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Intelligent Planning Modeling and Optimization of UAV Cluster Based on Multi-Objective Optimization Algorithm

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Abstract: As a flight tool integrating carrier and reconnaissance, unmanned aerial vehicles (UAVs) are applied in various fields. In recent years, mission planning and path optimization have become the most important research focuses in the field of UAVs. With the continuous maturity of artificial intelligence technology, various search algorithms have been applied in the field of unmanned aerial vehicles. However, these algorithms have certain defects, which lead to problems, such as large search volume and low efficiency in task planning, and cannot meet the requirements of path planning. The objective optimization algorithm has a good performance in solving optimization problems. In this paper, the intelligent planning model of UAV cluster was established based on multi-objective optimization algorithm, and its path is optimized. In the aspect of modeling, this paper studied and analyzed online task planning, search rules and cluster formation control using an agent-based intelligent modeling method. For mission planning and optimization, it combined multi-objective optimization algorithm to build the model from three aspects of mission allocation, route planning and planning evaluation. The final simulation results showed that the UAV cluster intelligent planning modeling method and path optimization method based on multi-objective optimization algorithm met the requirements of route design and improved the path search efficiency with 2.26% task completion satisfaction.

Keywords: smart modeling; path optimization; UAV cluster; multi-objective optimization algorithm

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1. Introduction

At present, the traditional task planning algorithm exposes many defects, resulting in low efficiency of path planning. This paper poses an attempt to apply multi-objective optimization algorithm to UAV mission planning and path optimization. In this paper, online task planning, search rules and clustering formation control are studied and analyzed using an agent-based intelligent modeling method, and then combined with multi-objective optimization algorithm. UAV task planning and optimization are innovated from three aspects of task allocation, route planning and planning evaluation. The research shows that the optimization method proposed in this paper improves the path search efficiency and task completion of UAV.

With the development of science and technology, the application of UAV has become more and more extensive, and the research on modeling is also ever increasing. Baldi Simone proposed a new design method of adaptive autopilot, and studied the uncertain Eulerian Lagrangian dynamics based on UAV, in which the control can explicitly consider the driving problem in dynamics and reduce the structural knowledge of cross coupling and trim points [1]. Wang Ximan proposed a new vector field rule, which can deal with the uncertain course time constant and state related uncertainty in course dynamics caused by coupling. Then the stability is studied under the framework of Lyapunov, and the reliability of the proposed method is tested on the loop UAV simulator. Simulation results show that the proposed method is superior to the standard vector field method in the presence of such uncertainty [2]. Spandan Roy has studied an autopilot framework in which there is no need to understand UAV dynamics and trim points. The proposed design can simulate the behavior of a carefully adjusted ready-made autopilot without using its prior knowledge through complex unmanned vehicle dynamics tests [3]. Wang Ximan proposed a vector field method which does not require prior knowledge of UAV heading time constant, coupling effect and wind direction. Stability and performance are evaluated using Lyapunov theory. The method has been tested on the software and hardware in the loop UAV platforms, which shows that the proposed guidance law is superior to the most advanced guidance controller and standard vector field method in the presence of significant uncertainties [4].

Multi-objective optimization algorithm is outstanding in dealing with optimization problems. At present, the research into UAV is increasing. Zhou D proposed a multi-objective optimization algorithm based on collaborative path planning and accurately planned the cooperative combat path of UAV by introducing the cooperative evolution strategy [5]. WY Ruan applied the multi-objective pigeon swarm optimization algorithm to the UAV formation obstacle avoidance process. The effectiveness of the proposed algorithm was verified by simulating the flight process of UAV in a complex, obstacle-filled environment [6]. Yan F applied the multi-objective particle optimization algorithm to the path planning method of the rotating UAV. The simulation results showed that the algorithm can improve the accuracy of path optimization [7]. Tseng FH designed a UAV tracking model by applying a multi-objective optimization algorithm. The simulation results showed that the model is reasonable and the tracking effect is good [8]. Yang F applied the multi-objective optimization algorithm to the UAV wing design and improved the aerodynamic performance of the airframe by using the wings [9]. Wei M proposed a UAV flight path search model in combination with the multi-objective optimization algorithm and verified the effectiveness of the model through experimental comparison [10]. Zhou W applied the multi-objective optimization algorithm to the research of UAV flight efficiency, which improved the flight efficiency through path arrangement [11]. These researches on the application of multi-objective optimization algorithm to UAV are relatively detailed, but there are few related to UAV path planning modeling.

Mission planning and path selection have always been the focuses of UAV operation. However, with the continuous advancement of science and technology, the traditional task planning method can no longer meet the task planning requirements in the new era. This paper first analyzed the modeling of UAV intelligent modeling method based on the agent and then used multi-objective optimization algorithm to model the task allocation and path planning. The final experimental results showed that the new method proposed in this paper can obviously improve the efficiency of UAV mission planning.

2. Digital Twin Technology and Agent-Based Intelligent Modeling Method

Digital twin technology is used to create a virtual model of physical entities in a digital way, simulate the behavior of physical entities in the real environment with data, and add or expand new functions for physical entities by means of virtual real interaction feedback, data fusion analysis, decision-making iteration optimization, etc. As a technology that makes full use of models, data, intelligence and integrates multiple disciplines, digital twin is oriented towards the whole life cycle process of products, playing a role as a bridge and link between the physical world and the information world, and providing more real-time, efficient and intelligent services. Digital twin-based UAV is a virtual UAV model in the whole life cycle of the UAV. It can provide a collaborative simulation and simulation environment driven by functional models, and has the ability to map the virtual reality of the real physical system, and add and expand new functions for the UAV.

Agent-based modeling is most commonly used in intelligent modeling. In different domains, the definition of an agent is also different. In the field of modeling and simulation, an agent is defined as an individual or unit that has initiative in a system.

As shown in Figure 1, the structure of a single agent consists of perceptron, effector and processor. Agents can be divided into three types: reactive, deliberative and mixed.

Reactive agents can respond quickly to environmental stimuli, but they are not intelligent enough. Although the deliberative agent has strong intelligence, its response speed is slow. The mixed agent draws on the advantages of both with high intelligence and fast response speed [12].

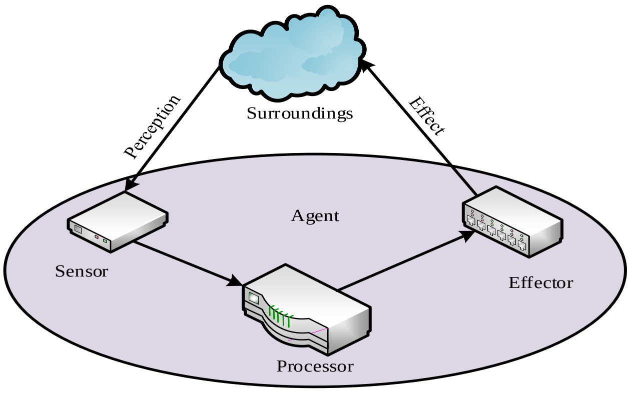

Figure 1. Basic structure of a single agent.

3. UAV Cluster Intelligent Planning Modeling Method

The intelligent modeling of UAV cluster is mainly embodied in three aspects: online task planning, search rules and cluster formation control.

(1) Online task planning

UAV cluster online mission planning is a task to be completed during the flight process of UAV, mainly including task allocation and path planning. This paper presented a distributed online task planning method for UAV cluster based on the agent. Under this method, the content of online task planning for each UAV agent includes individual task execution, state evaluation, cluster state prediction, and local task planning. In these planning contents, status assessment is not easy to understand. It refers to the assessment of task status according to task requirements, such as the risk level of the task, the time spent on the task, etc.

(2) Search rules and search algorithms

A. Search Rules

Search rules are the premise of UAV cluster search, in which target search rules and path selection rules are the most important at the decision-making point of UAV flight mission, that is, the direction of each UAV search path. The most common search rule is random search with infinite angles, which easily leads to repeated search and low efficiency. In order to improve the search efficiency, we must try to avoid repeated search. In addition, search rules can usually be arranged with search algorithm or target optimization algorithm. The path selection rule is used to select an optimal path from the starting point to the destination, which requires the support of the corresponding objective optimization algorithm, such as the multi-objective optimization algorithm applied in this paper. In unfamiliar flight environments, for relatively small targets, UAVs can only use a simple agent to complete the search task, but the agent must have a certain computing power. Through the interaction between these agents and the environment, a group system is finally formed to optimize the search path until the target location is found.

B. Multi UAV cooperative search algorithm based on coevolutionary genetic algorithm

This paper adopts the rolling optimization idea, that is, at time t, limit each UAV to plan a path forward. UAVs only execute the first step of the planned path. At time $t + 1$, they re-plan the path based on the new system state and environmental information. Use m subpopulations to evolve the search path of m UAVs respectively. If the UAV is located in cell (x, y) at time t, the result of path planning at time t is a path with a length of starting from (x, y).

(3) Cluster formation control

The control of UAV cluster is used not only to maintain the cluster shape, but also to transform and rotate the formation and avoid obstacles. UAV cluster formation control can be divided into centralized control and distributed control. This paper prefers distributed control. The reason is that distributed control requires less information and is simple to calculate with the advantages of high reliability, which is more suitable for controlling the formation of small UAV clusters.

4. Task Planning of UAV Based on Multi-Objective Optimization Algorithm

Combined with the multi-objective algorithm, this paper analyzed the modeling from three aspects: task allocation, route planning and planning evaluation. Figure 2 showed the specific process of UAV mission planning combined with multi-objective optimization algorithm. First, after receiving the task, the data are collated and analyzed, and the task target is analyzed according to the collated content; next, the load, track and link are planned as a whole through environment modeling; Finally, the planning result is output and sent to the terminal device.

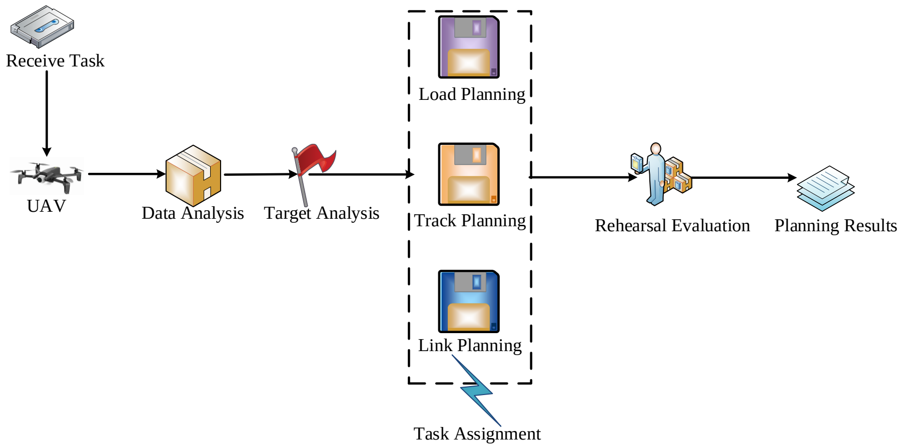

Figure 2. The specific process of UAV mission planning.

(1) Task assignment

The task allocation problem of the clustered UAV system belongs to the basic combinatorial optimization problem. At the beginning of the model establishment, the model elements UAV and task are set up first. It is supposed that there are n tasks, and the task set of m UAVs is $Task = \{Task_1, Task_2 \ldots, Task_n\}$; the UAV set is $\mathrm{UAV} = \{\mathrm{UAV}_1, \mathrm{UAV}_2, \ldots, \mathrm{UAV}_m\}$. As the task planning forms of rotary wing UAV and fixed wing UAV are basically similar, this paper takes the rotary wing UAV as an example to show pictures. The allocation model shown in Figure 3 can be established based on whether the number of UAVs performing tasks m_1 and the number of tasks n are the same in the system of m UAVs.

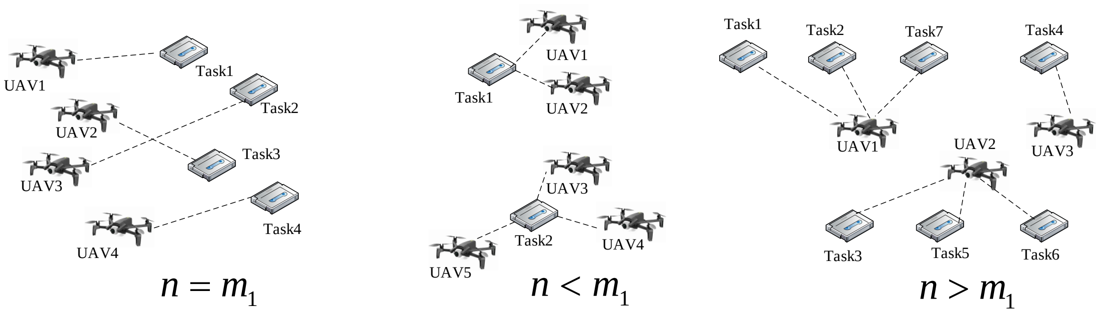

Figure 3. UAV task assignment model.

A. $n = m_1$ is a single task performed by a single UAV, and its model is:

$$x_{ij} = \begin{cases} 1 & \mathrm{Task_i \text{ is executed by } UAV_j} \\ 0 & \text{otherwise} \end{cases} \tag{1}$$

$n < m_1$ is a single task performed by multiple UAVs, and its model is:

$$x_{ij} = \{x_{ijs}, x_{ijt}\} = \begin{cases} 1 & \mathrm{Task_i \text{ is executed by } UAV_{js}, \ldots, UAV_{jt}} \\ 0 & \text{otherwise} \end{cases} \tag{2}$$

$n > m_1$ is a multi-task performed by a single UAV, and its model is:

$$x_{ij} = \{x_{ipj}, \ldots, x_{iqj}\} = \begin{cases} 1 & \mathrm{Task_{ip}, \ldots, Task_{iq} \text{ is executed sequentially by } UAV_j} \\ 0 & \text{otherwise} \end{cases} \tag{3}$$

Based on the above three formulas, a unified mathematical distribution model can be further established:

$$x_{\overline{ij}} = \begin{cases} x_{ij} & n = m_1 \\ x_{\bar{i}j} & n > m_1 \\ x_{i\bar{j}} & n < m_1 \end{cases} \tag{4}$$

Different allocation models have different cost matrices [13]. The following is the cost matrix corresponding to the above models.

When it is $n = m_1$, the cost matrix of single task performed by a single UAV is:

$$C_1 = \begin{pmatrix} c_{11} & \cdots & c_{1m} \\ \vdots & \ddots & \vdots \\ c_{n1} & \cdots & c_{nm} \end{pmatrix} \tag{5}$$

In the formula, C_1 is a square matrix, and C_{nm} represents the cost of task n completed by UAV m.

When it is $n < m_1$, the cost matrix of single task performed by multiple UAVs is:

$$C_3 = \begin{pmatrix} c_{11} & \cdots & c_{1m} \\ \vdots & \ddots & \vdots \\ c_{n1} & \cdots & c_{nm} \end{pmatrix} \tag{6}$$

In the formula, C_3 is a square matrix, and C_{nm} represents the cost of task n completed by UAV m.

When it is $n > m_1$, the cost matrix of multiple tasks performed by a single UAV is:

$$C_2 = \begin{pmatrix} G \\ H \end{pmatrix} = \begin{pmatrix} g_{11} & \cdots & g_{1m} \\ \vdots & \ddots & \vdots \\ g_{n1} & \cdots & g_{nm} \\ 0 & \cdots & h_{1m} \\ \vdots & \ddots & \vdots \\ h_{n1} & \cdots & 0 \end{pmatrix} \tag{7}$$

Among them, G represents the cost matrix between the UAV performing the task and the corresponding task, and g_{nm} represents the cost of task n completed by UAV m. H represents the cost matrix between tasks. $h_{i_1 i_2}$ represents the cost of UAV from task i_1 to task i_2.

In order to make the model clearer, the distance cost and the maximum flight time of the three models are obtained by Equations (8) and (9).

$$D = \begin{cases} \sum\limits_{i=1}^{n}\sum\limits_{j=1}^{m} d_{ij}x_{ij} & n = m_1 \\ \sum\limits_{i=1}^{n}\sum\limits_{u=1}^{n}\sum\limits_{j=1}^{m}\left(d_{ij}x_{\bar{i}j} + d_{iu}x_{\bar{i}j}\right) & n > m_1 \\ \sum\limits_{i=1}^{n}\sum\limits_{j=1}^{m} d_{ij}x_{i\bar{j}} & n < m_1 \end{cases} \tag{8}$$

$$T = \begin{cases} \max\{d_{ij}x_{ij}/v_j\} & n = m_1 \\ \max\left\{d_{ij}x_{\bar{i}j}/v_j + \sum\limits_{i=1}^{n}\sum\limits_{u=1}^{n} d_{iu}x_{\bar{i}j}/v_j\right\} & n > m_1 \\ \max\left\{d_{ij}x_{i\bar{j}}/v_j\right\} & n < m_1 \end{cases} \tag{9}$$

Among them, d_{ij} represents the flight distance of UAV_j to complete $Task_i$. v_j is the speed of UAV_j. d_{iu} represents the distance between $Task_i$ and $Task_u$.

The goal of task allocation is to minimize the global objective function, which can be expressed as follows:

$$Q = \min J \tag{10}$$

Among them, J can be obtained by Equation (11).

$$J = \begin{cases} \sum\limits_{i=1}^{n}\sum\limits_{j=1}^{m} c_{ij}x_{ij} & n = m_1 \\ \sum\limits_{i=1}^{n}\sum\limits_{u=1}^{n}\sum\limits_{j=1}^{m}\left(g_{ij}x_{\bar{i}j} + h_{iu}x_{\bar{i}j}\right) & n > m_1 \\ \sum\limits_{i=1}^{n}\sum\limits_{j=1}^{m} c_{ij}x_{i\bar{j}} & n < m_1 \end{cases} \tag{11}$$

(2) Track planning

Track planning is used to find the optimal track composed of an ordered sequence from the starting point to the target point when the specific boundary conditions and performance indicators in the planning space are fully considered. Its objective function can be expressed as:

$$F = \begin{cases} \min f(x) \\ s.t. x \in \Omega \end{cases} \tag{12}$$

Among them, $x = (x_1, x_2, \ldots, x_n)^T \in R$ represents the decision variable and $\Omega \subset R^n$ represents the constraint set; $f(x)$ represents the objective function.

Smoothness refers to whether the UAV can fly smoothly along the planned track. The track generated by conventional algorithm is basically formed by connecting the track points into a straight line, which can lead to discontinuity [14]. If this problem needs to be solved, the track has to be smoothed. The common processing methods include cubic spline interpolation, B-spline curve and Bezier curve.

Bezier curve is a polynomial curve fitted by a few control nodes [15]. If there are $n + 1$ control points with coordinate value of $p_i(i = 0, 1, \ldots, n)$, the parameter equation of each point on the n-order Bezier curve can be expressed as:

$$p(u) = \sum_{i=0}^{n} p_i B_{i,n}(u) \quad u \in [0, 1] \tag{13}$$

Among them, $B_{i,n}(u) = C_n^i u^i (1 - u)^{n-1}$, and $i = 0, 1, \ldots, n$. n refers to the n-times Bezier curves.

The k-order B-spline of $n + 1$ control nodes (x_0, y_0, z_0), (x_1, y_1, z_1),..., (x_n, y_n, z_n) in three-dimensional space is as follows:

$$\begin{cases} x(t) = \sum_{i=0}^{n} x_i \cdot B_{i,k}(t) \\ y(t) = \sum_{i=0}^{n} y_i \cdot B_{i,k}(t) \\ z(t) = \sum_{i=0}^{n} z_i \cdot B_{i,k}(t) \end{cases} \tag{14}$$

Among them, $0 \leq t \leq 1$ and $B_{i,k}(t)$ are k-times B-spline basis functions. When it is $i < k$, then $note_i = 0$; when $k \leq i < n$, then $note_i = i - k + 1$; when $n < i$, then $note_i = n - k + 2$, which can be expressed as:

$$B_{i,1}(t) = \begin{cases} 1, & note_i \leq t < note_{i+1} \\ 0, & \text{other} \end{cases} \tag{15}$$

$$B_{i,k}(t) = \frac{(t - note_i)B_{i,k-1}(t)}{note_{i+k-1} - note_i} + \frac{(note_{i+k} - t)B_{i+1,k-1}(t)}{note_{i+k} - note_{i+1}} \tag{16}$$

$n + 1$ nodes $a = x_0 < x_1 < \cdots < x_n = b$ are taken in the interval $[a, b]$. If $g(x)$ can be expressed as $g_i(x) = a_i + b_i x + c_i x^2 + d_i x^3, i = 0, 1, 2, \cdots, n - 1$ in each interval $[x_i, x_{i+1}]$, $g(x)$, $\hat{g}(x)$ and $\widetilde{g}(x)$ are continuous in the interval $[a, b]$ and meet the following conditions.

The $n + 1$ interpolation conditions are:

$$g(x_i) = y_i, i = 0, 1, 2, \ldots, n \tag{17}$$

$g(x_i)$ is continuous at the interpolation point:

$$g_-(x_i) = g_+(x_i), i = 1, 2, \ldots, n - 1 \tag{18}$$

At the interpolation point, the first and second derivatives of b are continuous:

$$\hat{g}_-(x_i) = \hat{g}_+(x_i), i = 1, 2, \ldots, n - 1 \tag{19}$$

$$\widetilde{g}_-(x_i) = \widetilde{g}_+(x_i), i = 1, 2, \ldots, n - 1 \tag{20}$$

Since there are $4n - 2$ equations from Equation (17) to Equation (20) and $4n$ unknowns to be solved, the first or second derivative value 0 of the two endpoints is usually added, which is:

$$\hat{g}(a) = \hat{g}(b) = 0 \tag{21}$$

(3) Evaluation of route planning

After the optimal track is obtained through model construction and algorithm operation, the track quality must be evaluated before it can be put to use. Generally, the constraint index function is constructed according to the track quality index, and then the track quality is evaluated again according to the value of the comprehensive constraint index function [16]. Figure 4 is the corresponding UAV track planning evaluation index chart, including flight time, track length, threat avoidance capability and track reliability. Track quality can be quantified using comprehensive constraint index function, which can be expressed as:

$$J = \text{argmax}\,\omega_1 J_1 + \omega_2 J_2 + \omega_3 J_3 + \omega_4 J_4 \tag{22}$$

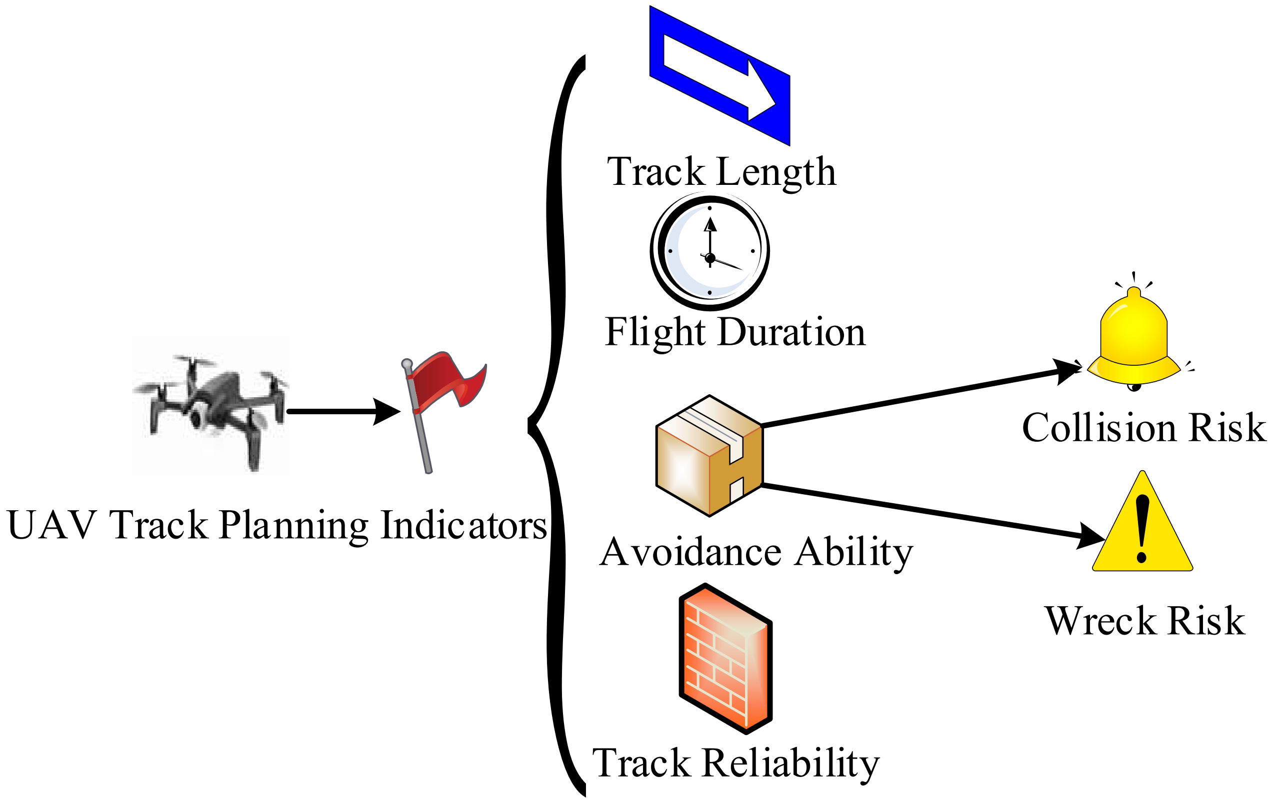

Figure 4. Evaluation index diagram of UAV track planning.

Among them, J is the comprehensive constraint index function, and $\omega_1 + \omega_2 + \omega_3 + \omega_4 = 1$ is the flight time, which is also the time required for the UAV to complete the task after the flight route planning.

Flight time refers to the time from the starting point to the destination. The flight time of UAV on the planned route shall be less than the set value because the smaller the value, the less fuel the UAV consumes and the higher the track quality.

The track length refers to the length from the starting point to the destination of the UAV. The planned route length shall be less than the maximum allowed flight. The shorter the search route length is, the less fuel the UAV consumes in flight, which can reduce the probability of encountering threats and improve the track quality.

Threat avoidance capability refers to the ability of UAVs to avoid threats such as mountains, hills and houses. The stronger the ability of UAV to avoid threats, the stronger the search track, which can reduce the possibility of re-planning and improve the track quality [17].

Track reliability refers to the possibility of safe flight plan route of UAV under space and time constraints. The higher the reliability of the route, the less likely the UAV is to be destroyed when confronted with threats and the higher the track quality.

5. Experimental Results of Task Planning Method Combined with Multi-Objective Optimization Algorithm

In order to verify the effectiveness of the new UAV mission planning method, the flight mission was tested in the MATLAB 2016b simulation platform with an area of 500 m $\times$ 500 m. First, the distance, time and task completion degree of a single UAV were tested in a fixed task. Mission planning methods are divided into traditional methods and new methods. Threat factors are set in the flight area and the type of UAV is a consumer class 4-axis UAV. The normal flight speed of the UAV is 60 km/h. The test results are shown in Table 1.

Table 1. Travel distance, time and task completion degree of the UAV under two mission planning methods.

Project	Traditional Method	New Method
Distance spent	238 m	199 m
Time spent	14.28 s	11.94 s
Task completion	96.4%	98.7%

From the data in Table 1, it can be concluded that under the two task planning methods, there is a significant gap in the distance, time and task completion of the UAV. Under the same task, the distance of the traditional method is nearly 40 m higher than that of the new method, and it takes more than 2 s compared to the new method. However, the task completion under the traditional method is not as high as that under the new method. These three types of data clearly show that the task completion efficiency under the new method is better.

Track planning is mentioned in the analysis of UAV mission planning methods, which is the core of mission execution. The selection of an optimal track plays a decisive role in the completion of the UAV mission. The shorter the length of the optimal track, the higher the flight efficiency of the UAV. The traditional method is defined as Method A, and the method in this paper is defined as Method B. The optimal path planning length of five flight missions under the two methods is tested, and the test results are shown in Figure 5.

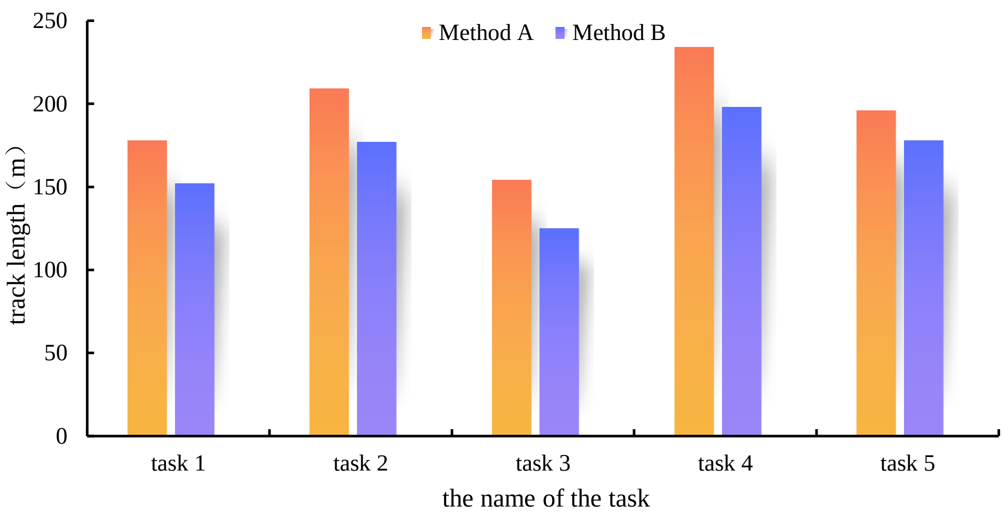

Figure 5. Optimal flight path planning lengths for five flight missions under two methods.

It is easy to see from the histogram in Figure 5 that the optimal path planning length under method B is shorter than that under method A in the five flight missions. Among them, the planning length gap of task 5 is the smallest, and that of task 4 is the largest. When the track length of Task 4 is planned, the length planned by Method A exceeds 200 m, and the length planned by Method B is still below 200 m. These results show that the optimal track planned in this paper is shorter than that planned by traditional methods, and it can provide the shortest and optimal path for UAV mission execution.

Generally, before performing UAV tasks, the UAV operators need to check and evaluate the route planning. Figure 6 shows the ratings given by operators for the route planning under the two methods, the flight missions of which are still the five missions mentioned above. The traditional method refers to the route planning method without specific optimization algorithm.

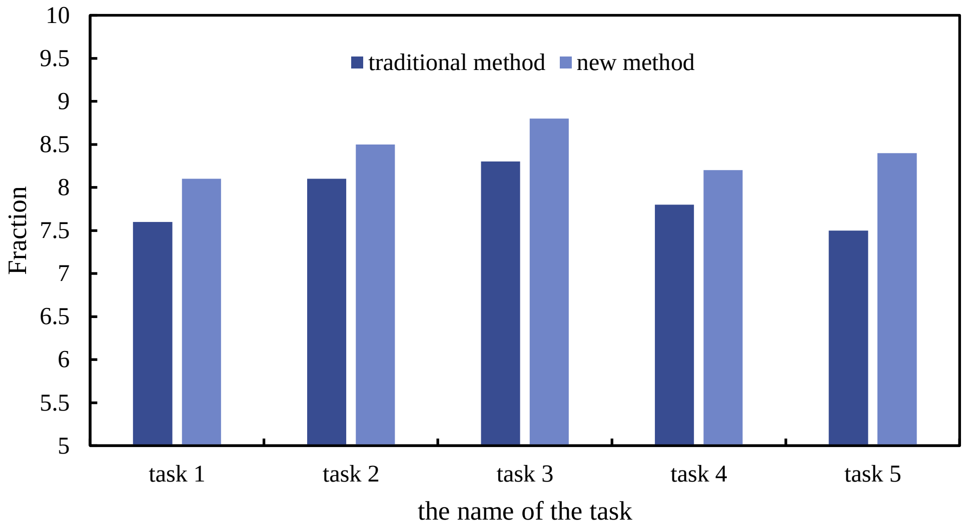

Figure 6. The scores of the UAV operators on the trajectory planning under the two methods.

It can be seen from Figure 6 that the UAV operators are very strict in their assessment and scoring of the route planning, and the scores are basically below 9 points. The score of route planning under the new method is higher than that under the traditional method in the five missions. In the route planning of Task 3, both methods get the highest score: the traditional method is more than 8 points, while the new method is more than 8.5 points. These scoring results can reflect that the quality of route planning under the new method is better than that of the traditional method.

In this paper, multi-objective optimization algorithm is applied to UAV mission planning to improve the efficiency of mission planning. For the specific effect, the time of UAV task planning is tested under the two algorithms. The specific flight tasks are the five tasks mentioned above, and the test results are shown in Figure 7.

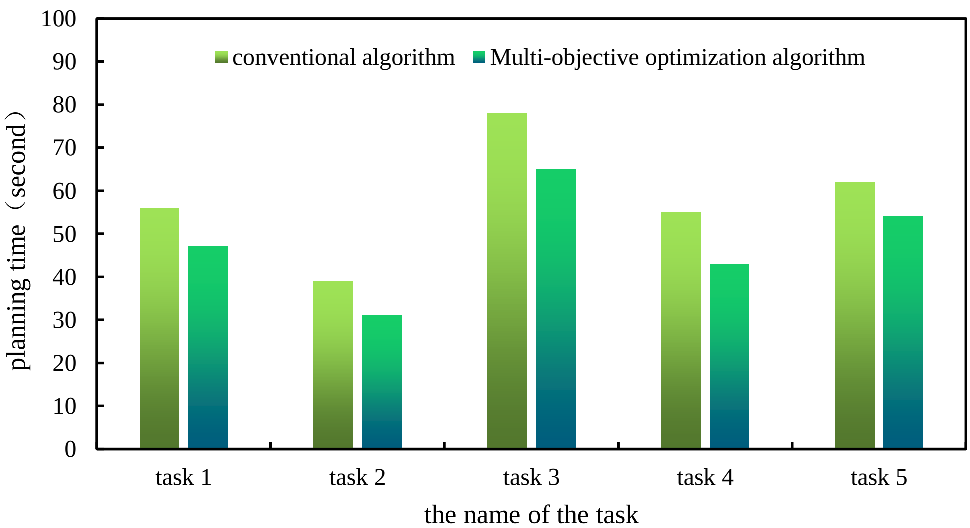

Figure 7. Time spent in UAV mission planning under the two algorithms.

It can be seen that in the five tasks, the time spent for UAV task planning under the two algorithms is very different. As far as the planning of task 3 is concerned, it takes a lot of time under both algorithms. The conventional algorithm takes more than 70 s, while the multi-objective optimization algorithm takes more than 60 s. In general, in each task, the task planning under the multi-objective optimization algorithm takes less time than the conventional algorithm, which also shows that the task planning method combined with the multi-objective optimization algorithm is more efficient.

After the flight mission, there is a satisfaction survey of completion. In this paper, 20 conventional tasks are selected to be executed by UAVs in turn, and their satisfaction with the completion of tasks is investigated. Task planning routes include those under conventional algorithms and those under multi-objective optimization algorithms. The results of the survey are shown in Figure 8.

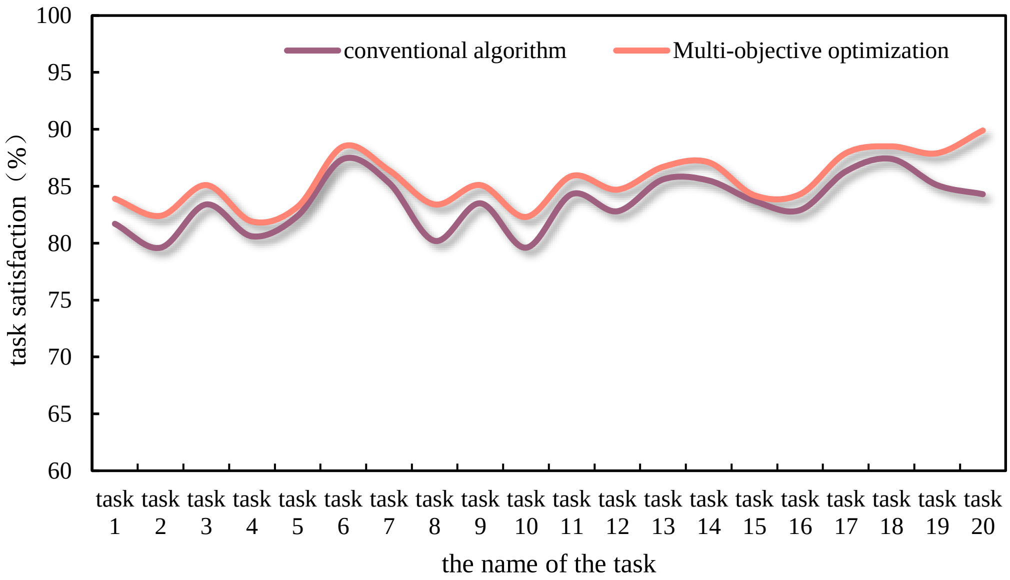

Figure 8. Satisfaction of UAV task completion under two algorithms.

It can be seen that the satisfaction of each task is different based on whether the task planning route is conducted under the conventional algorithm or the multi-objective optimization algorithm. Generally, it shows a fluctuating trend, because each task has a different number of tasks. In contrast, the satisfaction of multi-objective optimization algorithm in each task is higher than that of conventional algorithm, and the overall satisfaction is 2.26% higher.

6. Discussion

In recent years, the path planning algorithm of UAV has become increasingly intelligent and complex. The manual planning on paper maps has gradually changed to computer-based planning using digital maps. For different threat environments, finding the corresponding route planning algorithm is the focus of future UAV route planning. The traditional UAV trajectory planning method is only a method to avoid dangerous spaces in theory, which is mainly based on the completion of tasks. However, considering the limitations of UAV, the existing planning methods are no longer applicable. In this regard, future research must also take into account the physical constraints of the UAV itself in route planning, and plan accurate, short-time flights that meet all constraints. Finally, the existing UAV route planning algorithms are mainly concentrated on a single UAV. In the joint military and multi task areas, more research and resources need to be invested to extend the route planning method to the joint planning field involving multiple UAVs.

7. Conclusions

With the progress of technology, the application field of UAV has become increasingly extensive and mature. When a UAV executes flight mission, task allocation and route planning are the fundamental preconditions to complete the mission successfully. At present, the traditional task planning methods and path search algorithms are too outdated to keep up with the technological developments, resulting in low efficiency of task planning, which hinders the successful completion of tasks. Multi-objective optimization algorithm is the product of intelligent technology and information technology. Its application in UAV intelligent planning modeling and path optimization is conducive to promoting the development of and research into UAVs.

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References

1. Baldi, S. An underactuated control system design for adaptive autopilot of fixed-wing drones. *IEEE/ASME Trans. Mechatron.* **2022**, *27*, 4045–4056. [CrossRef]
2. Wang, X. The problem of reliable design of vector-field path following in the presence of uncertain course dynamics. *IFAC-Pap. Online* **2020**, *53*, 9399–9404. [CrossRef]
3. Baldi, S.; Spandan, R.; Kang, Y. Towards adaptive autopilots for fixed-wing unmanned aerial vehicles. In Proceedings of the 2020 59th IEEE Conference on Decision and Control (CDC), Jeju Island, Republic of Korea, 14–18 December 2020.
4. Wang, X. Adaptive Vector Field Guidance Without a Priori Knowledge of Course Dynamics and Wind. *IEEE/ASME Trans. Mechatron.* **2022**, *27*, 4597–4607. [CrossRef]
5. Zhou, D.; Wang, P.; Li, X. Cooperative path planning of multi-UAV based on multi-objective optimization algorithm. *Syst. Eng. Electron.* **2017**, *39*, 782–787.
6. Ruan, W.Y.; Duan, H.B. Multi-UAV obstacle avoidance control via multi-objective social learning pigeon-inspired optimization. *Front. Inf. Technol. Electron. Eng.* **2020**, *21*, 740–748. [CrossRef]
7. Yan, F. Gauss interference ant colony algorithm-based optimization of UAV mission planning. *J. Supercomput.* **2020**, *76*, 1170–1179. [CrossRef]
8. Tseng, F.H.; Lee, C.H.; Chou, L.D. Multi-Objective Genetic Algorithm for Civil UAV Path Planning Using 3G Communication Networks. *J. Comput.* **2017**, *28*, 26–37.
9. Yang, F.; Chen, Z. Multi-objective aerodynamic optimization using active multi-output Gaussian process and mesh deformation method. *J. Aerosp. Eng.* **2022**, *236*, 767–776. [CrossRef]
10. Wei, M.; Sun, B.; Wu, W. A multiple objective optimization model for aircraft arrival and departure scheduling on multiple runways. *Math. Biosci. Eng.* **2020**, *17*, 5545–5560. [CrossRef]
11. Zhou, W.; Bai, J.; Qiao, L. A Study of Multi-Objective Aerodynamic Optimization Design for Variable Camber Airfoils and High Lift Devices. *J. Northwest. Polytech. Univ.* **2018**, *36*, 83–90. [CrossRef]
12. Baik, H.; Valenzuela, J. An optimization drone routing model for inspecting wind farms. *Soft Comput.* **2021**, *25*, 2483–2498. [CrossRef]
13. Galiautdinov, R. The Math Model of Drone Behavior in the Hive, Providing Algorithmic Architecture. *Int. J. Softw. Sci. Comput. Intell.* **2020**, *12*, 15–33. [CrossRef]
14. Shi, L.; Ahmad, I.; He, Y.; Chang, K. Hidden Markov model based drone sound recognition using MFCC technique in practical noisy environments. *J. Commun. Netw.* **2018**, *20*, 509–518. [CrossRef]
15. Jung, Y.B.; Park, E.S.; Cho, S.J. Estimation of Volume Variation in Snow Stockpile for Olympic Winter Games in PyeongChang using Snow Melting Model and Drone based Areal Mapping. *J. Korean Soc. Miner. Energy Resour. Eng.* **2017**, *54*, 679–689. [CrossRef]
16. Alpdemir, M.N. Tactical UAV path optimization under radar threat using deep reinforcement learning. *Neural Comput. Appl.* **2022**, *34*, 5649–5664. [CrossRef]
17. Brust, M.R.; Danoy, G.; Stolfi, D.H.; Bouvry, P. Swarm-based counter UAV defense system. *Discov. Internet Things* **2021**, *1*, 2. [CrossRef]