Research on UAV formation optimization based on emergence effect of swarm intelligence

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ABSTRACT

In order to explore the application of the emergence effect of swarm intelligence in the formation optimization of unmanned aerial vehicle (UAV), this study conducted an in-depth study on the control strategy of UAV formation by constructing a theoretical model based on the swarm intelligence and carrying out simulation experiments. By simulating the swarm behavior of organisms in nature, this study designed a UAV formation control strategy that can adapt to complex environments and task requirements. The results suggest that compared to the traditional centralized control method, the control strategy based on swarm intelligence emergence shows significant advantages in improving the task execution efficiency and enhancing the robustness of the system. This study not only provides a new theoretical support and technical path for the research and application of UAV formation flight technology, but also opens up a new horizon for the development and interdisciplinary application of swarm intelligence theory.

Keywords: UAV formation, emergence effect of swarm intelligence, control strategy

1. INTRODUCTION

As an advanced technological tool, drones have been widely used in many fields such as military, civil, and commercial. The UAV formation flight technology has become a hot topic of research today because of its high efficiency in performing multi-tasks[1]. This technology can achieve multi-aircraft collaboration, which improves the flexibility and efficiency of task execution through distributed operations and effectively overcome the limitations of a single UAV in the face of complex environments and tasks.

Although there have been some advances in the field of drone formation, most of them rely on traditional, centralized control strategies, which are often inflexible in the face of complex environments and missions. In addition, these methods often require precise prior knowledge of the environment, limiting the application of drone formations in unknown or dynamically changing environments[2]. At the same time, although swarm intelligence emergence theory has been applied in other fields such as robot cooperation and traffic flow optimization, its exploration in UAV formation is still relatively preliminary, and its potential has not been fully tapped.

Therefore, this study aims to explore the UAV formation optimization method based on swarm intelligence emergence effect. By establishing the corresponding theoretical model and simulation experiments, the effect of swarm intelligence emergence effect in UAV formation is analyzed and verified. This study not only expands the application of swarm intelligence emergence theory in the field of UAV formation, but also provides a new perspective and method for the control strategy and behavior optimization of UAV formation, which has important theoretical and practical significance for promoting the development of UAV formation technology.

2. OVERVIEW OF THE EMERGENCE EFFECT OF SWARM INTELLIGENCE

The emergent effect of swarm intelligence, a concept derived from the field of biology, describes how complex global patterns are generated through simple interactions between individuals. This phenomenon is ubiquitous in nature, such as the path finding of ant colonies or the predator-evading behavior of fish schools[3]. This effect provides a new perspective to examine and design the control logic of UAV formations by simulating the cluster behavior of organisms in nature to guide the collaborative work of UAV formations, thereby automating complex tasks without central control.

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In the study of UAV formation control, the core idea of swarm intelligence emergence effect is to use the local interaction between UAVs to achieve global coordination and optimization[4]. The advantage of this approach is that it does not rely on a central control unit to direct the behavior of each UAV, but achieves the goals of the entire formation through a decentralized and self-organizing approach, thus enhancing the robustness and flexibility of the system, especially in the face of dynamic changing environments and uncertain mission conditions. The application of swarm intelligence emergence effect in UAV formation is mainly reflected in the following aspects:

2.1 Self-organization

This is a core feature of swarm intelligence emergence, which refers to the ability of drone formations to form orderly structures and behavioral patterns by themselves through individual interactions without central control. This self-organizing capability enables the UAV formation flexibility to cope with environmental changes and quickly adapt to new mission requirements.

2.2 Local interaction with simple rules

Each UAV in a UAV fleet follows a simple set of behavioral rules that determine how they interact with surrounding UAVs. Through local interaction, UAVs can pass information between each other and coordinate their actions, thus enabling the entire formation to achieve complex collective behavior.

2.3 Scalability and flexibility

Since swarm intelligence emergence is based on local interactions between individuals, the formation can easily adapt to changes in the number of members, whether increasing or decreasing the number of UAVs, it will not have a fundamental impact on the performance of the entire system. This scalability and flexibility are essential to perform tasks of different scales and complexities.

2.4 Robustness

The swarm intelligence emergence effect gives the UAV formation a high degree of robustness[5]. Even if some UAVs fail or are destroyed, the remaining UAVs can continue to perform tasks and maintain the overall performance of the formation through local information exchange and cooperation.

By applying swarm intelligence emergence effect to UAV formation control, a series of algorithms based on simple local rules can be designed to drive UAV formation to form complex behavior and task execution patterns, such as obstacle avoidance, target search, and area monitoring. The key of this approach is how to precisely design individual behavior rules and interaction mechanisms to ensure that UAV formations can achieve the desired global behavior in various situations.

3. UAV FORMATION MODELING

In this study, UAV formation modeling is based on the swarm intelligence emergence effect with the aim of designing UAV formation control strategy that can be self-organized and adaptive. The interaction between UAVs and environmental factors are considered in this model, in order to achieve efficient task execution and rapid response to environmental changes.

3.1 Dynamic model of UAV

The dynamic behavior of a UAV can be described by its position and velocity in space. For the i th UAV, its position vector and velocity vector are denoted by $x_i(t)$ and $v_i(t)$, respectively, where t represents the time. The acceleration of the UAV, the time derivative of the velocity, is a function of the forces determined by the interaction between the UAVs and their response to the environment. Therefore, we can describe the dynamic behavior of UAV through the following differential equations:

$$\frac{dx_i(t)}{dt} = v_i(t) \tag{1}$$

$$\frac{dv_i(t)}{dt} = a_i(t) \tag{2}$$

Among them, $a_i(t)$ is the total acceleration acting on the UAV i at time t, which integrates the effects from other UAVs and their response to environmental factors.

3.2 The interaction between UAV

The interaction between UAVs is the key to the emergence of formation behavior[6]. These interactions are based on the following three basic rules that simulate swarm intelligence emergence behavior in bird flight:

Separation rule. To avoid collisions, each UAV will try to keep a certain distance and avoid getting too close to other UAVs around it. This can be modeled by a repulsive force that is inversely proportional to the distance between the UAVs.

$$F_{sep,i} = \sum_{j\neq i,\|x_j - x_i\|<r_{sep}}^{N} -k_{sep} \cdot \frac{x_j - x_i}{\|x_j - x_i\|^2} \tag{3}$$

Of these, the r_{sep} is the separation radius. and only when other UAVs enter this radius, the separation force will be effective. k_{sep} is a proportional constant, which is used to adjust the strength of the separation force.

Alignment rules. The UAV adjusts its speed by matching the average speed of the surrounding UAVs, thus achieving consistency in direction.

$$F_{ali,i} = k_{ali} \cdot \left(\frac{1}{N_{ali,i}} \sum_{j\neq i,\|x_j - x_i\|<r_{ali}}^{N} v_j - v_i \right) \tag{4}$$

r_{ali} is the alignment radius, which defines which surrounding UAVs will affect the alignment behavior of the current UAV; $N_{ali,i}$ is the number of UAVs within the alignment radius; k_{ali} adjust the strength of the alignment force.

Agglomeration rules. The UAV moves towards the average position of the surrounding UAV to achieve the agglomeration of the group.

$$F_{coh,i} = k_{coh} \cdot \left(\frac{1}{N_{coh,i}} \sum_{j\neq i,\|x_j - x_i\|<r_{coh}}^{N} x_j - x_i \right) \tag{5}$$

r_{coh} is the agglomeration radius, which determines that surrounding UAVs will affect the aggregation behavior of the current UAVs; $N_{coh,i}$ is the number of UAVs within the cohesive radius; k_{coh} adjusts the strength of cohesion.

By combining these three basic rules, the acceleration a of each UAV can be calculated as:

$$a_i(t) = F_{sep,i} + F_{ali,i} + F_{coh,i} \tag{6}$$

The model framework not only captures the dynamic interactions within the UAV formation, but also provides a basis for further consideration of environmental factors. By adjusting the parameters in the model, the behavior of UAV formation in different environments can be simulated, which provides theoretical basis and simulation support for the design and optimization of UAV formation control strategy.

3.3 Control strategy for single-platform rotorcraft UAV

The core of the control strategy is to define how the UAV adjusts its behavior based on its surroundings and the state of other UAVs. The strategy consists of two main parts: behavioral decision making and motor control[7].

Behavioral decision-making. The behavioral decision-making mainly relies on several basic behaviors of separation, alignment, and Agglomeration. In addition, two additional behaviors of target tracking and obstacle avoidance are introduced to enhance the functionality of UAV formation.

The UAV needs to move towards the intended target. If the target position is set as x_{target}, the target tracking force can be represented as:

$$F_{target,i} = k_{target} \cdot \left(x_{target} - x_i \right) \tag{7}$$

The UAV needs to sense and avoid obstacles. For each UAV i and obstacle o, the obstacle avoidance force can be expressed as follows.

$$F_{obs,i} = \sum_o -k_{obs} \cdot \frac{x_o - x_i}{\left\| x_o - x_i \right\|^3} \tag{8}$$

where, x_o is the position of obstacle o, k_{obs} is the coefficient that adjusts the strength of the obstacle avoidance force.

Motion control. At the level of motion control, the UAV's acceleration $a_i(t)$ is determined by the linear combination of the above forces:

$$a_i(t) = \omega_{sep} \cdot F_{sep,i} + \omega_{ali} \cdot F_{ali,i} + \omega_{coh} \cdot F_{coh,i} + \omega_{target} \cdot F_{target,i} + \omega_{obs} \cdot F_{obs,i} \tag{9}$$

ω_{sep}, ω_{ali}, ω_{coh}, ω_{target}, ω_{obs} is the weight parameter, which is used to adjust the relative importance of each behavior.

The core of these control strategies is how individual drones make decisions based on simple local rules, which can generate complex and efficient behavior patterns at the group level[7]. These basic behaviors enable UAVs to efficiently navigate to a target location or perform search tasks while maintaining formation and avoiding collisions. In addition, the introduction of target tracking and obstacle avoidance behavior not only increases the functionality of the formation, but also improves its adaptability and robustness in complex environments.

3.4 UAV formation controller design

To design a UAV formation controller, several key control strategies are integrated, including target localization, formation maintenance, collision avoidance, and path planning. It is assumed that each UAV is able to measure the relative position and velocity with neighboring UAVs, and is able to receive global target information from the leader UAV or the control center.

The state of each UAV can be described by its position $p_i = [x_i, y_i]^T$ and velocity $v_i = [v_{x_i}, v_{y_i}]^T$ in two-dimensional space and the UAV can directly control its acceleration $a_i = [a_{x_i}, a_{y_i}]^T$.

The concept of a virtual leader is introduced to achieve target localization. The position $p_{lead}(t)$ of the virtual leader represents the desired position of the formation, whose dynamics are determined by the overall task of the formation. To maintain a specific formation, each UAV will try to keep its relative position to the virtual leader constant. If the desired relative position of UAV i is r_i, then its desired absolute position is $p_i^* = p_{lead} + r_i$.

Collision avoidance is achieved by introducing a repulsive force that is inversely proportional to the distance between the drones. For UAVs i and j, if the distance between them is less than the safe distance d_{safe}, then UAV i will be repulsive from UAV j as follows.

$$F_{rep,ij} = k_{rep} \cdot \left(1 - \frac{\left\| p_i - p_j \right\|}{d_{safe}} \right) \cdot \frac{p_i - p_j}{\left\| p_i - p_j \right\|} \tag{10}$$

Among them, k_{rep} is the coefficient of repulsive force.

Combined with the above control strategy, the acceleration control command of UAV i can be expressed as:

$$a_i = k_{pos} \cdot \left(p_i^* - p_i \right) + k_{vel} \cdot \left(v_{lead} - v_i \right) + \sum_{j \neq i} F_{rep,ij} \tag{11}$$

Among them, k_{pos} and k_{vel} are respectively the gain coefficient of position and speed control, v_{lead} is the speed of the virtual navigator.

4. SIMULATION VERIFICATION

In this study, a simulation environment is constructed to verify the proposed UAV formation control strategy. The simulation environment is designed to simulate a scenario where a swarm of UAVs is moving towards to designated target location in a space containing static obstacles. Each UAV is assumed to be a point mass that can move freely in two-dimensional space, and its dynamics are described by a position vector x_i and a velocity vector v_i, where i represents the index of the drone. Considering the practical application scenario, the communication between UAVs is limited by the distance d_{comm}, and only when the distance between UAVs is less than this threshold, can they communicate with each other.

Three obstacles are set up in the simulation environment, each obstacle is defined by its central position $x_{obstacle}$ and radius $r_{obstacle}$. These obstacles are designed to test the effectiveness of the control strategy in maintaining the formation structure of UAVs and avoiding collisions. Target location $x_{obstacle}$ is set to be the point that all UAVs need to reach. The above strategy takes the minimum safe distance d_{safe} into account that must be maintained between UAVs in order to avoid collisions, and assumes that the UAV can avoid the obstacle by adjusting its flight direction when it detects an obstacle. The simulation process follows the following steps: Firstly, the position and velocity of the UAVs are initialized to ensure that all the UAVs are at the starting position which is far from the target position. Subsequently, the UAV updates its speed and position by calculating the acceleration command at each time step according to the control strategy. Throughout the simulation, obstacle avoidance rules are repeatedly checked and applied to ensure that the UAV does not collide with any obstacles or other UAVs. Finally, the simulation ends when all UAVs are close to the target position. Specific simulation parameters include: 20 UAVs, communication distance d_{comm} which is 50 meters, safety distance d_{safe} which is 10 meters. There are three obstacles, respectively located between the starting position of the UAV and the target position, to simulate the obstacles that may be encountered in actual flight. The target position is set at the coordinates (100, 100), and the initial position of the drone is randomly distributed around the origin of the coordinates.

At the beginning of the simulation, the initial position of the drone swarm is shown as a blue dot in Figure 1, randomly distributed in the environment. The red transparent circle indicates the location and size of the obstacle, and the target location is indicated by a green “X” mark.

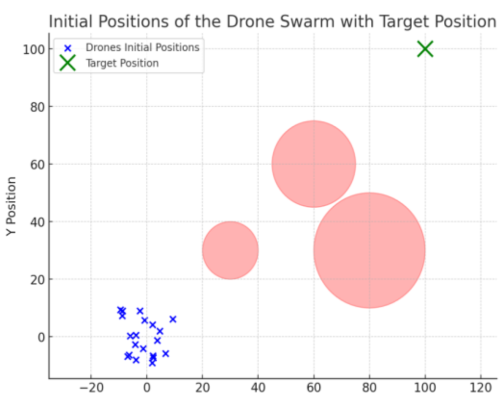

Figure 1. Schematic of the initial position.

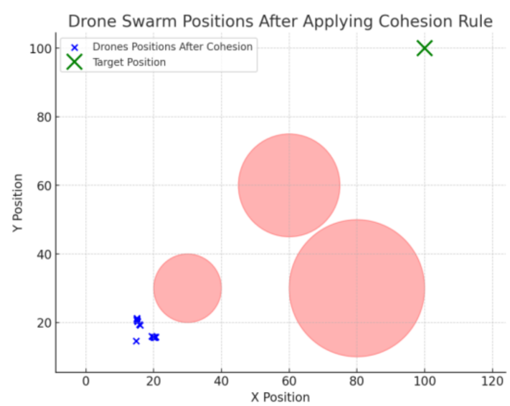

Figure 2. Schematic of automatic gathering.

As shown in Figure 2, through the cohesion rule, the UAV swarm strives to maintain an appropriate distance from each other to form a more compact and orderly formation structure. This behavior pattern helps to improve the overall efficiency and coordination of the group, enabling UAVs to collectively reach the target location in a relatively centralized manner, while improving obstacle avoidance efficiency.

In this paper, the navigation strategy and behavior pattern of UAV formation in complex environment are deeply analyzed by means of cluster center trajectory by calculating and tracking the geometric center of the UAV swarm, the response of the whole swarm to the control strategy and its obstacle avoidance behavior are observed from a macroscopic perspective. As shown in Figure 3, the simulation results show that the control strategy adopted can effectively guide the UAV swarm to cooperatively reach the specified target position while avoiding obstacles. By intelligently adjusting the flight path and speed, the UAV not only successfully avoided collision with obstacles, but also maintained the stability of the formation, showing good coordination and adaptability.

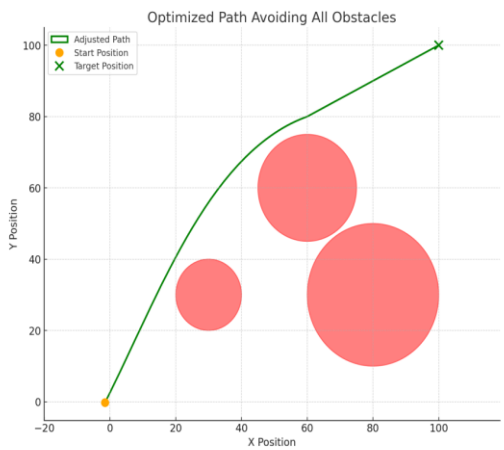

Figure 3. Schematic of automatic obstacle avoidance path.

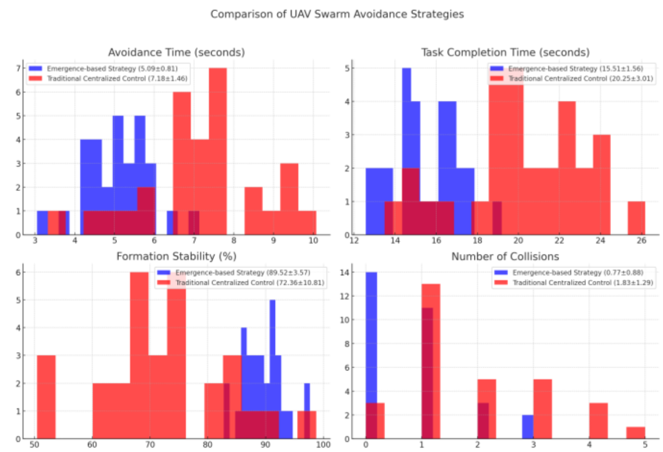

Figure 4. Comparison of UAV swarm obstacle avoidance.

The traditional centralized control strategy is used to carry out the same simulation experiment. as shown in Figure 4, we measured several key indicators such as obstacle avoidance time, task completion time, formation stability and collision frequency, and used them to compare with the optimization strategy based on crowd intelligence emergence.

Centralized control strategy. Under centralized control, all UAV actions are determined by a central controller. This strategy is more efficient when the environment is simple with little change. However, in the face of emergencies or complex obstacle environments, the decision-making time of the central controller is significantly increased, which slows down the reaction speed of obstacle avoidance. Although the strict formation can still be maintained, it has less flexibility to adjust the formation in a complex environment. When a certain UAV encounters an obstacle and needs to change its path suddenly, it may cause the whole formation to be readjusted and affect the overall task execution efficiency. When there is a malfunction at the central control point, the entire system may also be paralyzed.

Strategies based on emergent effect of swarm intelligence. Each UAV makes response decisions autonomously according to local information, which greatly reduces the time of information processing and decision-making. Thus, the whole swarm can adapt to environmental changes faster and improve the efficiency of obstacle avoidance. The UAV can instantly adjust its formation to adapt to changes in the environment, maintaining their formation while ensuring efficiency. Even if some UAVs fail or lose contact, the remaining UAVs can continue to perform tasks, and the overall system is more robust.

5. CONCLUSION

The UAV formation obstacle-avoidance flying method proposed in this study demonstrates a significant improvement over the existing technology, especially in improving the efficiency of obstacle avoidance and maintaining the stability of formation structure. Traditional centralized control strategies tend to focus on improving the obstacle avoidance ability of a single UAV, while ignoring the maintenance of the overall formation form, which may lead to lose or disordered formation structure when avoiding obstacles, thus affecting the efficiency and safety of task execution. In contrast, the method proposed in this study adopts a swarm intelligence-based strategy, which not only considers the local obstacle avoidance behavior of each drone, but also optimizes the communication and coordination mechanisms within the formation to ensure that the predetermined formation can be quickly restored or maintained while bypassing obstacles. This strategy also effectively reduces path deviation caused through obstacle avoidance by dynamically adjusting the relative position and speed between UAVs, thereby improving flight efficiency and energy utilization. The simulation results show that the proposed strategy can Make the flight formation more flexible and stable for obstacle avoidance in complex and variable flight environments, demonstrating its potential advantages in dealing with unknown environments and performing multi-tasks. Therefore, this study not only provides a new solution for obstacle avoidance flight of UAV formation, but also lays a solid theoretical foundation for the future development of UAV swarm intelligent control field.

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