Intelligent Exclusion Techniques for Unmanned Aircraft Swarms A Review of Research on Situational Awareness in Complex Scenarios

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Abstract: In order to cope with the practical needs of UAV swarm situational awareness in complex scenarios such as battlefield enemy screening and disaster area rescue, this paper systematically compiles the research progress of intelligent screening technology in the field of heterogeneous UAV swarm situational awareness. The research focuses on two core technology directions: first, analyzing the UAV target tracking and motion planning technology in complex environments, focusing on the multimodal target detection scheme integrating YOLOv5 algorithm and OpenPose attitude detection, and the spatial and temporal trajectory optimization method based on unconstrained Minimum Control Quantity trajectory (MINCO); second, exploring the key methods of cooperative control of UAV clusters, including distance division based coalition formation control algorithm, and hierarchical recursive distributed self-repair algorithm for UAV damage. By analyzing the existing research results, experimental data and simulation verification, we clarify the technical advantages and applicable scenarios, and provide theoretical support for the engineering application of UAV swarm intelligent inspection technology.

Keywords: Multimodal Fusion Detection; MINCO Trajectory Optimization; Distributed Self-Repair Algorithm; Intelligent Exclusion of Complex Scenes

1. Introduction

Nowadays, trade wars and international conflicts are getting more and more intense, which in turn prompts science and technology to be in constant progress, especially in the field of unmanned aerial vehicles (UAVs), which has unprecedentedly got unprecedented opportunities and challenges, so that he has organically fused with all kinds of things in the field and even at the cross-field level. In complex scenarios such as battlefield enemy situation investigation and rescue of trapped people in disaster areas, the application value of UAV technology is becoming more and more prominent. In the battlefield enemy situation checking scenario, UAV swarm can break through the limitations of traditional artificial reconnaissance, such as poor timeliness, high cost, low security, etc., and through real-time situational awareness to enhance the scientificity of battlefield decision-making, enhance the ability of dynamic offense and defense, and have military application value. In the rescue of disaster areas, UAV swarms can quickly obtain geographic information and track trapped people, solving the limitations of complex geographic conditions and the golden rescue time window, and improving rescue efficiency and safety, which has significant civil rescue value. For example, in the Fukushima nuclear power plant accident in Japan in 2011, drones were used for reconnaissance and monitoring of radiation levels; in the Paris hostage incident in France in 2015, drones were involved in the rescue operation; in the Russian-Ukrainian conflict since the beginning of 2022 to the present day, drones have taken up a central position in the military actions of both sides and continue to influence the war situation and the security situation in Europe to the present day; as well as in China's 2008 Wenchuan earthquake, drones successfully carried out aerial photography and photography. UAVs successfully carried out aerial photography and disaster assessment missions in China's 2008 Wenchuan earthquake, to name a few. Here, I will sort out the research progress of intelligent ranking techniques in the field of heterogeneous UAV swarm situational awareness:

Firstly, analyze the core technology of target tracking and motion planning in complex environments by Chen Lin [1], focusing on the aspects of target detection and trajectory prediction.

Secondly, explore the key methods of UAV cluster cooperative control by Fu Xiaowei et al. [2], focusing on summarizing the technological breakthroughs of coalition formation control algorithms and distributed recursive self-repair algorithms.

And then summarize the technical advantages of the existing research, put forward the future research direction and suggestions, aiming to provide theoretical support and practical reference for the deepening research and engineering application of UAV swarm intelligent troubleshooting technology.

2. Core Technology of Target Tracking and Motion Planning

2.1 Target Detection

The first step to realize target tracking is to detect the target through the on-board sensors, and due to the payload limitation of micro aerial vehicles, the visual sensor is the most suitable sensor for UAVs to carry. The accuracy of target localization significantly affects the stability and success rate of the subsequent tracking process, while the motion prediction of the target directly affects the quality of motion planning.

Therefore, the detection and localization of targets and trajectory prediction using highly robust methods is one of the focuses of the research on the technology of tracking dynamic targets by UAVs in complex environments. Based on the needs of target tracking in complex environments, as well as the comprehensive consideration of the cost of the UAVs and the load capacity and other factors, Chen Lin adopts the binocular vision system for detecting and localizing the moving targets, and hereby proposes a visual detection scheme incorporating human body postures Firstly, the neural network-based method is used to train the model and the YOLOv5 algorithm[3] is utilized to detect the motion targets, but the single YOLOv5 model is easy to miss and misdetect the human targets in the complex environment, as shown in Figure 1.

Figure 1. False Detection Phenomenon of Single YOLOv5 Algorithm

The lightweight OpenPose algorithm[4] developed by Carnegie Mellon University is utilized to improve the YOLOv5 algorithm by inputting a single frame of the latter's detection results into the former for posture detection, realizing the tandem detection scheme, obtaining the location of key points of each human skeleton, and then matching them through Euclidean distances to specifically detect each one so as to accurately determine the target, greatly reducing the incidence of false detection problems, as shown in Figure 2.

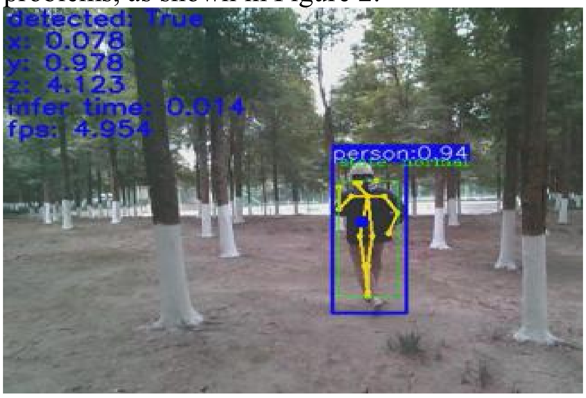

Figure 2. Improved YOLOv5 Algorithm Detection Effect

In the outdoor experimental environment, by setting different detection distance conditions, the false detection rate and leakage rate of the single YOLO algorithm and the improved algorithm are compared, and the specific indicators are shown in Table 1.

Table 1. Comparison of Improved YOLOv5 Algorithm

Distance (m)	Single YOLO false detection rate	Improved algorithm false detection rate	Single YOLO missed detection rate	Improved algorithm missed detection rate
2.00	10.8%	1.3%	5.8%	1.3%
3.00	11.2%	2.5%	11.8%	2.1%
4.00	12.5%	4.4%	15.8%	4.4%
5.00	23%	5.5%	20.8%	7.8%

2.2 Target Detection

For the problem of tracking a moving target in a complex environment, trajectory planning needs to consider factors such as target visibility in addition to airframe dynamics feasibility. These task constraints require the UAV to simultaneously adjust the characteristics of the flight trajectory in both the spatial and temporal domains. Therefore, simultaneous planning of trajectory shape and time allocation, also known as spatio-temporal trajectory planning, is crucial for safe and efficient UAV flight. In order to perform simultaneous spatio-temporal trajectory planning, Chen Lin partially introduces the research of Wang et al. [5]: unconstrained minimum control volume trajectory (MINCO for short).

In the MINCO method, fast spatio-temporal optimization is achieved by decoupling the spatial and temporal parameters in the calculation of the objective function and realizing the linear complexity mapping between the optimization variables and the intermediate variables representing the trajectory.

In addition to this, Chen Lin incorporates the proven theory that all three-rotors, four-rotors and six-rotors, such as Mu[6], etc., have differential flatness properties, which eliminates the necessity for UAVs to carry out intensive computations in the full state space, and only requires trajectory planning for the low-dimensional differential flatness output space, thus bringing an extreme level of convenience to trajectory planning.

Accordingly, the trajectory optimization problem can be reduced to the following formulation:

$$\begin{aligned} \min_{x(t),T}\ & J_0=\int_0^T \left\|x^{(3)}(t)\right\|^2 dt+\rho T \\ s.t.\ & x^{(s-1)}(0)=\bar{x}_0\ ,\ x^{(s-1)}(T)=\bar{x}_f\ , \\ & \left\|x^{(1)}(t)\right\|\le v_m\ ,\ \left\|x^{(2)}(t)\right\|\le a_m\ , \\ & x(t)\in C\ ,\ \forall t\in[0\ ,\ T]\ , \\ & d_l\le\|x(t_k)\|\le d_u\ ,\ \forall t_k\in\tilde{T}\ , \\ & x(t_k)\in O_k\ ,\ \forall t_k\in\tilde{T} \\ & T\ge T_p\ , \end{aligned} \tag{1}$$

where the first term of the optimization objective is to control the energy loss term, which is generally defined as the higher order derivatives of the trajectory, where the order s = 3 is taken, and the third order derivative of the position is the additive acceleration jerk, and the second term of the optimization objective is the time loss term, where ρ is an adjustable parameter. The first term of the constraint is the boundary condition constraint, i.e., the planned trajectory needs to satisfy the given initial and final states: including position, velocity, and acceleration.

The second term of the constraint is the dynamics constraint,v_m and a_m are the velocity and acceleration bounds, i.e., they cannot exceed the maximum velocity and acceleration limits of the UAV dynamics model. The third term is the safety constraint, which ensures that the UAV is within the safe flight corridor C . The fourth term of the constraint is the distance keeping term, which is responsible for constraining the UAV's tracking distance to the target within a reasonable range. The fifth constraint is the visibility region guarantee, which sets the visual visibility region O_k and constrains the trajectory to be within this region. This constraint is used to avoid obstacles from blocking the UAV's observation field. The sixth constraint is the time constraint, T_P is the predicted timestamp, and the total duration of the trajectory is expected to be $\tilde{T}$ ($\tilde{T}\ge T_P$).

The MINCO trajectory after the comprehensive constraints of Chenlin is compared with the traditional B-spline curve trajectory representation, as shown in Figure 3.

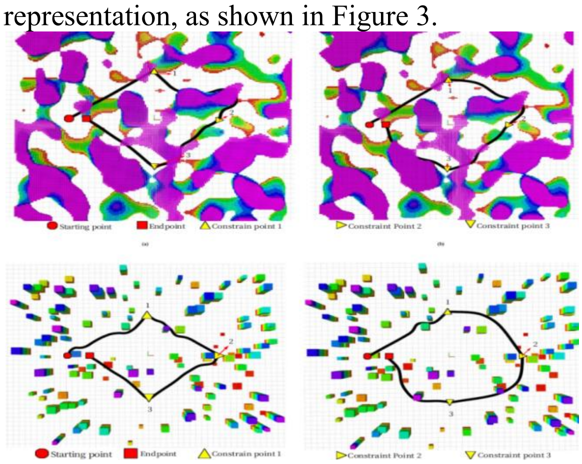

Figure 3. Comparison of Trajectories in Complex Environment

B-spline trajectory

MINCO trajectory

B-spline trajectory in regular obstacles

MINCO trajectory in a regular obstacle.

In order to make a more intuitive and effective comparison, in the irregular obstacle distribution scenario, this paper sets four constraint points (0,10), (10,0), (0,-10), (-10,0), where the starting point of the trajectory is (-13,0), the end point of the trajectory is also the last constraint point, and sets the UAV dynamics limitations, including the maximal velocity of 2m/s and the maximal acceleration of 4m/s². In the regular obstacle distribution environment, the settings are identical except for the location of constraint point 3 at (12,0). The UAV will complete the online generation of the trajectory and execute the flight mission according to the set constraint points, and the trajectory is shown as the black curve in Figure 3 above. The experimental results are shown in Figure 3.

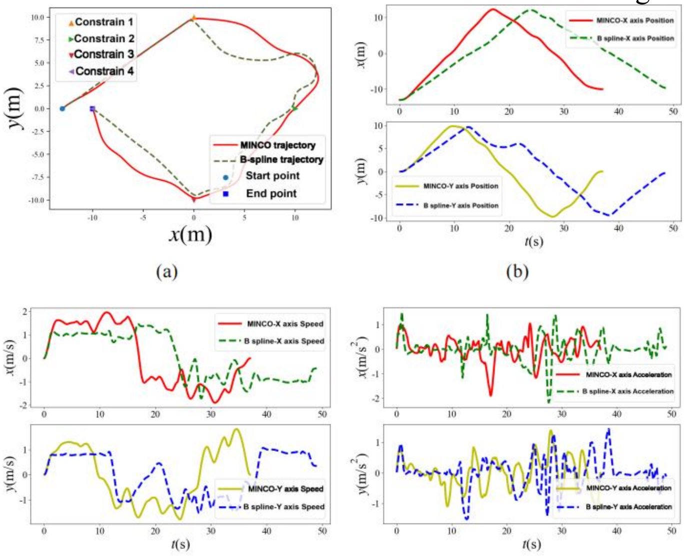

Figure 4. Comparison of Trajectories under Specified Targets

Comparison of 2D projection of trajectory
Comparison of position curve
Velocity curve comparison
Acceleration curve comparison

From the velocity profile Figure 4(c), it can be seen that the MINCO trajectory is faster most of the time, which is the reason for completing the task faster. In addition, the MINCO trajectories all reach the maximum limit of the velocity in amplitude at time t ∈ {11.3, 34.5}s, which indicates that the MINCO method makes full use of the degrees of freedom of each segment of the trajectory in the adjustment time, thus realizing lower conservatism and reaching the performance limit compared with the traditional trajectory representation method. In this paper, a change of 1.5 m/s² in acceleration within 2 s is defined as a sudden change in acceleration, and from the acceleration curve Figure 4(d), it can be seen that the number of sudden changes in acceleration in the MINCO method is 3, which is obviously less than the number of 7 changes in the B-spline, and it can be seen that the trajectory of the MINCO method is smoother. From the results in the figure, it can be seen that compared with the traditional B-spline trajectory representation, the MINCO method brings significant improvement in trajectory quality and computational efficiency.

In terms of control energy, in the aforementioned obstacle environment and completely empty environment, respectively, the MINCO method is more efficient.

In terms of control energy, comparison experiments are carried out in the above obstacle environment and completely empty environment respectively, and the constraints of the experiments are exactly the same as those in Figs. 4-14. In this paper, the control energy is measured by integrating the square of the absolute value of acceleration over the time, i.e., the control energy is equal to $\int_0^T // a //$, where a denotes the acceleration. The experimental results are shown in Figure 5.

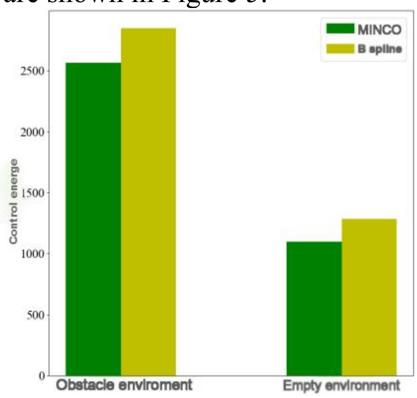

Figure 5. Comparison of Control Cost of Two Trajectory Representation Methods in Different Environments

3. Key Methods for Cooperative Control of UAV Cluster

3.1 Introduction to the Concept

UAV cluster refers to the self-organization mechanism, so that multiple UAVs with limited autonomy can achieve a higher degree of autonomous collaboration through mutual information communication to produce an overall effect without centralized command and control, so that they can accomplish the desired mission objectives with as little personnel intervention as possible.

The most important advantage of multi-UAV collaboration over traditional UAV collaboration is that it can accomplish the desired mission objectives with minimal personnel intervention. The biggest difference with the traditional multi-UAV collaboration is that no one UAV in the UAV cluster is in the position of the center controlling the dominant flight, and it pays more attention to the mutual autonomous coordination among the UAVs in the cluster. Fu Xiaowei et al. focus on the research of UAV cluster formation flight control method. Formation flight formation control refers to how UAV clusters form and maintain a specific geometric configuration to adapt to the environment, friendly aircraft and mission requirements when performing a mission. Currently, the UAV cluster formation control techniques that are widely used in the international are: the long aircraft wingman method, the virtual structure method, the behavior-

-based control method and the consistency algor-

-ithm based on multi-intelligent body system [7-10].

3.2 Cluster Formation Control Algorithms

3.2.1 Individual formation controller design

Based on the consistency method, Fu Xiaowei et al. designed the formation individual control law as:

$$u_i(t)= \underbrace{\beta_1 \sum_{j=Ni}^{N} a_{ij}(p)(v_j-v_i)}_{Speed\ \ remains\ \ consistent} - \underbrace{\beta_2(v_i-v_\nabla)}_{Virtual\ leader\ speed\ tracking} - \underbrace{\beta_3 \sum_{j=Ni}^{N} a_{ij}(p)(x_j-x_i-(h_j-h_i))}_{Ma\ int\ a\ in\ \ \ relative\ \ \ position} +\bar{v}_\nabla \quad (2)$$

Where β_1 and β_2 are normal numbers; u_i denotes the control input of UAV i, i.e., the acceleration vector of UAV; v_i and x_i denote the velocity and position vectors of UAV i, and v_j and x_j are the same; x_∇ and v_∇ denote the position and velocity vectors of VM, respectively; h_i and h_j are the position vectors of UAV i and j in expected formation, which are calculated only once at the initial moment of preparing to change the target formation; $\dot{v}_\nabla$ denotes the control input of VM, i.e., the acceleration vector of VM; is the acceleration vector of VM, which is the acceleration vector of VM, which is the acceleration vector of VM. acceleration vector of the virtual long aircraft; β_1 parameter term denotes the velocity consistency term; β_2 parameter term denotes the velocity tracking of the UAV to the virtual long aircraft; β_3 parameter term denotes the position consistency term between the UAVs; $a_{ij}(p)$ denotes the adjacency matrix formed by the communication relationship of each UAV in the UAV cluster. The above equation, the control law of each UAV is the same.

3.2.2 Cluster alliance formation

The UAV cluster is divided into several coal-

-itions based on the principle of distance, and when the distance between sub-networks in the cluster is greater than the communication radius, the network is said to be an independent sub-network. A coali-

-tion is formed from an independent sub-network

, as shown in Figure 6, in which the cluster consists

of three independent sub-networks, then the cluster is divided into three coalitions, and the coalition-

-based localized communication method is designed-

-ned.

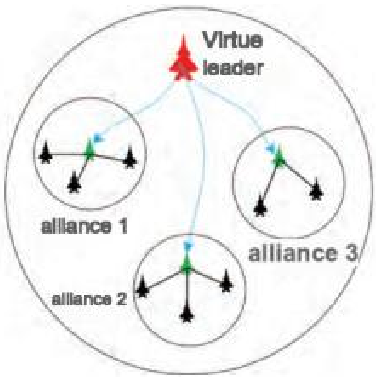

Figure 6. Information Interaction Method between Virtual Long Aircraft and Alliance

By selecting the navigation information UAVs, it is guaranteed that each alliance of the cluster can directly obtain the information of the virtual long aircraft at any moment, and the non-navigation information UAVs only need to interact with the other UAVs in the neighboring domains, and indirectly obtain the information of the virtual long aircraft from the navigation information UAVs in the alliance through the communication link, and the members of the alliance track the expected relative position vectors of the members of the alliance to form the formation formation, and the speed matching among the neighbors ensures that the final speed of the alliance converges, and the final speed of the alliance converges to the same speed. The final velocity within the alliance converges, while the number of alliances decreases over time through alliance merging, and the final cluster consists of a single alliance and the state remains converged to ensure smooth mission execution.

Accordingly, Fu et al. set up a simulation with a cluster system of 5 UAVs and 25 UAVs (some simulation results are selected in this paper): starting from an unordered formation (Figure 7), assuming that the desired formation is a V formation in the time interval [0s, 200s] (Figure 8), and in the time interval [200s, 400s], the formation task is changed, and the desired formation is transformed to a horizontal formation (Figure 9).

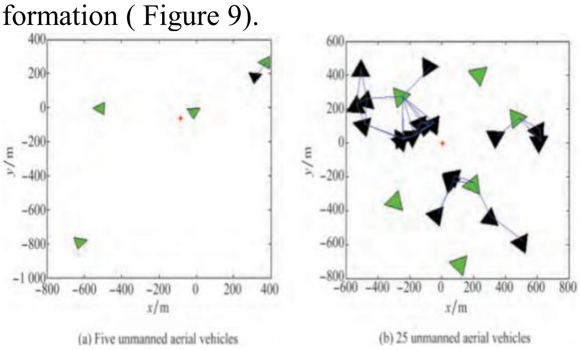

Figure 7. Distribution of Initial Positions of Cluster

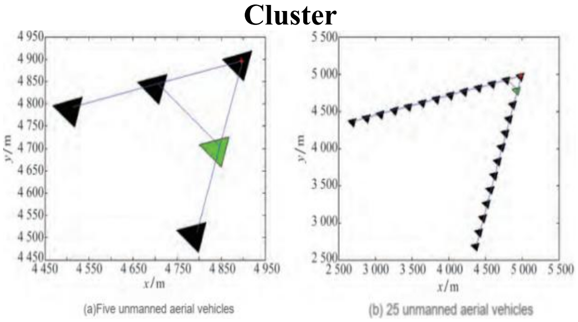

Figure 8. Cluster Formation V-team Formation

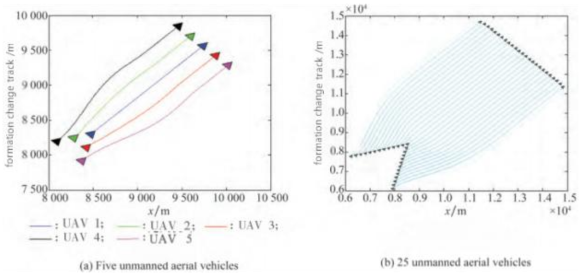

Figure 9. Trajectory Diagram of Cluster V-Team-Horizontal-Team Switching

3.3 Cluster formation control algorithm

In practice, it is difficult to avoid the failure or loss of UAVs in the cluster to leave the formation. Although the UAV cluster system has high robustness as a redundant system, if the above UAV absence situation is not handled accordingly, it will often reduce the overall efficiency of the formation, and may even lead to mission failure. Therefore, when UAV damage occurs, the UAV cluster needs to have the ability to autonomously restore the original formation formation. The key issue of its self-repair lies in how to utilize the distributed control method to complete the formation reconfiguration without destroying the network topology relationship of the formation as much as possible. Therefore, this paper proposes a hierarchical recursive [11] based self-repair algorithm, and the main algorithm framework is shown in Figure 10. Before the cluster departs, the relative position of each UAV in the expected formation is specified in advance, and the specific way is shown in Figure 11.

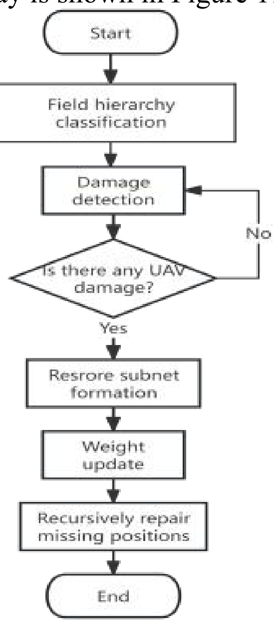

Figure 10. Recursive Self-repair Algorithm Framework Diagram

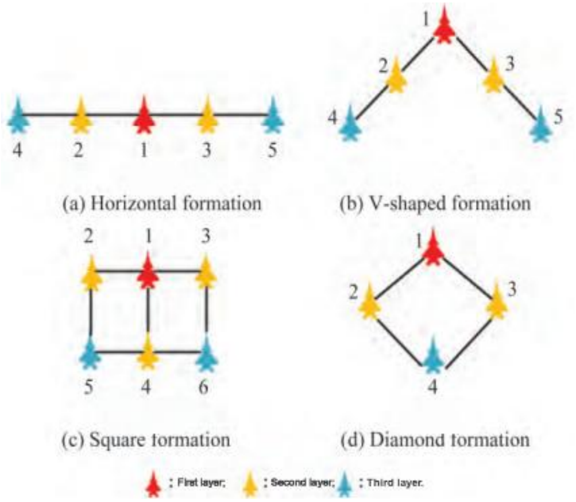

Figure 11. Relative Position Selection Criteria

3.3.1 The specific algorithm is as follows

Neighborhood Hierarchical Division Firstly, the cluster expected formation is divided into hierarchical divisions artificially and offline, and then according to the positional differences of each UAV in the expected formation, the UAV nodes are assigned offline, and the specific hierarchical division and assignment rules are shown in Figure 12.

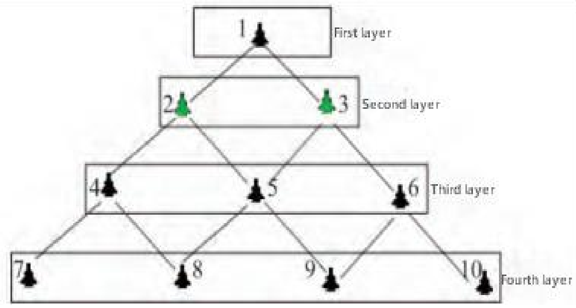

Figure 12. Neighborhood Hierarchical Division

According to different queues, select the first layer of the queue (generally the center node in the queue) and designate the UAV as the No. 1 UAV of the current queue, as shown in Figure 11.

Taking the center node as the root and going down along the communication link, take all the one-layer neighbor nodes of the center node as the second layer, and specify the expected relative position of each UAV in order from left to right, and then take all the neighbors of the second-layer nodes to form the third layer, and similarly stratify and specify the relative position of all the nodes.

After completing the layering, the nodes are assigned weights, and the weights of the nodes are composed of the layer weights r_q and the intra-layer position weights r_p , with the first layer node having the largest r_q , and the layers decreasing downward r_q in order, and r_p decreasing from the smallest to the largest in order of the number. For any queue, the nodes within the same layer r_q are equal, r_p are not equal, and $r_q \gg r_p$.

3.3.2 Repair subnet formation

For a node, the nodes in its subordinate layer that have direct neighbor relationship with that node are called the children of that node, and the two are defined as parent-child relationship.

3.3.3 Weight update

After the formation of the repair subnet is completed, each UAV in the repair subnet calculates its own weight value according to the current formation, and then sends the weight value to the root node UAV of the repair subnet through the link. The root node UAV sums the received weights and its own weights and updates its own weights.

In Figure 12, in the repair subnet composed of nodes 4, 7, and 8, the weight value of node 4 is equal to the sum of the weight values of all nodes in the current repair subnet.

3.3.4 Missing position recursive repair

The sub-node UAV that damages the UAV needs to repair the missing position, while the new vacant position left by this sub-node UAV is repaired by other sub-node UAVs.

Accordingly, Fu Xiaowei et al. simulated a cluster system with 9 UAVs, assuming that the desired formation is V formation in the time interval [0s, 100s], and UAV damage randomly occurs in the cluster in the time interval [100s, 200s], and UAV damage randomly occurs in the cluster in the time interval [200s, 300s], and the simulation results are shown in Figure 13 to Figure 22. Figure 13 and Figure 15 show the 1st and 2nd occurrence of damage in the cluster respectively, and Figure 14 and Figure 18 show the repair results of the 1st and 2nd damage in the cluster respectively. It can be seen that when there is a missing UAV, the cluster can effectively repair the missing location. Figure 19 and Figure 20 show the repair trajectories for the 1st and 2nd damage, respectively. Figure 21 and Figure 22 show the change curves of the speed and yaw angle of the UAV at each moment, respectively, and it can be seen that the speed and yaw angle of the UAV can be well tracked to the expected values. Thus, it shows the effectiveness of the damage self-repair algorithm method given in this paper.

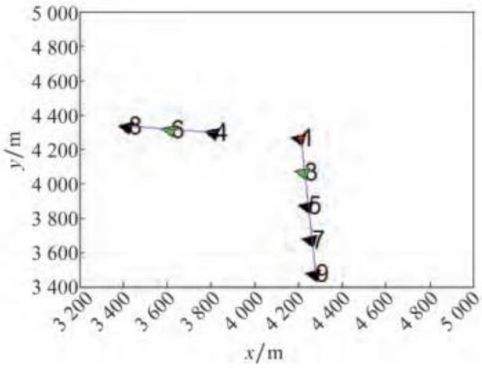

Figure 13. 1st Missing

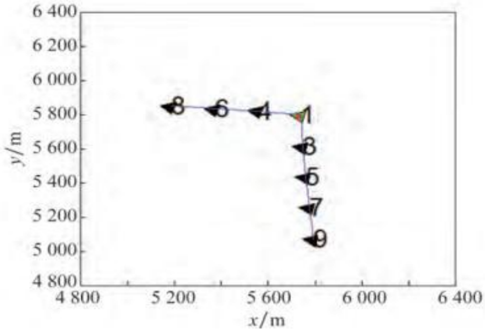

Figure 14. 1st Repair

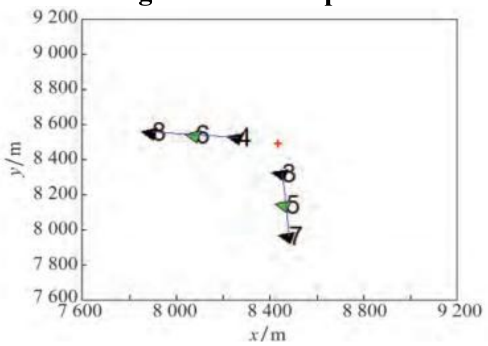

Figure 15. 2nd Missing

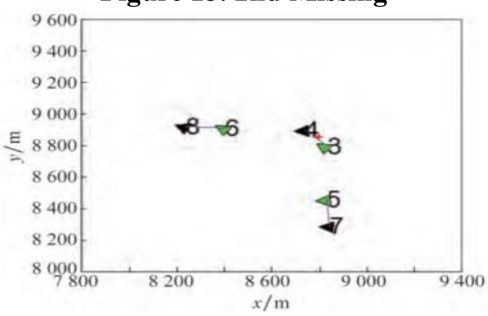

Figure 16. Competition between #3 and #4

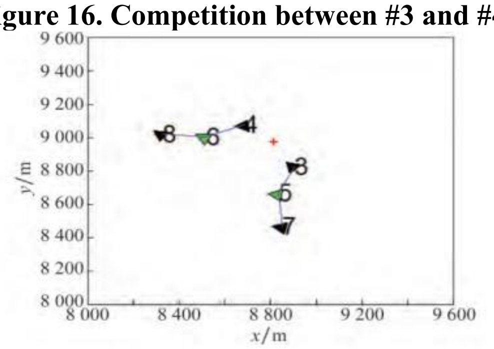

Figure 17. Successful Competition

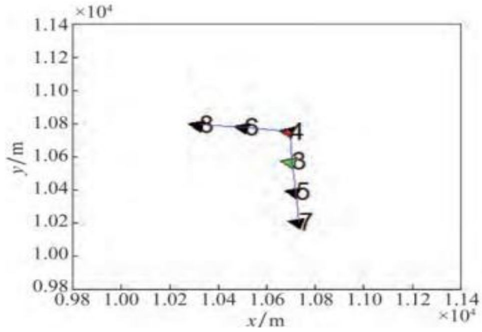

Figure 18. 2nd Repair

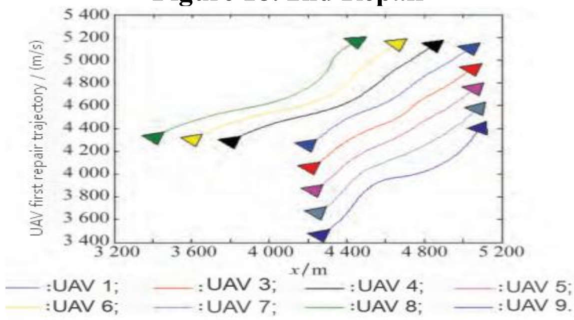

Figure 19. 1st Repair Trajectory

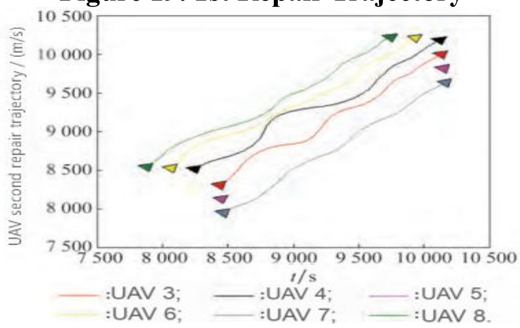

Figure 20. 2nd Repair Trajectory

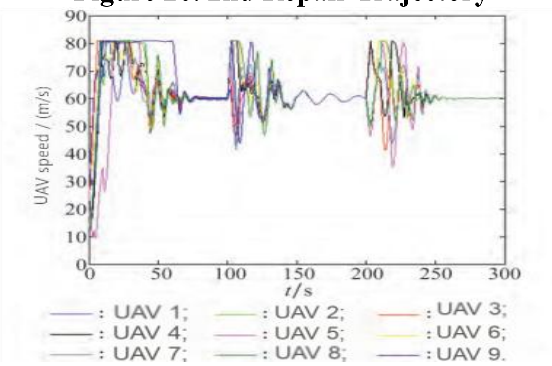

Figure 21. Velocity Change Curve

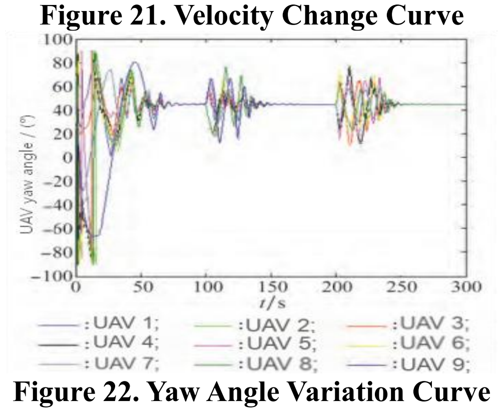

Figure 22. Yaw Angle Variation Curve

4. Conclusion Discussion

This paper focuses on the key technical pain points of target tracking, trajectory planning and cluster control of UAV swarms in complex scenarios, refines the key findings based on the core research results, and clarifies the value and practical significance of each technological breakthrough, which are analyzed as follows:

4.1 Multi-modal Fusion: Significantly Improve Target Detection Robustness

In the complex environment, a single visual detection algorithm is susceptible to light, obstruction and other interferences, resulting in misdetection and omission, which is difficult to meet the reliability requirements of UAV dynamic target tracking. In this paper, through the multimodal fusion scheme of "vision+posture", visual detection (such as YOLO series algorithms) is combined with human skeletal posture detection, so that visual information can be used to locate the approximate range of the target, and posture features can be used to accurately match the identity of the target, thus forming a dual verification mechanism. This fusion not only makes up for the scene adaptability defects of a single visual algorithm, but also provides reliable feature support for target behavior prediction, effectively reduces the phenomenon of false leakage detection, so that the detection system can still maintain stable performance in complex environments, and significantly improves the robustness of target detection.

4.2 MINCO Trajectory Optimization: Reducing Energy Consumption and Acceleration Sudden Change

When a UAV is tracking a dynamic target, traditional trajectory planning methods are often coupled with spatial and temporal parameters and are not fully adapted to the dynamics, resulting in high flight energy consumption and frequent acceleration variations, which affects the stability of the airframe and the mission endurance. The MINCO trajectory optimization scheme adopted in this paper, by decoupling the spatial and temporal parameters of the trajectory and combining them with the UAV dynamics constraints for planning, can reduce the control energy loss to the maximum extent while meeting the tracking timeliness; at the same time, the optimization method can smooth the trajectory changes, reduce the number of sudden changes in the acceleration and improve the stability of the UAV's flight to provide trajectory-level guarantees for efficient, safe and dynamic target tracking. This optimization method can smooth the trajectory changes, reduce the number of sudden changes in acceleration, improve the stability of UAV flight, and provide trajectory level guarantee for efficient and safe dynamic target tracking.

4.3 Distributed Self-Repairing Algorithm: Significantly Enhance the Anti-Destructive Capability of the Cluster

UAV cluster in the switching topology network environment, easy due to part of the node lost connection led to connectivity break; and when the UAV is damaged, the traditional centralized control is difficult to quickly reconfigure the formation, easy to cause task interruption. The distributed self-repair algorithm proposed in this paper guarantees connectivity when the cluster faces topology switching by dividing the cluster alliance by distance in advance, constructing a neighborhood hierarchy model offline for the expected formation, and reconfiguring the formation autonomously by forming a repair subnetwork and filling in the missing positions recursively after the UAV is damaged. The algorithm does not need to rely on the central control node, can quickly respond to the abnormal state of the cluster, effectively enhance the destruction resistance of the UAV swarm, and ensure that the mission can still continue to advance under the equipment damage scenario.

However, it still has the following limitations:

Insufficient adaptability to extreme environments

Although fusion reduces the interference of conventional occlusion and illumination changes, the feature extraction capability of the YOLO series algorithms will still be significantly attenuated under extreme weather such as strong direct light, dense fog, and sand and dust, and the accuracy of OpenPose for detecting the skeletal keypoints of the lower-resolution targets plummets, which makes it difficult to maintain a stable dual-verification effect.

High dependence on the front-end path

The optimization effect of MINCO is highly dependent on the constraints generated by the front-end path search, and the delay in updating the front-end path will lead to the constraints' deviation from the actual environment if the dynamic obstacles in the complex environment are dense, which will cause a pseudo-safety risk for the trajectory optimized by MINCO; the delay in the front-end path updating can lead to the deviation in the actual environment. The risk of "pseudo-safety" exists in the trajectory optimized by MINCO;

At present, the field still needs in-depth research in the following aspects:

Cross-modal learning (e.g. radar + vision fusion).

Lightweight deployment of edge computing and onboard AI chips.

Real-time path replanning in dynamic environments.

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