

A Review of Motion Planning Algorithms for Multi-UAV Formation: State-of-art and Future Perspectives

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Abstract. With advancements in artificial intelligence, sensor technology, and communication networks, Unmanned Aerial Vehicles (UAVs) have evolved from isolated units to highly collaborative swarm systems. Inspired by collective behaviors in nature, such as bird flocks and fish schools, UAV swarms exhibit superior performance in task efficiency, robustness, operational flexibility, and adaptability compared to single UAVs. Formation flight, a core technique in UAV swarm collaboration, involves maintaining specific geometric configurations crucial for area coverage, cooperative detection, data acquisition, and saturation attacks. This paper provides a comprehensive review of motion planning algorithms for multi-UAV formation, systematically summarizing traditional control methods, optimization-based approaches, and AI-driven algorithms. We analyze the current research status, highlight key application scenarios, identify existing challenges, and offer perspectives for future research directions. The review finds that while traditional algorithms are computationally efficient and well-suited for structured tasks, their performance deteriorates in dynamic, multi-agent environments. AI-based methods demonstrate better adaptability but suffer from interpretability and scalability issues. Bio-inspired algorithms are strong in global optimization but may face convergence delays and require hybridization for complex missions. We conclude that future research should focus on building robust, explainable, and scalable motion planning frameworks that can adapt to the evolving requirements of autonomous aerial systems. In particular, the integration of model-based and learning-based methods, development of communication-aware collaborative frameworks, and exploration of explainable AI mechanisms for decision transparency are expected to significantly enhance the autonomy, resilience, and applicability of multi-UAV formation systems in increasingly complex operational scenarios.

Keywords: Unmanned Aerial Vehicle (UAV) swarm, formation flight, motion planning, path planning, multi-agent systems, artificial intelligence, bio-inspired algorithms, review

1. Introduction

With advancements in artificial intelligence, sensor technology, and communication networks, Unmanned Aerial Vehicles (UAVs) have evolved from isolated units to highly collaborative swarm systems [1, 2]. Inspired by collective behaviors in nature, such as bird flocks and fish schools, UAV swarms exhibit superior performance in task efficiency, robustness, operational flexibility, and adaptability compared to single UAVs [3]. Formation flight, a core technique in UAV swarm collaboration, involves maintaining specific geometric configurations crucial for area coverage, cooperative detection, data acquisition, and saturation attacks [4-6].

Research on UAV swarm formation planning holds both significant theoretical value and strategic importance. Theoretically, it integrates control theory, artificial intelligence, graph theory, and optimization theory, driving advancements in multi-agent system (MAS) control [7, 8]. Strategically, UAV swarm technology promises transformative impacts on defense and national security, and substantial civilian applications in smart agriculture, emergency response, environmental monitoring, and logistics, thereby driving economic growth and enhancing productivity [9, 10].

This review systematically summarizes UAV swarm formation planning algorithms, covering traditional control methods, optimization-based approaches, and AI-driven algorithms. It analyzes current research status, highlights key application scenarios, identifies existing challenges, and offers perspectives for future research directions [8]. This aims to provide a comprehensive reference for advancing the field of UAV swarm technologies. Among them, RRT algorithm aPF algorithm and their new variants have been widely used in the field of multi-UAV trajectory planning.

2. Motion planning algorithms for multi-UAV formation

Currently, there are two primary classification methods of multi-UAV formation planning algorithms: one is based on the planning range and information acquisition, and the other is divided into global trajectory planning algorithms and local trajectory planning algorithms. The other is based on the algorithm's principle and implementation technology, and the algorithms are divided into traditional algorithms, artificial intelligence algorithms, and bio-inspired optimization algorithms [2]. In this paper, both methods are considered. While using the second classification method to write subtitles, each algorithm will also explain which category it belongs to under the first classification method. Figure 1 shows the detailed classification methods and the mainstream representative algorithms of different methods.

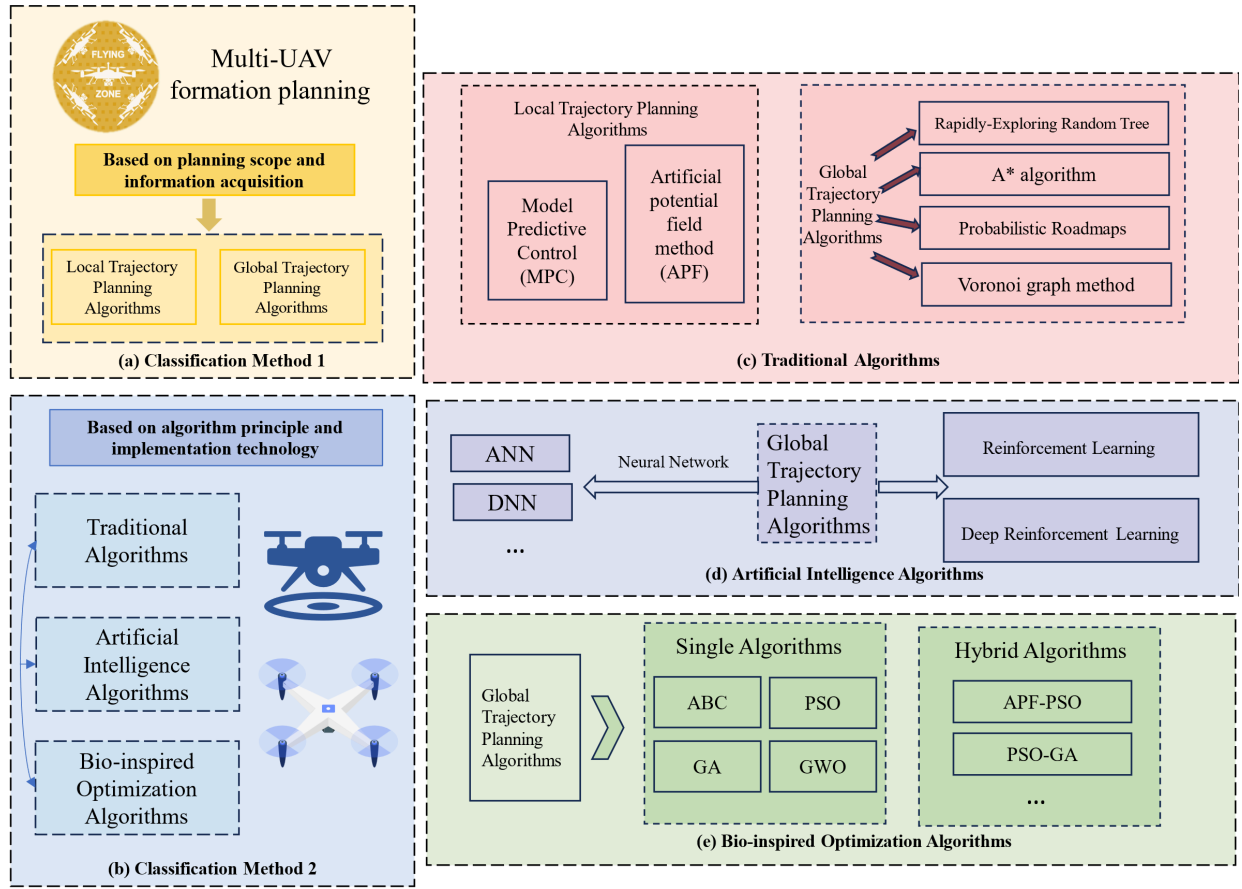


Figure 1. Two classification methods and the representative algorithms of different categories

In this section, multi-UAV formation planning algorithms are classified into three categories:

2.1. Traditional algorithms

Traditional algorithms rely on accurate environmental mathematical models (such, grid maps, topology maps, or potential field functions) to generate paths through analytical or iterative calculations. The existing algorithms mainly include A* algorithm, Model Predictive Control (MPC) method, Rapidly-Exploring Random Tree (RRT), Voronoi graph method, Probabilistic Roadmaps (PRM), and Artificial Potential Field (APF) method. Among them, the RRT algorithm, the APF algorithm, and their new variants have been widely used in motion planning for multi-UAV formation.

2.1.1. Rapidly-Exploring Random Tree (RRT)

Rapidly-Exploring Random Tree (RRT) is a global trajectory planning algorithm based on incremental sampling. It was proposed by Steven M. LaValle in 1998 to efficiently solve the motion planning problem in high-dimensional space [11]. Its core idea is to find a feasible path from the starting point x_{init} to the target point x_{goal} by randomly sampling in the state space $\mathcal{M}$ and expanding the search tree. The core steps are as follows: First, initialize the search tree T and set the starting point x_{init} join the tree. Then entering the loop, from the state space $\mathcal{M}$ random sampling to get points x_{rand} . After that, find the node x_{near} closest to x_{rand} in tree T . Euclidean distance is often

used to measure distance $d(x_{\text{rand}}, x_{\text{near}}) = \sqrt{(x_{\text{rand},x} - x_{\text{near},x})^2 + (x_{\text{rand},y} - x_{\text{near},y})^2}$. Then, along the direction from x_{near} to x_{rand} , a new node x_{new} is generated with a fixed step size 'StepSize'. The calculation formula is:

$$x_{\text{new}} = x_{\text{near}} + \text{StepSize} \cdot \frac{x_{\text{rand}} - x_{\text{near}}}{\|x_{\text{rand}} - x_{\text{near}}\|} \quad (1)$$

Then, detect whether the edges between the new node and the nearest node collide. If there is no collision, x_{new} and the corresponding edges are added to the tree T ; when x_{new} reaches the target point x_{goal} or reaches the maximum number of iterations, the algorithm terminates, and the path Γ can be obtained by backtracking the nodes in the tree [12].

The RRT algorithm has been extended from stand-alone applications to the field of multi-UAV collaborative planning. In the cluster scenario, generating conflict-free paths is a core challenge. Kothari et al. [13] proposed a solution in an environment with dense obstacles and limited time windows. Chen et al. [14] proposed the RRT-Forest algorithm, which is planned in a higher-dimensional configuration space to achieve closer collaboration of UAV clusters. In addition, in order to make the generated path conform to the physical characteristics of the UAV, the researchers directly integrate the kinematic and dynamic constraints of the UAV into the RRT expansion process to ensure the feasibility of the generated path.

2.1.2. Artificial potential field method (APF)

Artificial Potential Field (APF) is a classical local trajectory planning method [11]. Its core idea is to compare the motion of a UAV in the environment to the motion of particles in physics [15]. The whole environment is modelled as a composite potential field, which is composed of the attractive field generated by the target point and the repulsive field generated by the obstacle. Under the action of the resultant force generated by the potential field gradient, the UAV moves from the high potential energy region to the low potential energy region, and finally reaches the lowest point of potential energy, that is, the target position.

The APF method has been widely used in formation control and cooperative obstacle avoidance of UAV clusters due to its advantages of low computational complexity and strong real-time performance. In the potential field control model based on the 'leader-follower' architecture, the motion planning of the leader UAV is mainly driven by the superposition of the target point's gravitational field and the obstacle's repulsive field [16]. The control strategy of the follower UAV is more complex. In addition to the above basic potential field, the guidance potential field generated by the leader UAV and the cooperative potential field generated by other follower UAVs need to be introduced to achieve the precise maintenance of the preset formation. By constructing a nonlinear repulsive force function based on relative distance, the minimum safe distance between UAVs in the cluster can be effectively ensured, and the collision risk can be avoided while maintaining a stable formation configuration.

APF algorithm is efficient and straightforward, but as a heuristic algorithm, it is difficult to avoid the possibility of falling into a local minimum. If the target point is within the obstacle's influence range, the strong repulsion will prevent the UAV from reaching the end point. Ma et al. [17] proposed a Deflected Simulated Annealing-Adaptive Artificial Potential Field (DSA-AAPF) method that combines deflected simulated annealing. By introducing the momentum term to smooth the trajectory, the adaptive gain function is designed to dynamically adjust the speed, and the deflected simulated annealing mechanism is used to apply continuous rotation force, so that the UAV can

escape from the local minimum trap with a smooth arc path. The traditional APF algorithm completely falls into the local minimum point in the face of semi-closed obstacles, while DSA-AAPF can successfully escape and plan an efficient path.

2.2. Artificial intelligence algorithms

The artificial intelligence algorithm mainly simulates and implements human learning behavior, transforms the UAV formation trajectory planning problem into a decision-making problem, and learns complex patterns and strategies from massive data using continuous learning and interaction in a complex environment. With the rapid development of multi-agent algorithms, artificial intelligence algorithms have been gradually applied in UAV formation trajectory planning to deal with the dynamic environment full of uncertainty, which traditional algorithms find challenging. At present, artificial intelligence algorithms applied to UAV formation trajectory planning include neural network (NN) algorithms, reinforcement learning (RL) algorithms, and deep reinforcement learning (DRL) algorithms.

2.2.1. Neural network

The neural network (NN) algorithm belongs to the global planning algorithm. Based on the information obtained by each UAV sensor, this algorithm can quickly generate the action instructions that the UAV should perform. The algorithm simulates the control and feedback mechanism of the human brain through a complex network structure composed of many nonlinear units. It forms a nonlinear mapping system between the state and action spaces. With their powerful learning ability and fast planning ability, neural networks can effectively complete the trajectory planning task of UAV formation.

J et al. [18] proposed a trajectory optimization method based on a deep neural network (DNN). This significantly improves the efficiency and accuracy of UAV path planning through the Adam optimization algorithm and provides a new idea for intelligent navigation in complex scenes.

Godio et al. [19] proposed a method to solve the coverage path planning (CPP) problem of artificial intelligence-driven UAV swarms. They rely on the hybrid use of a decentralized artificial neural network (ANN) and an A* path search algorithm, taking into account congestion, collision avoidance, and path efficiency. This allows UAVs to perceive the environment and learn the reproduction strategy to provide support for complex scene planning.

2.2.2. Reinforcement learning and deep reinforcement learning

Reinforcement Learning (RL) is a machine learning paradigm that learns by trial and error. Its theoretical basis is Markov Decision Process (MDP), and the core elements include: Agent, Environment, State, Action and Reward. The goal of the agent is to learn a policy $\pi(a | s)$ through interaction with the environment to maximize the expected cumulative reward, that is reward $G_t = \sum_{k=0}^{\infty} \gamma^k R_{t+k+1}$, obtained during task execution. The core of RL is the evaluation of the value function. The state value function $V^{\pi}(s)$ and the action value function $Q^{\pi}(s, a)$ represent the expected return that can be obtained from the state S or after the state S performs the action a under the strategy π . They follow the Bellman expectation equation:

$$Q^{\pi}(s, a) = \mathbb{E}_{\pi} [R_{t+1} + \gamma Q^{\pi}(S_{t+1}, A_{t+1}) | S_t = s, A_t = a] \quad (2)$$

Deep reinforcement learning (DRL) is a combination of RL and deep learning, which uses deep neural network (DNN) as a function approximator to approximate the value function or strategy function. For example, the deep Q network (DQN) uses a neural network with a parameter of θ to estimate the optimal action value function $Q^*(s, a) \approx Q(s, a; \theta)$. It updates the network parameters by minimizing the loss function:

$$L(\theta) = \mathbb{E} \left[(y_i - Q(s, a; \theta))^2 \right] \quad (3)$$

$$y_i = r + \gamma \max_{a'} Q(s', a'; \theta^-) \quad (4)$$

Here, θ^- is a parameter of the target network for stable training. The policy gradient method directly parametrizes the policy $\pi_\theta(a | s)$ and updates the parameters along the direction that increases the expected return $J(\theta)$:

$$\nabla_\theta J(\theta) = \mathbb{E}_{\pi_\theta} [\nabla_\theta \log \pi_\theta(a | s) Q^{\pi_\theta}(s, a)] \quad (5)$$

This solves the 'dimensional disaster' problem faced by traditional RL in dealing with high-dimensional, continuous state and action space [20]. Figure 2 shows the structure of DRL in Multi-UAV formation.

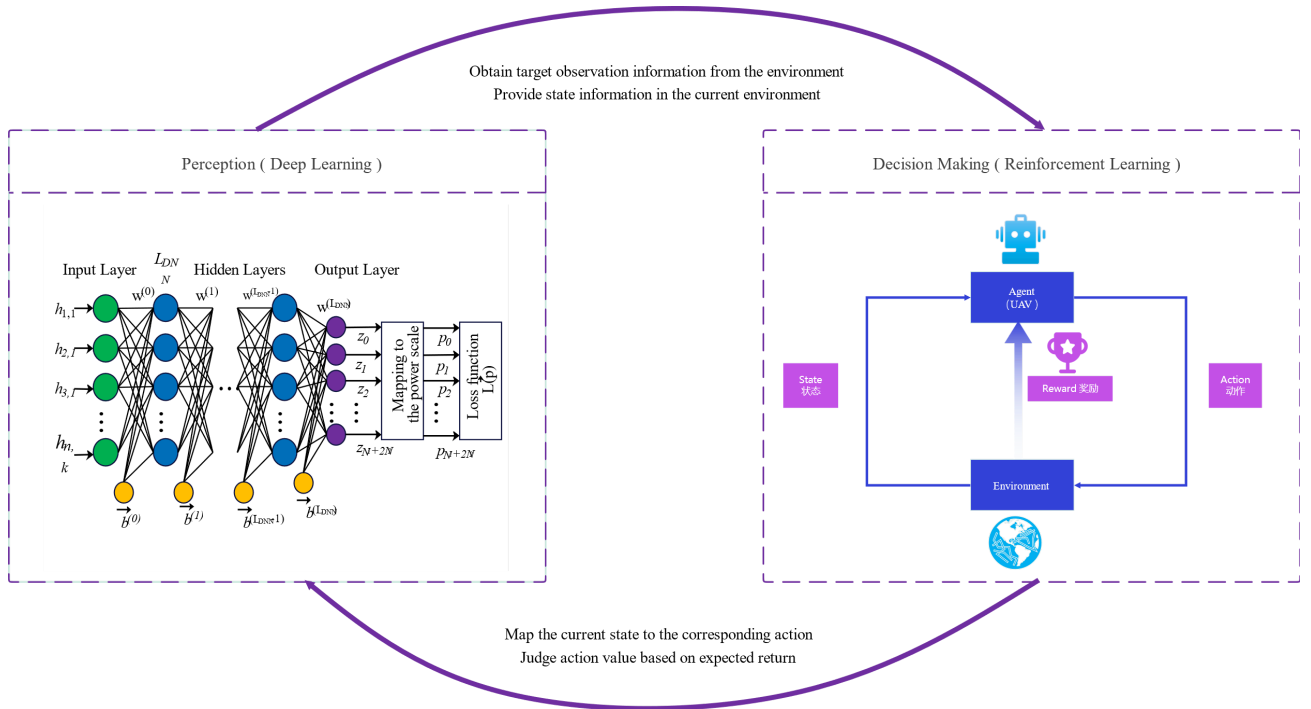


Figure 2. The structure of deep reinforcement learning

Wang et al. [21] proposed an autonomous navigation algorithm for UAVs based on deep reinforcement learning, which aims to improve the autonomous navigation ability of UAVs and reduce the computational complexity.

Gui et al. [22] proposed a multi-UAV mobile edge computing framework based on deep Q-learning, which optimizes quality of service (QoS) and routing planning through reinforcement learning, and provides an innovative solution for multi-UAV cooperative navigation.

2.3. Bio-inspired optimization algorithms

Bionic algorithm provides an innovative solution for UAV swarm motion planning by imitating natural organisms' behavior and evolution mechanism. This algorithm mainly draws on the collective intelligence and self-organizing behavior of biological groups such as bees, birds, and ants. It solves the path planning problem in complex environments by simulating biological evolution, group search, and collaborative behavior. The existing bionic algorithms mainly include Artificial Bee Colony (ABC), Particle Swarm Optimization (PSO), Genetic Algorithm (GA), Grey Wolf Optimization algorithm (GWO), and hybrid algorithms of multiple fusion strategies.

2.3.1. Artificial Bee Colony (ABC)

The Artificial Bee Colony (ABC) algorithm belongs to the global planning algorithm. The algorithm constructs an efficient swarm intelligence optimization mechanism by simulating the swarm behavior of bees foraging and information sharing. The artificial bee colony algorithm divides the whole bee colony into three categories: scout bees, employed bees, and onlooker bees. The employed bees are responsible for exploring the solution space around the current optimal solution, the scout bees randomly search for new possible solutions, and the follower bees select the most promising solution for further optimization based on the information provided by the employed bees. In this way, by simulating the cooperative search strategy of scout bees, the worker bees, and the follower bees, the location information is constantly updated and optimized to approximate the optimal path, and the rapid search of the global optimal solution is realized in the complex UAV path planning environment.

Erkin et al. [23] proposed an improved multi-swarm artificial bee colony (ABC) algorithm, which significantly improves the path planning performance of UAV and uncrewed combat aerial vehicle (UCAV) in hostile environments by modifying the observation bee stage and using multi-processor core parallel computing. The experimental comparison shows that the algorithm is superior to other meta-heuristic methods in dealing with threats, fuel consumption, and other constraints.

Shi et al. [24] proposed a multi-UAV path planning method based on an improved balanced artificial bee colony (IB-ABC) algorithm. By introducing a single-element point, a multi-element point, and an iterative constraint mechanism to optimize the bee colony behavior strategy, multi-objective path planning is realized in a complex mountain environment, significantly improving the algorithm's global and local search balance and convergence speed.

2.3.2. Particle Swarm Optimization (PSO)

The PSO algorithm's basic principle is derived from observing animal group behavior. Each 'particle' in the algorithm represents a potential solution in the solution space, with two key attributes of position and velocity. The core idea of the algorithm is to continuously update the position and speed of the particles by simulating the information interaction between individuals in the group and their experience learning, and finally converge to the optimal solution.

Fu et al. proposed a hybrid algorithm of Artificial Potential Field and Particle Swarm Optimization (APF-PSO) that combines artificial potential field and an adaptive mechanism. Through dynamic inertia weight adjustment and virtual force field constraint, the success rate of the multi-UAV system in the pollution source localization task is significantly improved (experiments show that the SR reaches 100 % when 10 UAVs are used). The search efficiency (the average path length is reduced by 45 % compared with the traditional PSO), and a real-machine verification

platform including VANET communication is constructed to verify the algorithm's feasibility in the real environment [25].

3. Conclusion

3.1. Summary

Multi-UAV formation motion planning is one of the core issues in the field of UAV cooperative control. Its goal is to plan an efficient and feasible flight path for multiple UAVs to ensure formation and safety. This paper systematically reviews the main multi-UAV formation motion planning algorithms, including traditional path planning methods, optimization-based bionic algorithms, and intelligent algorithms that have developed rapidly in recent years. The advantages and disadvantages of various methods and applicable scenarios are comprehensively evaluated. It has been found that traditional algorithms such as RRT and artificial potential field methods have the advantages of simple calculation and high efficiency, and they are suitable for path planning in static or regular environments. However, their performance in dynamic obstacles and multi-agent coordination is limited, and falling into a local optimum is easy. Bionic optimization algorithms, such as particle swarm optimization, artificial bee colony, and grey wolf optimization, improve the global search ability and multi-objective adaptability of planning by simulating the swarm intelligence of natural organisms. However, there is still room for improvement in convergence speed and algorithm stability. In recent years, with the improvement of computing power and sensing technology, intelligent methods such as deep learning and reinforcement learning have shown good adaptive and real-time advantages in path planning and formation control. However, due to the complexity and training dependence of the algorithm, the actual deployment still faces the challenges of insufficient interpretability and security guarantees.

This review highlights the dual value of multi-UAV system motion planning in theory and application. Multi-UAV formation technology promotes integrating and developing automatic control, optimization algorithms, and communication technology. It provides strong technical support for intelligent agriculture, environmental monitoring, emergency response, national defense security, and other fields. Especially in complex and changeable situations, the key to improving the system's overall efficiency is to realize efficient coordination and safe and stable flight between multiple UAVs.

However, the current field still faces many challenges that must be solved urgently. Firstly, how to realize robust and real-time path planning under the conditions of dynamic environment change, sensor uncertainty, and sudden task change is the basis for ensuring the safe and reliable operation of the UAV system. Secondly, a large-scale heterogeneous UAV swarm's communication, coordination, and distributed control strategy is not yet mature. How to deal with the interoperability and information delay of diversified platforms and ensure the coordination and stability of the overall formation is a technical bottleneck. Thirdly, despite the outstanding performance of intelligent algorithms, their black-box characteristics limit their wide application in security-critical scenarios, and improving the transparency and verifiability of algorithms has become an inevitable trend. Finally, the design and integration of hybrid methods are insufficient, and there is a lack of a unified framework that can consider global planning and local response, affecting the system's flexibility and adaptability.

3.2. Future research directions

Hybrid algorithm and real-time optimization: Develop a hybrid algorithm that combines traditional planning advantages and intelligent learning capabilities, ensuring computational efficiency and improving adaptability to complex environments. For example, environmental awareness and intelligent optimization strategies are introduced to improve the traditional algorithm to re-plan in a dynamic environment in real time to cope with sudden obstacles and task changes.

Large-scale heterogeneous cluster collaboration: A communication-aware distributed collaboration mechanism supporting large-scale heterogeneous UAV clusters is constructed to realize dynamic scheduling and collaboration of multi-platform and multi-task. In the future, efficient distributed decision-making algorithms and network architecture must be studied to solve the problems of communication delay and interoperability between heterogeneous platforms to ensure that the formation can still perform tasks stably and co-ordinately when the number of UAVs increases and the types are diversified.

Algorithm interpretability and security verification: Strengthen the algorithm's interpretability research and improve the transparency and security of the decision-making process. For black box models such as deep learning/reinforcement learning, the visualization and formal verification methods of decision logic are explored, and the training and control framework under security constraints is established to meet the reliability requirements of high-risk applications.

Real environment verification and engineering application: focus on the verification and application of the algorithm in the real environment

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