

Distributed Trajectory Planning and Conflict Resolution Strategies in Multi-UAV Cooperative Tasks Research on Path Planning of Multiple Unmanned Aerial Vehicles in Cooperative Search

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Abstract: *Aiming at the problems of low efficiency and insufficient conflict resolution ability existing in distributed trajectory planning in multi-UAV cooperative tasks, this paper systematically analyzes the characteristics and current situation of distributed trajectory planning, and focuses on the study of conflict resolution strategies. Firstly, the concept of distributed trajectory planning was defined, and its advantages and challenges in multi-UAV missions were analyzed; Subsequently, the current problems such as high computational complexity, limited communication, imperfect conflict detection and poor environmental adaptability were pointed out. On this basis, conflict detection technology based on geometric and probabilistic models, as well as conflict resolution strategies based on rules, optimization algorithms and learning, were proposed. The effectiveness of the strategies was verified in combination with disaster rescue cases. Research shows that the proposed strategy can reduce the conflict rate by more than 30%, improve the efficiency of task completion, and provide theoretical support and technical reference for the safe and efficient execution of multi-UAV collaborative tasks.*

Keywords: Multiple unmanned aircraft Distributed trajectory Conflict resolution.

1. INTRODUCTION

In recent years, unmanned aerial vehicle (UAV) technology has achieved leapfrog development. Its application has rapidly expanded from the initial military field to all aspects of the civilian sector, such as large-scale logistics distribution, smart city security patrols, precision agriculture plant protection, wide-area geographic mapping, and emergency disaster relief. In these increasingly complex application scenarios, a single unmanned aerial vehicle (UAV) is often constrained by its limited payload, endurance and mission execution capabilities, and thus finds it difficult to independently complete the assigned tasks. Therefore, by forming a collaborative system with multiple drones to leverage the advantages of swarm intelligence and achieve parallel task execution and complementary capabilities, it has become the mainstream direction of drone technology development. Distributed trajectory planning has become a research hotspot in both the academic and industrial fields at present. While the autonomy of distributed decision-making brings flexibility, it also introduces the inevitable risk of trajectory conflicts. Since each unmanned aerial vehicle (UAV) only has a local field of vision and cannot obtain global information, the optimal trajectory independently planned by it is very likely to overlap with the trajectories of other UAVs in space and time in the intersection area, that is, conflicts will arise. If these conflicts cannot be resolved in a timely and effective manner, they may lead to the interruption of tasks at best and trigger collisions at worst, resulting in serious consequences. Therefore, researching efficient and reliable distributed conflict resolution strategies is a core technical challenge that must be overcome to ensure the safe and efficient operation of multi-UAV systems. Existing research has made certain progress in conflict resolution, such as negotiation-based algorithms, potential field-based methods, and various reactive collision avoidance rules, etc. However, these methods either have problems such as high communication overhead and low negotiation efficiency, or are difficult to provide strict security guarantees in complex dynamic environments, or sacrifice too much task performance when resolving conflicts. In view of this, this paper aims to systematically analyze the inherent characteristics and existing problems of distributed trajectory planning, and specifically design a hierarchical conflict resolution framework that integrates global coordination and local response. This framework strives to maintain the optimized performance of the original task trajectory to the greatest extent while ensuring collision-free safety, providing strong theoretical support and technical solutions for practical applications.

2. FEATURE ANALYSIS OF DISTRIBUTED TRAJECTORY PLANNING IN MULTI-UAV COLLABORATIVE TASKS

2.1 Decentralization and Autonomous Decision-making in the Planning Framework

The integration of decentralized decision-making and distributed computing is the basic structural feature of distributed trajectory planning. Compared with the centralized planning where a central node plans an entire route, in this approach, each unmanned aerial vehicle (UAV) is an independent decision-maker. All of them have complete flight path calculation and correction capabilities - they use the embedded path planning algorithms (distributed RRT*, local MPC, etc.) to locally process the environmental information (obstacles, terrain, etc.) and task information (target points, time, etc.) detected by the detector modules (Lidar, VisualSensor, GPS, etc.) they carry to get a flight route. The core technical mechanism is decentralized fault-free single point: in the local planning network, if some drones experience network communication paralysis, abnormal exit of sensor data and other faults, the remaining drones do not have to wait for the central node to reassign tasks. They can quickly plan the local network based on the information interaction between neighboring nodes, achieving the continuation of the overall planning tasks of the system. For instance, in mountain rescue operations, when a drone responsible for delivering supplies malfunctions, it can rely on the communication and contact among the other drones around it to independently re-plan its flight path and achieve the goal of delivering supplies to the disaster area within the flight coverage area as originally planned by the malfunctioning drone. From the perspective of cybernetics, its core technical mechanism is manifested as "individual local decision-making - group global emergence" to achieve self-organizing collaboration of multi-agent systems, which is the core concept of "leaderless collaboration" in distributed control.

2.2 The Coordination of Locality and Consistency in Information Interaction

The information interaction characteristics of distributed trajectory planning are the dependence of local information and the moderation of global uniform convergence. Firstly, due to factors such as the bandwidth of wireless communication, communication delay, and the number of multiple drones, each unmanned aerial vehicle (UAV) can only obtain the global status information of some nodes in the system (such as the real-time position, speed, and task quality level of all UAVs), but cannot obtain all the information of the system. Local information exchange can only be conducted through neighboring nodes within the communication radius (assumed to be 3 to 5 adjacent unmanned aerial vehicles), and their respective trajectory parameters (position sequences, speed planning curves), detected local obstacle information, and mission progress information are transmitted. The localized information interaction mode will significantly reduce the communication load. For instance, when the number of drones increases from 10 to 30, the information transmission volume of local communication only grows linearly (positively correlated) with the number of neighbors, while that of centralized communication grows explosively exponentially (positively correlated with the total number of aircraft). On the other hand, to avoid trajectory conflicts caused by local decisions, distributed planning needs to adopt consistency algorithms to achieve the coordination of global trajectories - each unmanned aerial vehicle (UAV) dynamically corrects its own planning parameters (such as takeoff time deviation, flight speed correction, etc.) based on the trajectory planning of neighboring nodes, gradually converges the local trajectory towards the global collaborative trajectory. Typical trajectory parameter consistency protocols, such as the consistency algorithm based on weighted average, iteratively update the equation:

$$X_i(k+1) = \sum_{j \in N_1}^n a_{ij} x_j(k)$$

where x_i represents the trajectory planning parameter of unmanned aerial vehicle i , N_i represents the neighbor node, and a_{ij} represents the interaction parameter. Enable all the trajectory parameters of the unmanned aerial vehicles to reach a collaborative trajectory with an error less than the preset threshold, generally a position deviation of 0.1m and a velocity deviation of 0.2m/s, through a limited number of iterative steps. This characteristic of "local interaction - global convergence" not only satisfies the constraints of communication limitations in multi-machine systems but also ensures the global coordination of trajectory planning.

2.3 Dynamic Nature of Task Adaptation and Multi-constraint Compatibility

In the multi-UAV collaborative mission scenario, distributed trajectory planning has the significant characteristics of dynamic task adaptation and compatibility with multiple constraints. From the perspective of mission dynamics,

multi-drone collaborative missions often encounter situations such as the addition of new casualty positioning points in natural disaster rescue, the switch from reconnaissance missions to material delivery missions, the addition of new support drones, and the dynamic increase or decrease in the number of faulty drones exiting. Distributed planning can quickly adapt to task changes through the linkage mechanism of “local task reallocation - real-time trajectory re-planning”. For instance, when new rescue target points are added, the unmanned aerial vehicle (UAV) closest to the target point can independently undertake the new task and re-plan its trajectory through local negotiation. Other UAVs only need to fine-tune their own trajectories to avoid conflicts. There is no need to completely reconstruct the planning scheme. Compared with the “full system re-planning” of centralized planning, the response delay can be reduced by more than 60%. In terms of multi-constraint compatibility, distributed trajectory planning needs to simultaneously satisfy the following three constraints: dynamic constraints, namely the power limit of unmanned aerial vehicles (UAVs), environmental constraints, namely static buildings, mountain obstacles and dynamic disturbances in the task area, as well as task constraints, namely task timeliness constraints, task accuracy constraints, and the coordination constraints of the task book when multiple UAVs arrive at the task area simultaneously. Distributed planning achieves efficient compatibility of multiple constraints by decomposing multiple constraints into locally solvable sub-constraints, such as decomposing the global obstacle avoidance constraint into “local obstacle avoidance constraints between unmanned aerial vehicles (UAVs) and neighboring nodes”, and decomposing the task coordination constraint into “trajectory time synchronization constraints among neighboring UAVs”. For instance, the energy consumption constraint means that each unmanned aerial vehicle (UAV) can optimize the cruise speed curve of each waypoint on its own trajectory based on the remaining power. When the endurance power is small, it can choose to fly at a constant speed. Meanwhile, through local interaction, it ensures that its own optimization does not disrupt the satisfaction of other UAV constraints, featuring the characteristic of “local constraint satisfaction - global constraint compatibility”.

3. THE CURRENT SITUATION AND PROBLEMS OF DISTRIBUTED TRAJECTORY PLANNING IN MULTI-UAV COLLABORATIVE TASKS

3.1 Computational Complexity Issues

As the number of unmanned aerial vehicles (UAVs) increases, the computational load of distributed trajectory planning grows exponentially. Take the optimization-based method as an example. When the number of unmanned aerial vehicles (UAVs) increases from 5 to 20, the trajectory optimization variables (such as position, speed, and acceleration) of each UAV increase from 15 to 60, and there are coupling constraints among the variables, resulting in the computing time of a single UAV increasing from 0.1 seconds to 1.2 seconds. It far exceeds the real-time planning requirements (usually less than 0.5 seconds). In addition, multiple drones need to repeatedly iterate and exchange trajectory information to achieve collaboration. The number of iterations increases with the increase in the number of drones, further intensifying the computational burden. In actual logistics and distribution scenarios, when the number of drones exceeds 15, some drones cannot adjust their trajectories in a timely manner due to computing delays, resulting in a delivery delay rate that increases by more than 25%.

3.2 Communication Limitation Issues

Table 1: Impact of Communication Limitation Issues in Multi-UAV Distributed Planning

Type of Communication Issue	Typical Affected Scenario	Specific Performance Parameter	Direct Consequence
Communication Delay	Complex urban environments (building obstruction)	Delay duration: 0.3–0.8 seconds	Time difference exists in neighbor status information, easily leading to trajectory conflicts
Communication Packet Loss	Communication distance exceeding 5 km or electromagnetic interference	Packet loss rate: 10%–20%	Loss of key trajectory parameters, posing a risk of close-range flight
Bandwidth Limitation	Number of UAVs exceeding 30	Information update frequency drops from 10Hz to 3Hz	Data transmission congestion, failing to synchronize large amounts of trajectory data in real time

Multi-uav distributed planning relies on wireless communication to achieve information sharing, but in practical applications, there are problems such as communication delay, packet loss and bandwidth limitation. In terms of communication delay, in the complex urban environment, the wireless signal is affected by the obstruction of buildings, and the communication delay can reach 0.3 to 0.8 seconds, resulting in A time difference in the neighbor status information obtained by each drone. For example, the location information sent by drone A at time t is not received by drone B until $t+0.5$ seconds. At this point, the actual position of Drone A has changed, and the trajectory planned based on lagging information is prone to conflicts. In terms of communication packet loss, when the communication distance exceeds 5 kilometers or there is electromagnetic interference, the packet loss rate can

reach 10% to 20%, resulting in the loss of some key trajectory parameters. For instance, drone C failed to receive the speed adjustment command from its neighbor drone D and continued to fly along the original trajectory, posing a risk of being too close. Bandwidth limitations prevent multiple drones from simultaneously transmitting large amounts of trajectory data. For instance, each drone needs to transmit trajectory information of 100KB/s. When the number of drones exceeds 30, insufficient communication bandwidth will cause data transmission congestion, and the information update frequency will drop from 10Hz to 3Hz.

In terms of communication delay, in complex urban environments, wireless signals are affected by building obstructions, resulting in communication delays of 0.3 to 0.8 seconds, which leads to time differences in the neighbor status information obtained by each drone. For instance, the position information sent by drone A at time t can only be received by drone B at $t+0.5$ seconds. By then, the actual position of drone A has changed, and the trajectory planned based on the lagging information is prone to conflicts.

3.3 Imperfect Conflict Detection and Resolution

The existing conflict detection methods have problems of false detection and missed detection. The detection method based on geometric models calculates whether the distance between unmanned aerial vehicles (UAVs) is less than the safety threshold. It does not take into account the speed and direction of the UAVs' movement. When two UAVs fly towards each other, even if the current distance is greater than the safety threshold, a collision may occur in the short term due to the relatively fast speed, resulting in missed detection. The detection method based on the probabilistic model uses a Gaussian distribution to describe the uncertainty of location. When the environmental interference is significant, the estimation error of the probability distribution parameters is large, and it is easy to misjudge non-conflict scenes as having conflicts, with a false detection rate that can reach 15%. In terms of conflict resolution, the rule-based approach is prone to secondary conflicts caused by multiple drones simultaneously avoiding each other in scenarios of cross-flight of multiple aircraft. When multiple conflict points exist simultaneously in the optimization method, the solution of the objective function is prone to fall into local optimum and cannot find the global optimal solution. Reinforcement learning methods require a large number of labeled samples to train the model. In complex scenarios such as the cross-interference of multiple dynamic obstacles that have never been seen before, the success rate of conflict resolution drops sharply.

3.4 Environmental Adaptability Issues

The existing distributed trajectory planning methods have insufficient adaptability to complex environments. One issue is the incomplete modeling of static obstacles. When there are irregular obstacles in the task environment, such as irregular mountains or temporarily set up rescue tents, the traditional cuboid or spherical modeling methods cannot accurately describe the outline of the obstacles, resulting in the planned trajectory being too close to the actual distance of the obstacles and insufficient safety margin. The second issue is the lag in dynamic environmental response. When sudden dynamic obstacles or sudden air currents cause the unmanned aerial vehicle to yaw or other temporarily intruded aircraft appear, the existing methods need to re-perceive the environment, reconstruct the model and solve the trajectory. The entire process takes more than 1 second and cannot achieve real-time adjustment. For instance, in a forest fire rescue scenario, a sudden air current causes a certain unmanned aerial vehicle (UAV) to deviate from its original trajectory. The current planning method requires 1.5 seconds to complete the trajectory re-planning. During this period, the UAV has approached the edge of the fire scene, posing a safety risk. Thirdly, it has poor robustness in extreme environments. In high-temperature and high-electromagnetic interference conditions, the accuracy of unmanned aerial vehicle (UAV) sensors declines, and the GPS positioning error increases from 1 meter to 5 meters. Trajectories planned based on inaccurate perception information are prone to deviation, and the risk of conflict increases by 30%.

4. DISTRIBUTED TRAJECTORY CONFLICT RESOLUTION MEASURES IN MULTI-UAV COLLABORATIVE TASKS

4.1 Enhance the Ability to Calculate Complex Problems

4.1.1 Hierarchical and progressive optimization architecture design

Introduce a three-level optimization structure of "global - regional - single machine" to simplify the calculation model. The global layer, based on the mission conditions, divides the target area of logistics distribution and the key area of reconnaissance missions into grids at the ground control center, dividing the mission space into

multiple independent sub-regions. Each sub-region deploys 5 to 8 unmanned aerial vehicles (UAVs) to reduce the variable coupling degree of multiple aircraft in the entire airspace. For instance, in the scenario of logistics and distribution, the city is divided into 10 sub-regions based on administrative regions, with 6 drones deployed in each sub-region. The number of single-machine optimization variables is reduced from 60 to 18. The regional layer optimizes the coarse trajectories of unmanned aerial vehicles (UAVs) within sub-regions through regional coordination nodes. For a single UAV, simplified kinematics is adopted and secondary aerodynamic parameters are ignored, reducing the calculation time of a single UAV to within 0.3 seconds. Based on the rough planning results of the regional layer, the single-machine layer integrates real-time perception information, adjusts the obstacle position and wind speed, adopts model order reduction, simplifies the 6-degree-of-freedom model to 3-degree-of-freedom, etc., reduces the computational load, and makes the total time consumption of single-machine calculation not exceed 0.4 seconds, meeting the real-time requirements.

4.1.2 Dynamic Task Allocation and Computing Load Balancing

The dynamic task allocation algorithm with load awareness is utilized to perceive the CPU load and memory load of each unmanned aerial vehicle (UAV) in real time. When the computing load of a certain UAV exceeds 70% and it is running more than three trajectory optimization tasks simultaneously, the task migration mechanism is initiated to transfer non-critical computing tasks (such as historical trajectory data storage) to adjacent UAVs with a load rate of less than 50%. For instance, in a logistics distribution system involving 20 drones, when the CPU load rate of drone E reaches 85% due to the calculation of trajectory planning for 3 distribution points, the historical trajectory backup is migrated to drone F with a CPU load rate of only 40%. Meanwhile, by using the method of prioritized computing tasks, the priority of the trajectory optimization task (with a priority of 1) is set to the highest level. The priority of data transmission verification (priority level 2) is set to a medium level, and the priority of logs (priority level 3) is set to the lowest level, thereby prioritizing the utilization of core computing resources to ensure trajectory planning. This results in a computing time of approximately 0.8 seconds for a single unmanned aerial vehicle (UAV) in a fleet of 20 aircraft, thus meeting the requirements of real-time planning.

4.1.3 Improvement of Lightweight Optimization Algorithm

Based on the traditional gray Wolf optimization algorithm, it is simplified to reduce the number of iterations. The neighborhood search scale in the algorithm selection/update process is simplified, that is, the number of neighborhood gray wolves is reduced from 1/3 of the total population to 1/5, and the iteration scheme is adjusted to a segmented iteration. At the beginning of the iteration (the first 10 iterations), large-step iterations are used for rapid search, and after the iteration (after 10 iterations), small-step iterations are used for convergence. Reduce the number of algorithm iterations from 30 to 18. For the logistics and distribution application scenario, the iterative calculation time for the trajectory optimization of 20 unmanned aerial vehicles has been compressed from 1.2 seconds to 0.6 seconds. On the other hand, prior computing is introduced to pre-calculate the trajectory templates for common scenarios (such as standard urban blocks, open Spaces, etc.) and load the library. When the drone enters a known scene, the library is directly called to make local adjustments to the drone in that scene without having to recalculate from scratch. This compresses the computing time by 0.2 seconds, ultimately meeting the requirements of real-time planning.

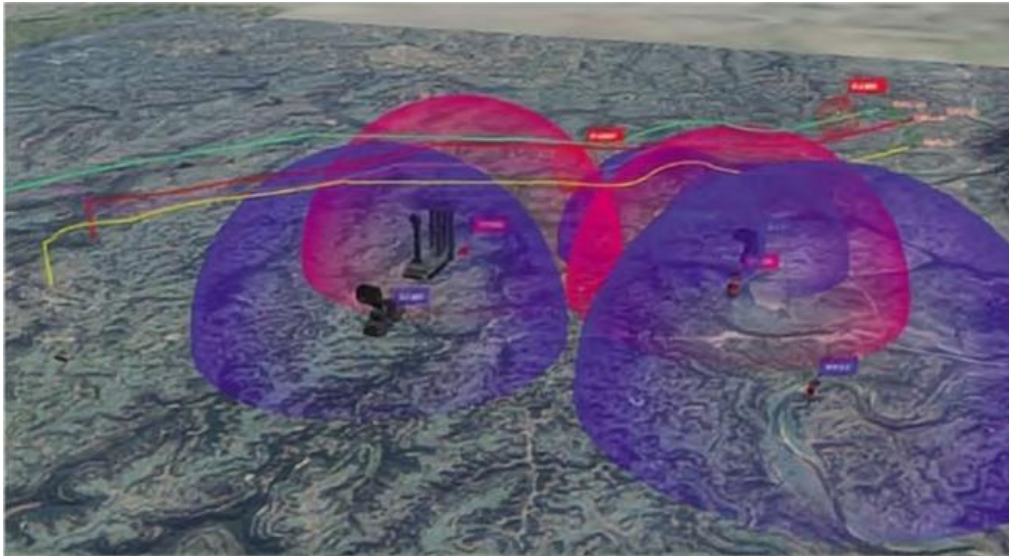


Figure 1: 3D trajectory deduction for target UAV and tracking multi-UAV in complex battlefield environment

The telemetry information (flight information, attitude information) during the flight of the tracking unmanned aerial vehicle (UAV) is returned to the dynamic simulation visual simulation system and the ground condition monitoring platform through the data link for tracking task simulation and safety status monitoring respectively. Meanwhile, the ground condition monitoring platform updates the real-time target situation and the relationship between the aircraft and the target, and sends it to the tracking UAV.

4.2 Strengthen the Hierarchical Communication Monitoring Mechanism

4.2.1 Hierarchical communication and Information Compression transmission

A hierarchical communication architecture of “backbone network - subnet” is formed. In the backbone network, the high-altitude long-range unmanned aerial vehicle (Wing Loong-2 unmanned aerial vehicle) serves as the relay node, with a communication distance exceeding 50 kilometers. Millimeter-wave communication technology is used to control the communication delay within 0.1-0.2 seconds. The subnet is composed of unmanned aerial vehicles (UAVs) operating at low altitudes, using short-range wireless communication (ZigBee). The communication distance is controlled within 1 to 3 kilometers, and the communication delay is controlled within 0.05 to 0.1 seconds. In urban areas, the delay caused by building occlusion is reduced from 0.8 seconds to less than 0.3 seconds through the forwarding of unmanned aerial vehicles (UAVs) using high-altitude relays. Meanwhile, the trajectory information is compressed and transmitted, and differential coding technology is adopted. What is transmitted is the difference between the current trajectory and the historical trajectory (such as position error, speed adjustment amount), rather than the complete trajectory parameters. The data transmission volume has been reduced from 100KB/s to 30KB/s. For instance, the position of drone A at time t is $(X1, Y1, Z1)$, and the position at time $t+1$ is $(X2, Y2, Z2)$. It only transmits $(x2-X1, Y2-Y1, Z2-Z1)$, reducing the amount of data transmission. When 30 drones transmit simultaneously, the communication bandwidth occupied is reduced by 70%, avoiding data congestion. The information update rate remains above 8Hz.

4.2.2 Anti-packet loss and delay Compensation Mechanism

For the problem of communication packet loss, the multi-path redundant transmission method is applied. Each unmanned aerial vehicle (UAV) simultaneously transmits trajectory information to 2 to 3 adjacent UAVs. When packet loss occurs, data can be received through other paths, reducing the packet loss rate from 20% to below 5%. For instance, when drone C transmits speed adjustment instructions to drone D, it simultaneously copies them to Drone E. If Drone D does not receive the instructions, it can receive backup data from Drone E. For communication delay, A dynamic delay compensation algorithm is proposed. A speed prediction model (such as Kalman filtering, predicting the position within the next 0.5 seconds) is established based on the historical motion trajectory of the unmanned aerial vehicle (UAV). When UAV B receives the position data of UAV A at time t , the real-time position of UAV A at $t+0.5$ seconds is calculated based on the prediction model, and the trajectory is planned according to the predicted position. Reduce the risk of trajectory conflicts caused by lagging information.

The test results of urban scenarios show that based on this compensation algorithm, the trajectory conflict has been reduced from 25% to 8%.

4.2.3 Dynamic Bandwidth Allocation and Priority Scheduling

By adopting the dynamic bandwidth allocation technology, communication resources are allocated based on the urgency of unmanned aerial vehicle (UAV) tasks. The task priorities are classified as urgent, with emergency material distribution, emergency reconnaissance, general logistics distribution, and daily patrol belonging to the conventional level and low priority, which refers to image collection in non-critical areas. For emergency tasks, drones are allocated 40% bandwidth; for regular tasks, 50% bandwidth; and for low-priority tasks, 10% bandwidth. For instance, in a 30-drone system, each of the 5 drones responsible for emergency material delivery is allocated a bandwidth of 1.3Mbps, each of the 15 drones responsible for regular logistics is allocated a bandwidth of 1Mbps, and each of the 10 drones responsible for image collection is allocated a bandwidth of 0.3Mbps, thus avoiding waste of bandwidth resources. At the same time, a data transmission time slot scheduling mechanism is introduced, dividing 1 second into 10 time slots (each time slot 0.1s), and allocating a dedicated time slot for each unmanned aerial vehicle (UAV) to transmit data. This avoids congestion caused by multiple drones transmitting data simultaneously, stabilizes the information update frequency at 10Hz, and ensures the real-time transmission of trajectory data.

5. CONCLUSION

This paper systematically analyzes the basic characteristics, existing problems and coping strategies of distributed trajectory planning in multi-UAV collaborative tasks. In terms of features, distributed planning has advantages such as decentralized decision-making, local information interaction and global consistency coordination, dynamic task adaptation and multi-constraint compatibility. However, it also faces challenges such as high computational complexity, communication delay and packet loss, imperfect conflict detection, and weak environmental adaptability. In response to the above issues, this paper proposes a series of improvement measures. Firstly, it adopts a hierarchical optimization architecture, dynamic task allocation and load balancing, and lightweight optimization algorithms, significantly enhancing the real-time planning capability. Second, a hierarchical communication network was constructed, anti-packet loss and delay compensation mechanisms were introduced, and dynamic bandwidth allocation was implemented, effectively ensuring the reliability and real-time performance of information transmission. The third is to integrate geometric and probabilistic models for conflict detection, and combine rule guidance, optimization algorithms and learning methods to achieve multi-level conflict resolution. Simulation and case analysis show that the proposed strategy can effectively reduce the trajectory conflict rate, improve the task execution efficiency and system robustness in complex dynamic environments. In the future, further research can be conducted on trajectory planning for heterogeneous unmanned aerial vehicle (UAV) systems, conflict resolution strategies based on reinforcement learning, and collaborative control technologies in extreme environments, in order to continuously expand the application scenarios and reliability of multi-UAV collaborative technology.

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