary to address trajectory problems of multiple UAVs.

A 3D multi-UAV cooperative trajectory planning model based on MaOEA, which can simultaneously optimize trajectory distance, trajectory time, trajectory threat, and trajectory cooperative distance costs, is presented. This model avoids the conversion of multiple objectives into a single objective. A dynamic segmentation crossover strategy is also designed. In this model, the multi-UAV trajectory is generally treated as an individual in the population in the algorithm and simultaneously optimized.

The remainder of this paper is organized as follows. The related work of UAV trajectory planning is presented in Section 2. The modeling of the multi-UAV cooperative trajectory planning is provided in Section 3. A segmented crossover strategy based on NSGA-III is also proposed, and dynamic crossover probabilities are designed in Section 4. A comparative experiment, as well as an experimental analysis, subsequently followed in Section 5. Finally, a summary and outlook of the current work are presented in Section 6.

2 Related Work

UAVs play an influential role in urban reconnaissance and strike as well as battlefield environment assessment. The planning of multiple UAV trajectories is also fundamental to their safe and efficient mission execution in complex environments. UAV trajectory planning algorithms are the core of UAV trajectory planning. Researchers have developed a variety of methods to handle the multiple factors and complex environments of UAV trajectory planning. The generally used research methods for multi-UAV trajectory planning are currently classified into four categories as follows.

The mathematical optimization and graph theory methods are both mathematical methods. The first method is based on mathematical optimization methods[3–6], such as dynamic programming and the exhaustive method. These algorithms obtain the optimal path by adjusting the model parameters to minimize the cost function. However, these methods are too computationally time-consuming for large-scale problems. The second method is based on graph theory methods, such as the random tree and the Voronoi diagram methods. In these methods, a pathway graph is formed in accordance with various conditions, and the optimal path is obtained in the pathway graph. The Voronoi diagram method divides the space into several co-sided polygons according to the threat, and these polygons are connected to form a pathway diagram. However, the division approach of the space in three dimensions must be studied.

The heuristic search and intelligent optimization algorithms are employed in searching by using certain heuristic information or behaviors. The first algorithm is based on heuristic search algorithms[7–10], such as A* and D* Lite. These algorithms use heuristic information to estimate the next node position and keep searching for the optimal trajectory. Therefore, these methods have additional nodes and require additional time and large memory. The intelligence optimization algorithms[11–16] include ant colony algorithms (ACO), particle swarm algorithms (PSO), and genetic algorithms. Intelligent optimization algorithms use the idea of biological behavior to search for the optimal path and are often employed in UAV trajectory planning.

In recent years, optimization algorithms have been rapidly developed and used in various aspects, such as production scheduling, circuit design, and mechanical design. In practical problems, the number of optimization objectives is not only limited to two or three but often reaches four or more. In such a case, the traditional MOEAs encounter the problems of search capability, computational cost, and visualization in solving many-objective optimization problems (MAOPs). Therefore, MaOEAs are becoming a research hotspot[17].

Thus far, optimization algorithms have also been applied by numerous researchers to address UAV trajectory planning issues[18−23]. In 3D trajectory planning, Wang et al.[24] proposed an adaptive sensitivity decision operator with the PSO algorithm to improve the convergence speed. Shao et al.[25] optimized the UAV trajectory by adopting the PSO algorithm. Chen et al.[26] presented the ACO algorithm with adaptive parameters and bidirectional tuning, which handles the optimization of UAV trajectories with multiconstraints. However, these researchers only considered single factors and did not meet the actual needs. Qu et al.[27] proposed a new hybrid algorithm that combines SGWO and an improved MSOS, leading to enhanced convergence and diversity of the algorithm. Therefore, MOEA is applied for addressing multi-UAV trajectory planning issues.

Some researchers have recently utilized MOEA to deal with the aforementioned issue[28]. Xu et al.[29] introduced an improved multi-objective PSO algorithm for path planning of R-UAVs to optimize the length, height, and angle of the path. The efficiency of the algorithm is improved by adding vibration functions. Xu et al.[30] presented a constrained evolutionary algorithm for path planning of single UAVs, which optimizes the flight distance and risk under the constraints of UAV height, angle, and slope. Xu et al.[31] modeled the two objectives of threats and fuel cost with cooperative constraints. An improvement of the gray wolf optimization algorithm was then utilized to solve the aforementioned issue. The algorithm can obtain optimal paths and converge quickly. Numerous factors lead to poor results when using MAOP to solve the above-mentioned issue in the multi-UAV trajectory planning problem. Therefore, this problem should be addressed using MaOEA[32, 33].

Overall, most researchers did not consider sufficient factors, and the constructed UAV mission environment was unsuitable in reality. The cost model of the trajectory is established considering the complex environment, the UAV performance, and cooperation to deal with the above-mentioned problems, and MaOEA is used to optimize the multi-UAV trajectory.

3 Multi-UAV Cooperative Trajectory Planning Model

3.1 Description of the problem

In a complex environment, a cluster of multiple UAVs performs a certain coordinated combat mission. This cluster of UAVs will move from different starting positions to the same target point. This condition is a problem of multi-UAV coordinated trajectory planning. In this process, considering factors such as terrain, weather, threats, and the performance of the UAVs, is necessary. A certain distance must be maintained between the UAVs during the flight of the UAV cluster to ensure the absence of collision, and the mission completion time for the UAVs should be considered. The trajectory planning problem is the path optimization problem, which aims to search for the optimal trajectory in the determined space. MOP is the search for the Pareto optimal solution by optimizing more than three objectives in a certain region. The Pareto optimal solution is not only a globally optimal solution but a collection of multiple optimal solutions. Multi-UAV trajectory planning has many factors, and finding more than three objectives is easy. Therefore, the problem can be solved by many-objective optimization.

3.2 Model establishment

3.2.1 Multi-UAV cooperative trajectory cost model

Trajectory cost, UAV attributes, and UAV coordination must be considered for coordinated trajectory planning of multiple UAVs. However, trajectory cost includes trajectory distance, trajectory time, trajectory threat, and trajectory coordination distance costs. UAV trajectory cost is an objective function, and the attributes of the UAV and the time coordination of the UAV are constraints. The trajectory planning aims to maintain a small trajectory cost under constrained conditions.

(1) **Distance cost of trajectory**

In the process of trajectory planning, the entire trajectory is divided into n trajectory segments, and q UAVs perform coordinated combat tasks. The distance cost of the trajectory is the distance of q UAVs in n trajectory segments. The distance cost of the track is as follows:

$$f_{distance} = \sum_{u=1}^{q} \sum_{l=1}^{n} d_{ul} \tag{1}$$

where d_{ul} refers to the length of the u-th UAV in the l-th track segment.

(2) **Time cost of trajectory**

In the process of trajectory planning, the entire trajectory is divided into n trajectory segments, and each trajectory segment has a flight speed. The trajectory time cost is the time of q UAVs in n trajectory segments. The time cost of the trajectory is specifically expressed as follows:

$$f_{time} = \sum_{u=1}^{q}\sum_{l=1}^{n}\frac{d_{ul}}{v_{ul}} \tag{2}$$

where v_{ul} represents the flight speed of the u-th UAV in the l-th track segment.

(3) **Threat cost of trajectory**

UAVs will be threatened by radars and environments when encountering dangerous areas during flight. The threat cost of the trajectory aims to stay away from the threat as much as possible. The threat area is represented by a spherical area in this paper. The trajectory threat cost of q UAVs is as follows:

$$f_{threat} = \sum_{u=1}^{q}\sum_{l=1}^{n} w_{ul} \tag{3}$$

where w_{ul} refers to the length of the u-th UAV in the threat zone on the l-th trajectory.

(4) **Coordination distance cost of the trajectory**

The UAV must collect a considerable amount of different information and send it back to the base station, and the UAV must safely complete this mission. Therefore, the distance of UAVs from each other must be as large as possible, thus enabling increased drone coverage. The coordination distance cost of the trajectory of multiple UAVs is shown below.

$$f_{coordination} = (\sum_{u=1}^{q}\sum_{l=1}^{n} d(k_1,k_2))/2 \tag{4}$$

where $d(k_1,k_2)$ represents their distance between two different UAVs in a certain track segment.

3.2.2 UAV performance constraints

(1) **Flying height**

The flying height of the UAV must be considered in trajectory planning. The flying height of the UAV cannot be too high or low. If the flying height is too high, then the UAV will encounter threats, such as enemy radar. If the flying height is too low, then the danger of hitting the mountain is also possible. The flying height of the UAV should be controlled within a certain range to complete the mission safely. The flight height of each trajectory h_l is expressed as follows:

$$h_{\min} < h_l < h_{\max}, \quad l = 1,2,3,\ldots,n \tag{5}$$

where h_l represents the flight altitude of the l-th track segment.

(2) **Flight distance**

The fuel carried by the UAV and the time for the mission completion are limited. Thus, the flying distance of the UAV is also limited. The UAV checks the total distance flown at this point in each trajectory segment during the trajectory planning process. If the distance is invalid, then the trajectory is replanned. The flying distance L of the UAV is expressed as follows:

$$L < L_{\max} \tag{6}$$

where $L_{\max}$ represents the farthest distance flown by the UAV.

3.2.3 UAV collaborative constraints

(1) **Space coordination constraints**

The UAV will not be able to collide with other UAVs and obstacles in the environment to complete the combat mission safely. Therefore, the distance between UAVs at any one time in multi-UAV trajectory planning is larger than the safety distance between UAVs, and the UAV cannot hit the mountain. The specific representation is as follows:

$$\|d_i(t) - d_j(t)\| \geqslant d_{safe}, \quad i \neq j \tag{7}$$

$$h > d_{mountain} \tag{8}$$

where i and j represent different UAVs, d_{safe} represents the safe distance between UAVs, $d_{mountain}$ represents the actual height of the mountain, and h represents the altitude of the UAV at this moment.

(2) **Time constraints**

The mission completion time for each UAV is determined by its trajectory length and flight speed. Each UAV does not need to arrive in order but must safely arrive at its target point within the specified period. The specific expression is as follows:

$$t_{\min} < t_i < t_{\max} \tag{9}$$

where t_i represents the time for the i-th UAV to complete the mission.

4 Dynamic Segmentation Crossover Strategy Based on NSGA-III

4.1 NSGA-III

Most MOEAs are only suitable for issues with less than four objectives. However, more than four objectives that must be optimized are often observed in reality.

Therefore, Deb and Jain[34] proposed NSGA-III based on NSGA-II. Non-dominated sorting was applied to NSGA-II and NSGA-III. However, their selection strategies at the critical level are different. A congestion distance is used for NSGA-II. However, NSGA-III adopts a strategy of reference points. This algorithm solves the overcomplicated computation problem of congestion between numerous non-dominated solutions for high-dimensional spaces. The core of this algorithm lies in the non-dominant sorting and reference point methods. This algorithm selects the solutions with good convergence in the population via non-dominated ranking, while the best solution is identified by filtering a large amount of non-dominated solutions through a reference point strategy. The algorithm flow of NSGA-III is shown in Algorithm 1.

4.2 Individual representation

The real coded approach is used in this paper to plan the trajectories of q UAVs in 3D space. The three-dimensional space is divided into n track segments, and each track point is generated on each track segment of each UAV. The line comprising L trajectory points forms the flight trajectory of UAVs. An individual represents the trajectory of q UAVs, and the individual is represented by a matrix $\boldsymbol{X} = [X_1, X_2, X_3, \ldots, X_u, \ldots, X_q]^{\mathrm{T}}$, where q represents the number of UAVs, and X_u is the trajectory of the u -th UAV in the individual. Individuals are represented as shown in Fig. 1.

Algorithm 1 NSGA-III

Input: Reference points, initial population

1. Calculating population size N
2. Cross mutation generates offspring
3. Paternal and offspring integration, generating new populations R_t
4. Calculate the ideal point $Z_{\min}$
5. Non-dominated sorting
6. Select non-dominated layers with high priority and retain individuals
7. **While** (Selected individuals<N)
8. Reference point strategy
9. Calculate the achievement scalarizing function ASF
10. Calculate the extreme point
11. Solving for hyperplane
12. Compute intercepts
13. Standardization of populations
14. Calculate the distance from the solution to the reference vector
15. Association operation
16. Select the remaining individuals
13. Standardization of populations
17. **End**

Output: New populations P_{t+1}

4.3 Mutation and crossover operations based on dynamic segmentation strategy

A dynamic segmentation crossover strategy is designed in this paper to accelerate the searching speed of the algorithm. The probability of mutation operator is set to 0.1 to prevent the algorithm from turning into a local optimal. The entire trajectory for the model built in this paper is segmented: the threat area containing radar and harsh weather is regarded as one segment, and the rest of the non-threat area is taken as another segment. Dynamic crossover probabilities are set within different segments and depend on individual fitness values of current and previous generation populations. In threat areas, it depends on trajectory threat and time costs. Meanwhile, in non-threatened areas, it is determined by trajectory distance and trajectory coordination distance costs. If the mean value of all individuals in the current population is greater or less than the previous generation on the two objectives, then the crossover probability of the threat area is set to 0.8. Otherwise, this probability is determined by the ratio of the average value of all individuals in current and previous generation populations on the two objectives. The crossover probability $p_{c1}(s)$ equation of the threat area is as follows:

$$\overline{f(s)} = \left(\sum_{k=1}^{N} f(s)\right)/N \tag{10}$$

where $f(s)$ represents the fitness value after normalization of the current population, and $\overline{f(s)}$ represents the average of the fitness values of all individuals in the current population.

$$p_{c1}(s) = \begin{cases} \max\left(\dfrac{\overline{f_{threat}(s)}}{f_{threat}(s-1)}, \dfrac{\overline{f_{time}(s)}}{f_{time}(s-1)}\right) \times 0.8, \\ \text{Formula (12);} \\ 0.8, \quad \text{other} \end{cases} \tag{11}$$

	$\xleftrightarrow{L}$				$\xleftrightarrow{L}$				$\xleftrightarrow{L}$			
X_1	x_{11}	x_{12}	…	x_{1L}	y_{11}	y_{12}	…	y_{1L}	z_{11}	z_{12}	…	z_{1L}
X_2	x_{21}	x_{22}	…	x_{2L}	y_{21}	y_{22}	…	y_{2L}	z_{21}	z_{22}	…	z_{2L}
		⋮				⋮				⋮		
X_q	x_{q1}	x_{q2}	…	x_{qL}	y_{q1}	y_{q2}	…	y_{qL}	z_{q1}	z_{q2}	…	z_{qL}

Fig. 1 Individual representation.

$$\begin{cases} \overline{f_{threat}(s)} \geqslant \overline{f_{threat}(s-1)} \text{ and } \overline{f_{time}(s)} \geqslant \overline{f_{time}(s-1)}, \\ \overline{f_{threat}(s)} \leqslant \overline{f_{threat}(s-1)} \text{ and } \overline{f_{time}(s)} \leqslant \overline{f_{time}(s-1)} \end{cases} \quad (12)$$

where s represents the current number of iterations, and $f_{threat}(s)$ and $f_{time}(s)$ indicate the individual fitness value on this trajectory threat and time costs, respectively.

The calculation method of the crossover probability of this non-threatened area is the same as that of the threat area. The specific formula is as follows:

$$p_{c2}(s) = \begin{cases} \max(\dfrac{\overline{f_{distance}(s)}}{\overline{f_{distance}(s-1)}}, \dfrac{\overline{f_{coordination}(s)}}{\overline{f_{coordination}(s-1)}}) \times 0.8, \\ \text{Formula (14);} \\ 0.8, \qquad \text{other} \end{cases} \quad (13)$$

$$\begin{cases} \overline{f_{distance}(s)} \geqslant \overline{f_{distance}(s-1)} \text{ and } \overline{f_{coordination}(s)} \geqslant \\ \overline{f_{coordination}(s-1)}, \\ \overline{f_{distance}(s)} \leqslant \overline{f_{distance}(s-1)} \text{ and } \overline{f_{coordination}(s)} \leqslant \\ \overline{f_{coordination}(s-1)} \end{cases} \quad (14)$$

where $f_{distance}$ and $f_{coordination}$ denote the individual fitness value of the current trajectory distance and trajectory coordination distance costs, respectively.

Each subpopulation is optimized using the NSGA-III algorithm, and the basic genetic operation operator is used for the other evolutionary operations. Whether the constraints of UAV performance and cooperation are satisfied is determined by the individuals in the population. Otherwise, the waypoints that do not satisfy the constraints are regenerated.

4.4 Algorithm framework

Figure 2 is an algorithm flowchart based on UAV trajectory planning.

The detailed steps of multi-UAV coordinated trajectory planning based on DSNSGA-III are as follows.

(1) Create a three-dimensional environment model of the UAV and define UAV mission starting and aiming points and the parameters in the NSGA-III algorithm.

(2) Initialize the number of iterations G and the population P.

(3) Calculate the trajectory distance, trajectory time, trajectory threat, and trajectory coordination distance costs of the individual by using Eqs. (2)−(4) and Formula (5).

(4) Calculate the algorithm crossover probability based on the goals of the current and previous generation populations and the location of the trajectory.

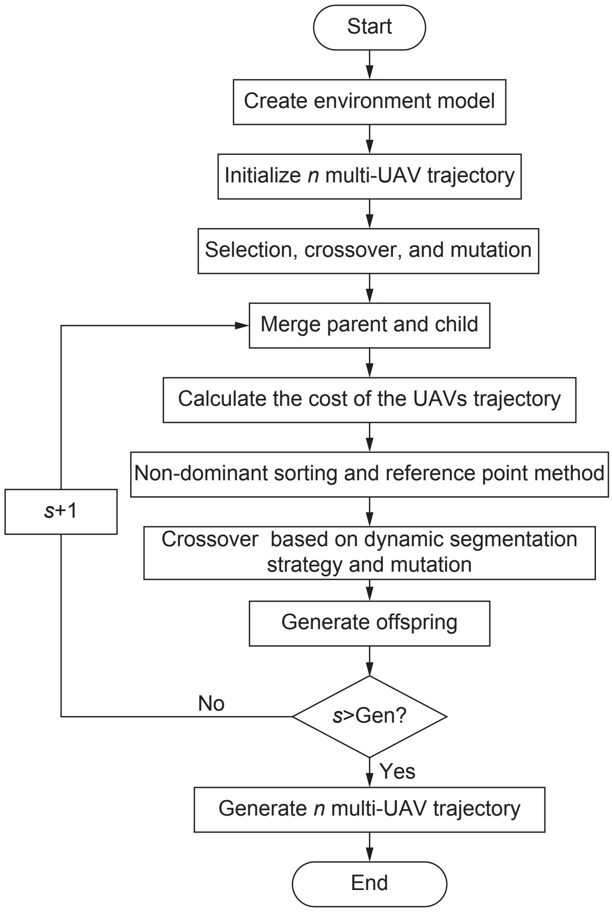

Fig. 2 Algorithm flowchart based on multi-UAV trajectory planning.

(5) Offspring is produced by parents through crossover and mutation.

(6) The parent and offspring merge into a new population, P_1.

(7) The new population P_1 uses the standard environmental selection strategy in NSGA-III to choose outstanding individuals. These individuals form a new population, and the number of algorithm iterations is increased by one.

(8) If the termination condition is met, then the procedure ends. Otherwise, skip to Step (3).

5 Experiment and Result

A 3D multi-UAV flight trajectory is simulated on MATLAB 2019b. The space size of this operational mission is 100 × 100 × 650, and three UAVs are available in the mission. Their starting positions are [1, 20, 160], [1, 35, 166], and [1, 50, 160]. The target point coordinates of the mission are [100, 80, 400]. Four radars are located in the mission space and are represented by spheres. Their central coordinates are

[26, 70, 480], [35, 20, 470], [60, 50, 500], and [80, 40, 460]. The severe weather in the mission space is represented by a rectangular parallelepiped. The length of this rectangular tube is 20, the width is 100, and the altitude is 650. The entire flight trajectory of the UAV is divided into 50 segments, yielding 51 trajectory points.

5.1 Performance analysis of individuals and iterations

One hundred individuals are selected for experiments with different iteration numbers according to the constructed model. The iteration number ranges from generation 100 to 1200. Each iteration is run 20 times independently. The results of the 20 runs are averaged. Figure 3 shows the experimental results of the four objectives of this model at different numbers of iterations. The horizontal coordinates in Fig. 3 indicate the number of iterations for the individual. The vertical coordinates represent the objective value of each objective. Figure 3a shows the objective of trajectory distance cost converges after 900 generations. Figure 3b reveals the trajectory time cost converges after 900 generations. Figure 3c demonstrates that the trajectory threat cost converges to 1000 generations. Figure 3d shows the trajectory coordination distance cost converges at 1100 generations. Overall, the objective values of all objectives after the 1100 generations are in a state of convergence.

Figure 3 shows that the number of convergence generations for each objective is 1100; therefore, this paper uses 1100 iterations for different individuals to perform the experiments. The number of individuals in the population is 50, 75, 100, 125, and 150. Figure 4 reveals the experimental results of the four objectives of this model on different numbers of individuals. The horizontal and vertical coordinates indicate the number of individuals in the population and the objective value of each objective, respectively. Figure 4a shows the trajectory distance cost converges after 100 individuals. Figure 4b demonstrates the trajectory time cost

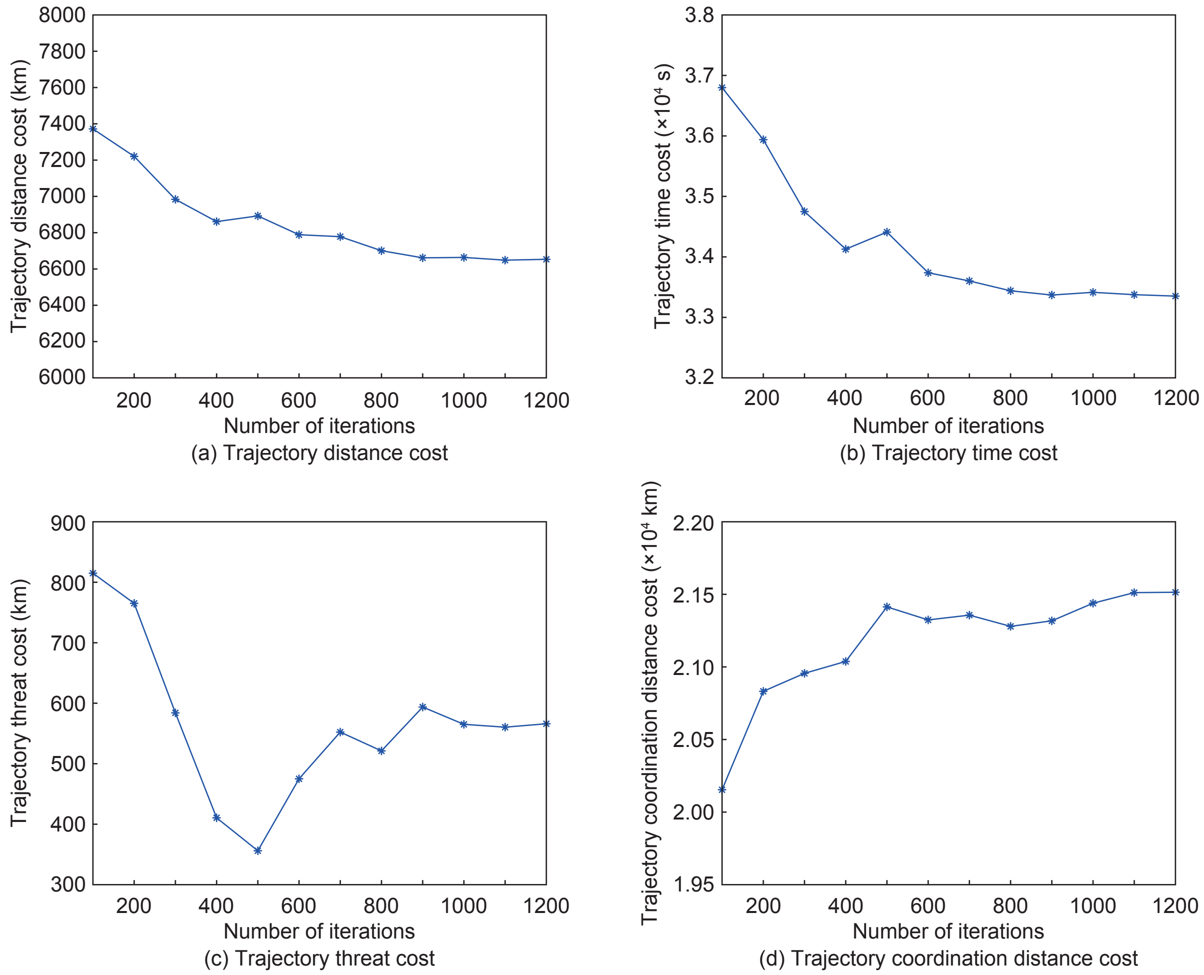

Fig. 3 Results of each objective at different iterations.

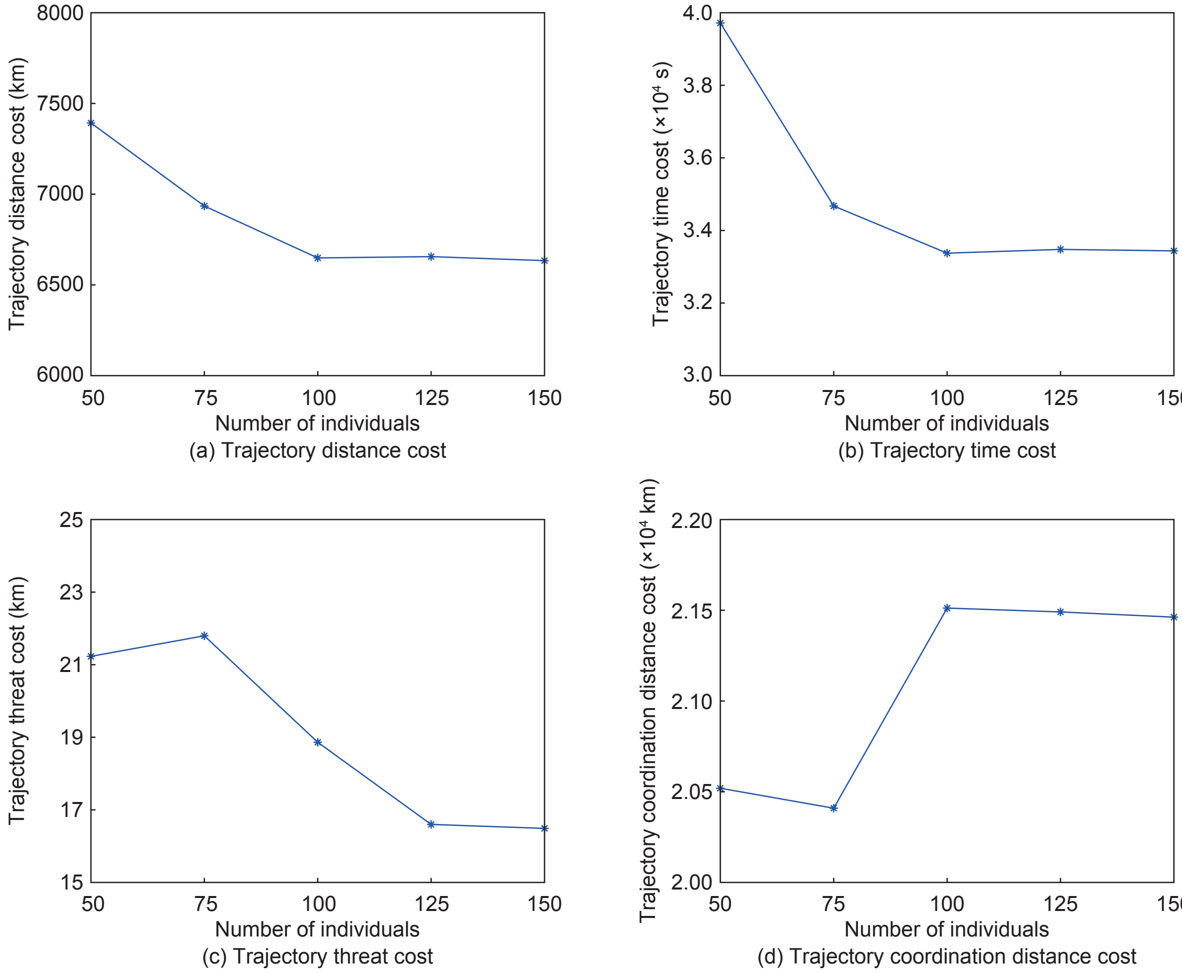

Fig. 4 Results of each objective at different individuals.

converges after 100 individuals. Figure 4c reveals the trajectory threat cost converges to 125 individuals. Figure 4d shows the trajectory coordination distance cost converges at 100 individuals. Overall, the objective values of all objectives are in a state of convergence at 125 individuals.

5.2 Comparison with proposed DSNSGA-III

In the case of 100 individuals and 1100 iterations, this paper compares the DSNSGA-III with the standard NSGA-III algorithm[34], RVEA algorithm[35], and GrEA algorithm[36]. NSGA-III uses a reference point strategy to select the best individuals among the non-dominated solutions to improve the convergence of the algorithm. RVEA uses a uniformly distributed reference vector to divide the decision space into several small subspaces to determine the superiority of an individual in the subspace. GrEA introduces three criteria to maintain diversity but overemphasizes diversity. The three many-objective algorithms are suitable for solving the proposed model in this paper. Figure 5 shows the comparison results of this model with multiple algorithms on each objective.

Based on the multi-UAV trajectory coordination planning problem, Fig. 5 shows that the DSNSGA-III significantly surpasses the other algorithms considering trajectory distance, trajectory time, and trajectory coordination distance costs.

The trajectory threat cost is 0 for most individuals; therefore, the objective is not represented by a box plot. Table 1 presents the results of the experiments using DSNSGA-III, standard NSGA-III, RVEA, and GrEA algorithms under the trajectory threat cost.

5.3 Trajectory simulation results

Figures 6 and 7 are the simulation results of the multi-UAV coordinated trajectory planning using the DSNSGA-III algorithm according to the above experiments of individuals and iterations. The trajectory planning results indicate that all UAV tracks did not intersect, satisfying the cooperativity of trajectory planning. Most of the trajectories also

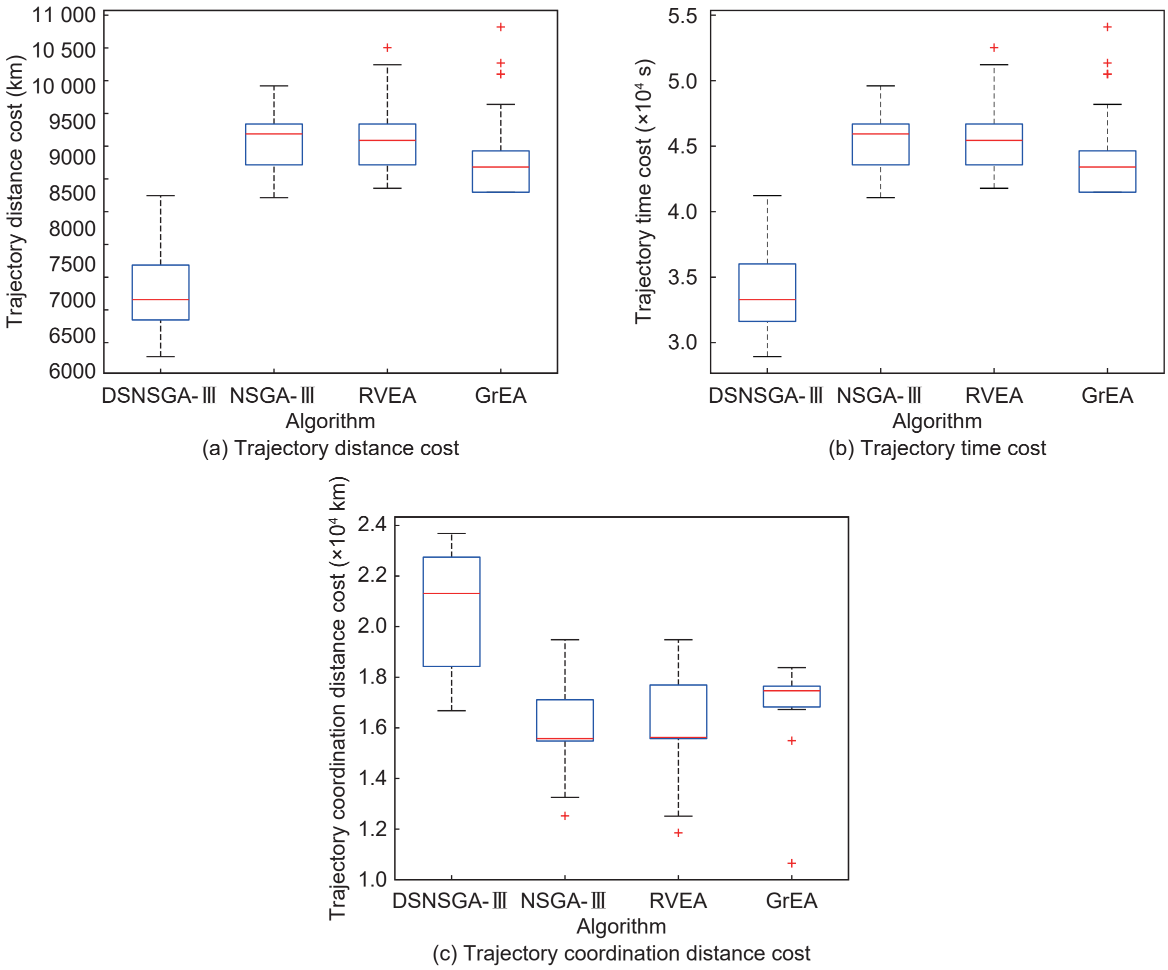

Fig. 5 Results of different objectives at different algorithms.

Table 1 Values of the threat cost.

Algorithm	Total cost of the threat (km)	Number of threatening tracks
DSNSGA-III	607.38	38
NSGA-III	213.88	46
RVEA	196.17	30
GrEA	458.32	33

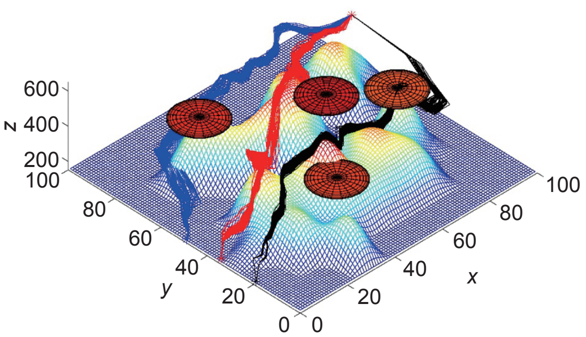

Fig. 6 Trajectory planning results.

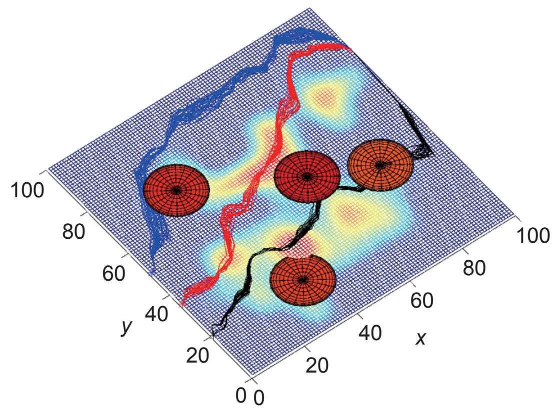

Fig. 7 Top view of the trajectory.

successfully avoided mountainous and dangerous areas. Simultaneously, the optimal trajectory of trajectory distance, trajectory time, and trajectory coordination distance costs is selected on the basis of the simulation results of population trajectory planning, as shown in Table 2.

Table 2 Optimal trajectory for each goal.

Objective	$f_{distance}$ (km)	$f_{coordination}$ (km)	f_{time} (s)
Trajectory distance cost	5786.12	17 636.93	28.93
Trajectory time cost	5893.42	17 054.76	29.46
Trajectory coordination distance cost	8075.54	23 683.71	40.37

6 Conclusion

Traditional UAV trajectory planning methods did not consider sufficient factors. Therefore, a three-dimensional multi-UAV coordinated trajectory planning is proposed in this paper based on DSNSGA-III in complex environments. Under the conditions of the UAV and cooperative constraints, trajectory distance, trajectory time, trajectory threat, and trajectory coordination distance costs of UAVs are optimized simultaneously to find a set of effective trajectories. A segment crossover method is designed in accordance with the characteristics of the model created in this paper, and dynamic probability is introduced to the crossover operator to accelerate the convergence speed of the operator. The simulation results in this paper prove that the algorithm can plan multiple sets of trajectories under the constraint conditions and meet different actual needs. The results also reveal the effectiveness of the algorithm in multi-UAV trajectory planning.

The coordinated trajectory planning of multiple UAVs under uncertain conditions and the time and space coordination algorithms between UAVs are then highlighted.

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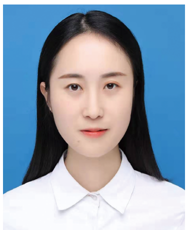

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