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DFM: A Distributed Flocking Model for UAV Swarm Networks

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ABSTRACT Flocking of the unmanned aerial vehicle (UAV) network refers to utilize the node's autonomous mobility to satisfy the principle of cohesion, separation, and alignment. A network with flocking ensures the connectivity between high-speed UAV nodes and simplifies the design of various swarm applications. In this paper, we propose a novel distributed flocking model for UAV swarm networks. The model follows the Boid principle and establishes the master–slave transmission mode among the nodes. The slave node performs the distributed autonomous regulation. An effective flocking method is proposed, which is based on the positioning and communication capabilities of Wi-Fi. The slave node can sense and adjust their distance and direction from the master node. The simulation and experimental results show that our model can guarantee the connectivity between all nodes and has 1.4× the network goodput gain outperforms the traditional flying ad hoc network.

INDEX TERMS UAV network, flocking, distributed model, Wi-Fi communication.

I. INTRODUCTION

Recently, it is witnessed that UAVs (Unmanned Aerial Vehicles) experienced an unprecedented development from single machine to multi-machine systems in military and civil applications [1]. Single UAV system still has many defects in functionality and survivability, which stimulated the research of multiple UAV systems with stronger functions and survivability. This also promoted the development of support technologies such as UAV networks or flying ad hoc networks (FANET) [2]. Recently, the collaborations among UAVs have become increasingly popular. It has been used in wide range of applications, including cooperative UAVs to perform military tasks such as investigations, surveillance, operations [3], multi-agent cooperative control [4], automatic parallel balancing payload [5], mobile sensor network [6], [7] and robot system [8], etc. In fact, one of the preconditions for ensuring that multiple UAVs can perform tasks collaboratively is that the UAVs must be interconnected and interoperable. Even if the speeds of UAVs are high, UAV networks are required to support reliable information exchange between nodes. Therefore, one of the challenges in this field is how to guarantee the QoS of wireless communications between nodes in a high dynamic environment. However, one-sided optimizing FANET performance [9] may be difficult to guarantee reliable communication between nodes under high dynamic conditions. As the UAV swarm networks are complex systems, it is necessary to analyze and solve the key technical problems in UAV networks in a hierarchical manner to deal with them. The flocking of the UAV network is only one of them.

In order to keep the connectivity of a UAV network, nodes in the multiple UAV systems should be aggregated within a certain range regardless of how the nodes to move. Therefore, for FANET nodes using Ad Hoc network technology, they are required to have some kind of ability to control their movement, which can eliminate the randomness of mobility. Once the distance between nodes is effectively controlled, the quality of wireless communication with a certain SNR can also be guaranteed. The current solution to this problem is to allow the UAV agent to imitate the swarm behavior, so that the nodes can act like insects or animals to work group cooperatively [10]. Flocking is the collective behavior of UAVs that interact in large numbers for common group goals. Inspired by biological research works, flocking without collision between each other can be achieved through the interaction process of simple individuals which only need to follow simple rules of behavior [11]. We define flocking of

UAV network as the features utilizing the node's autonomous mobility to make the nodes of UAV network satisfy the cohesion, separation, and alignment principles. In other words, when a network has flocking ability, all its nodes meet the following characteristics: they can aggregate themselves, and cannot walk randomly to become isolated nodes; they can maintain separation without colliding due to close proximity; they can have common movement tends and will not be out of sync in high-speed movement. If a new feature called flocking is added to the UAV network layer, the complex QoS control problem of the network will become transparent to the higher layer, and the application developers can simplify the design of the swarm systems and applications without having to pay attention to control the network node movement and other complicated issues.

Adding flocking to UAV networks involves many complex technical issues. Firstly, based on the wireless networking capabilities of Ad Hoc networks, how to make the set of network nodes act as the required group effects by adding certain control capabilities. One of the key issues is the principle to design the control model. Secondly, considering the limited resources of UAVs and the real-time nature of flocking control, the algorithm for implementing the model must be distributed and simple rather than centralized and optimal. Consequently, each UAV node can perform online real-time calculations and autonomous control. Thirdly, considering the high performance-to-price ratio of UAV swarm, the equipment required for the above model and algorithm should be consistent with the current technology level. In our paper, we propose a flocking model of UAV network based group intelligence to enable simple and autonomous real-time control of UAV nodes. A Wi-Fi-based positioning and communication capability is proposed to achieve the flocking of UAV network, which provides the possibility of using commercial equipment to realize our flocking algorithm.

This paper is organized as follows. Section II describes the flocking problem of UAV networks. Section III proposes a distributed flocking model (DFM) of UAV networks. Section IV proposes a method based on Wi-Fi to solve the positioning and alignment requirements at the same time. It also gives a method for the node to sense the distance to the master node, and proposes a method for synchronizing the directions of the slave node and the master node based on the DFM communication protocol. Section V designed a prototype system and conducted simulation tests on the OMNeT++ platform. Section VI summarizes related work and Section VII concludes the paper.

II. PROBLEM DESCRIPTION

The main purpose of this paper is to solve the interconnection problem of UAV networks, so that upper-layer applications running upon the network do not need to pay attention to the connectivity of the network, thus flocking of UAVs network can simplify the design and development of UAVs applications. Currently, there are two methods of controlling UAVs motion mainly. One is formation, the other is swarm. The UAVs in the formation fly according to waypoints which are calculated beforehand, so that the method has many deficiencies such as being beyond control in uncertain condition. The UAVs in the swarm, however, usually use ad hoc network technology and the nodes in unstable condition may move randomly, so the flocking model is needed for controlling UAV nodes autonomously in swarm. The necessary condition for UAV network to meet the interconnection is that there is at least one spanning tree in the topology diagram composed of UAV nodes. Therefore, this paper proposed a flocking model of UAVs network based on swarm intelligence. In the master-slave mode, a slave node (Follower, F for short) and its master node (Leader, L for short) form a communication link and all communication links form a spanning tree. In order to facilitate the analysis, we firstly consider only two UAVs in the network. One of them is the leader L, and the other one is the follower F. The node L can determine its flight trajectory according to the task and the environment state, while the node F needs to adjust its own distance and flight direction with L according to the state information of L. Assuming:

1) All UAVs fly at the same altitude;

2) When UAVs move, uncertain changes in speed and direction may occur due to application requirements and disturbances.

3) UAV can obtain its own position information $< lon, lat, height >$ and flight status $< speed, angle, omega >$ through sensors in a real time manner;

4) UAV can communicate with neighboring nodes and can publish its own information actively or request information from neighboring nodes passively.

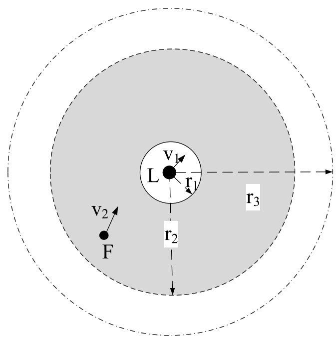

FIGURE 1. Flocking constraints between L and F.

For node L, the preferred location of F should be in the annular area centered on L (shaded in Fig.1.). Wherein, the distance d between F and L satisfies:

$$r_1 < d < r_2 \tag{1}$$

where r_1 denotes the safe distance, and r_2 is the reliable communication distance. We define r_3 as the unstable communication distance ($r_2 < r_3$). Obviously, in order to realize the goal of flocking (separation, aggregation and alignment); the following control strategies must be met:

(1) During the movement, no matter how L changes, F can always adjust itself so that it falls within the shaded area to satisfy the Formula (1).

(2) When F falls to the region that $d \leq r_1$ or $r_2 < d < r_3$, it needs to be adjusted within the time period Δt so that it enters the shaded region as soon as possible.

In practice, L and F are not always in the desired position as described above. For example, when the speed or course of L or F is changed due to external factors, if one of them fails to adjust in time, it will result in the loss of this flocking. Therefore, it is necessary to design a reasonable and reliable strategy for F, so that F and L can always satisfy the relation of the Formula (1).

For the network composed of n UAVs, we assume that each UAV node has been assigned an L node (other than the root node). There will be possible collisions between the nodes when considering the flocking problem between F and L. Without loss of generality, we only take into account collisions in the direction of movement of the node (as shown in Fig.2). The node UAV1 needs to constantly sense the front of the motion. When other node (such as UAV2) moves into the sensing range and the distance d_s between UAV1 and UAV2 meets $d_s \leq r_1$, the track of UAV1 should be adjusted immediately to avoid collision. Moreover, the priority of collision avoidance is higher than others.

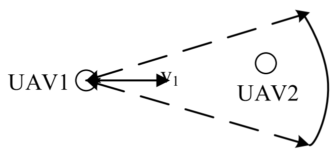

FIGURE 2. Obstacle avoidance between two followers.

III. DISTRIBUTED FLOCKING MODEL BASED ON AUTONOMOUSLY ADJUSTMENT

According to the group motion model, the Boid model [4], individuals can sense the flight information of neighboring individuals within a certain range and follow three basic rules of behavior: cohesion, separation, and alignment. It is always possible to satisfy the Formula (1) between the node F and the node L. In order to simplify the calculation and control process, F must be capable of autonomous adjustment based on relevant information. The principles of DFM are: 1) When F and L are too close, F should fly away from L; 2) When the distance is too far, F should fly in the direction of L; 3) When the distance between them is moderate, F should adjust itself to keep the same speed and direction with L.

As shown in Fig.3, a North-East-Land coordinate system was established. At any time t, suppose the flight state of node L is $< x_1(t), y_1(t), v_1(t), \varphi_1(t), \alpha_1(t), \omega_1(t) >$, and the flight state of node F is $< x_2(t), y_2(t), v_2(t), \varphi_2(t), \alpha_2(t), \omega_2(t) >$, where $< x_i(t), y_i(t) >$ is the position coordinate of UAV_i, $v_i(t)$ is the rate of UAVi ($v \in (v_{\min}, v_{\max})$), and $\varphi_i(t)$ is the heading angle (positive direction of X axis is 0 degree, counterclockwise is positive), $\alpha_i(t)$ is the acceleration ($|\alpha| \leq \alpha_{\max}$), and $\omega_i(t)$ is the angular velocity ($|\omega| \leq \omega_{\max}$).

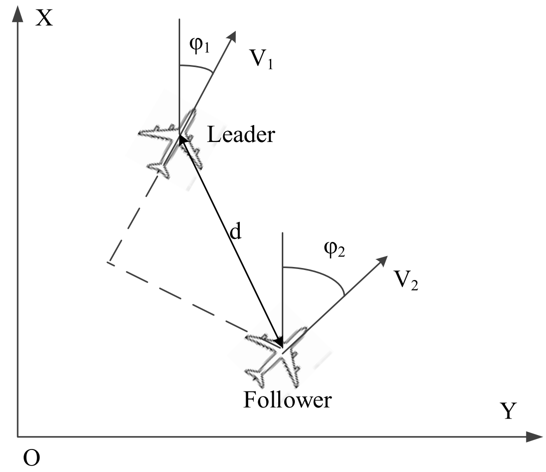

FIGURE 3. Quantitative analysis between L and F.

Therefore, at time t, the distance between node F and node L is $d(t) = \sqrt{(x_1(t) - x_2(t))^2 + (y_1(t) - y_2(t))^2}$, and the relative position of node L to node F is $< x_1(t) - x_2(t), y_1(t) - y_2(t) >$. According to the principle of separation and cohesion, when F and L are too close, F should fly in a direction away from L, that is, in the direction $< x_2(t) - x_1(t), y_2(t) - y_1(t) >$.When F and L are too far, F should fly in a direction near L, that is, in the direction $< x_1(t) - x_2(t), y_1(t) - y_2(t) >$. According to the principle of alignment, when F and L satisfy formula (1), F and L should maintain the same flying speed and direction, that is, adjusting the speed $v_2(t)$ and direction $\varphi_2(t)$ to make it consistent with the $v_1(t)$ and $\varphi_1(t)$.

Specifically, the adjustment decisions of F can be divided into the following categories:

(1) $d(t) \leq r_1$, the adjustment target at this time is to make F accelerate away from L, and the direction away from is $< x_2(t) - x_1(t), y_2(t) - y_1(t) >$. To convert into the direction angle:

$$\theta_0 = \arctan \left| \frac{y_2(t) - y_1(t)}{x_2(t) - x_1(t)} \right| \tag{2}$$

$$\theta = \begin{cases} \theta_0 & x_2(t) - x_1(t) > 0, y_2(t) - y_1(t) > 0 \\ \theta_0 + \pi & x_2(t) - x_1(t) < 0, y_2(t) - y_1(t) > 0 \\ \theta_0 + \pi & x_2(t) - x_1(t) < 0, y_2(t) - y_1(t) < 0 \\ \theta_0 + 2\pi & x_2(t) - x_1(t) > 0, y_2(t) - y_1(t) < 0 \end{cases} \tag{3}$$

If $0 < \theta - \varphi_2(t) < \pi$ or $\theta - \varphi_2(t) < -\pi$, then the angular velocity of F in the next cycle is $\omega_2(t + \Delta T) = \omega_{\max}$, and the acceleration is $\alpha_2(t+\Delta T) = \alpha_{\max}$. If $\theta - \varphi_2(t) > \pi$ or $-\pi < \theta - \varphi_2(t) < 0$, then the angular velocity of F in the next cycle is $\omega_2(t+\Delta T) = -\omega_{\max}$, and the acceleration is $\alpha_2(t+\Delta T) = \alpha_{\max}$.

(2) $d(t) \geq r_2$, the adjustment goal at this time is to make F accelerate closer to L, and the approach direction is $< x_1(t) - x_2(t), y_1(t) - y_2(t) >$. To convert into the direction angle:

$$\theta_0 = \arctan \left| \frac{y_1(t) - y_2(t)}{x_1(t) - x_2(t)} \right| \tag{4}$$

$$\theta = \begin{cases} \theta_0 & x_1(t) - x_2(t) > 0, y_1(t) - y_2(t) > 0 \\ \theta_0 + \pi & x_1(t) - x_2(t) < 0, y_1(t) - y_2(t) > 0 \\ \theta_0 + \pi & x_1(t) - x_2(t) < 0, y_1(t) - y_2(t) < 0 \\ \theta_0 + 2\pi & x_1(t) - x_2(t) > 0, y_1(t) - y_2(t) < 0 \end{cases} \quad (5)$$

If $0 < \theta - \varphi_2(t) < \pi$ or $\theta - \varphi_2(t) < -\pi$, then the angular velocity of F in the next cycle is $\omega_2(t + \Delta T) = \omega_{\max}$, and the acceleration is $\alpha_2(t+\Delta T) = \alpha_{\max}$. If $\theta - \varphi_2(t) > \pi$ or $-\pi < \theta - \varphi_2(t) < 0$, then the angular velocity of F in the next cycle is $\omega_2(t+\Delta T) = -\omega_{\max}$, and the acceleration is $\alpha_2(t+\Delta T) = \alpha_{\max}$.

(3) $r_1 \leq d(t) \leq r_2$, the adjustment goal is to align F to L, that is, keep the speed and direction consistent.

The new speed rate after L goes through the period ΔT is $v_1(t + \Delta T) = v_1(t) + \alpha_1(t)\Delta T$, and the new heading angle is $\varphi_1(t + \Delta T) = \varphi_1(t) + \omega_1(t)\Delta T$, so F should be aligned to $v_1(t + \Delta T)$ and $\varphi_1(t + \Delta T)$ as far as possible in the next cycle. This means:

If $v_2(t) < v_1(t+\Delta T)$,
$$\alpha_2(t+\Delta T) = \min[\alpha_{\max}, \frac{v_1(t+\Delta T) - v_2(t)}{\Delta T}].$$
If $v_2(t) \geq v_1(t+\Delta T)$,
$$\alpha_2(t+\Delta T) = \max[-\alpha_{\max}, \frac{v_1(t+\Delta T) - v_2(t)}{\Delta T}].$$
If $0 < \varphi_1(t+\Delta T) - \varphi_2(t) < \pi$,
$$\omega_2(t+\Delta T) = \min[\omega_{\max}, \frac{\varphi_1(t+\Delta T) - \varphi_2(t)}{\Delta T}].$$
If $\varphi_1(t+\Delta T) - \varphi_2(t) > \pi$,
$$\omega_2(t+\Delta T) = \max[-\omega_{\max}, -\frac{\varphi_2(t) + 2\pi - \varphi_1(t+\Delta T)}{\Delta T}].$$
If $-\pi < \varphi_1(t+\Delta T) - \varphi_2(t) < 0$,
$$\omega_2(t+\Delta T) = \max[-\omega_{\max}, \frac{\varphi_1(t+\Delta T) - \varphi_2(t)}{\Delta T}].$$
If $\varphi_1(t+\Delta T) - \varphi_2(t) < -\pi$,
$$\omega_2(t+\Delta T) = \min[\omega_{\max}, \frac{\varphi_1(t+\Delta T) + 2\pi - \varphi_2(t)}{\Delta T}].$$

The above discussion shows that F which needs to achieve the above self-adjustment strategy must obey the following rules: 1) F must be able to sense the distance of L in time to determine the distance d between them; 2) F must obtain the L's position information to adjust the speed and heading angel; 3) It is a basic condition to ensure effective communication between L and F. In fact, as long as Formula (1) is satisfied between F and L, the communication quality between them can be guaranteed.

IV. Wi-Fi BASED POSITIONING AND COMMUNICATION METHODS

A. F SENSES THE DISTANCE TO L

Although we can obtain the spatial coordinates of L and F through a positioning system such as GPS or Beidou and calculate their distance, it is still difficult to reach the accuracy requirements of bee colony control by using non-high-precision equipment. Also, it is costly to use the high-precision positioning equipment. Therefore, how to use low-cost equipment to obtain relevant information and accurately calculate the value of d is important.

Perceiving the distance to a point in space is not a technical problem, because in 3D space or in the plane, using a sensor can determine the distance to a specific target. However, the sensor usually has strong directionality, and it needs to deploy many sensors or adopting a sensor capable of rotating in all directions so as to achieve the desired effect. This makes the UAV with high cost performance unable to adopt such a scheme. Since there is currently no cheap, omni-directional distance sensor, it cannot meet technical requirements of the UAV swarm.

Considering that the Wi-Fi has the characteristics of omnidirectional transmission, its wireless signal can cover the sphere space centered on the source point. There have been many researches and applications in distance measurement [12]. Most importantly, the Wi-Fi is mature and cheap, and its equipment is light. The Received Signal Strength Indication (RSI) received by the node is an important technical parameter in the Wi-Fi network, which reflects the distance between the signal strength received by the receiving node and the signal transmission point. The relationship between the distance d of the transceiver node and the received RSSI value is shown in Formula (6) [12]:

$$d = 10^{\frac{(A - rssi + w)}{10n}} \quad (6)$$

Where A is apparent transmission power, n is a parameter describing attenuation properties of the environment, and w is a zero-mean Gaussian random variable used for modeling the shadow fading. Accordingly, the node F can infer its distance to the node L by the self-detected RSSI. Therefore, we use the Wi-Fi system as a full-range distance sensor. As long as the relationship between the distance d between two UAVs and the received RSSI strength of Wi-Fi can be measured in a specific environment, the value of d can be obtained from the obtained RSSI value. Although the wireless signal may be subject to different interference in different environments [13], [14], the model does not need to calculate the exact distance, but only needs to ensure that the network always satisfies the connectivity. Wi-Fi and GPS can be used together to realize the characteristic of flocking for UAV network. GPS can ensure that the UAVs do not collide when they are close, and Wi-Fi can ensure good communication quality between UAVs.

B. F INFERS THE ORIENTATION TO L AND ALIGNS TO L

Determining the orientation of F to L and their alignment are the two key issues to implement our model. In order to determine the position of F to L, F needs to know its own space coordinates and the space coordinates of L based on equations (2) and (4); F needs to exchange the direction of movement and the speed of movement between them in order to align with the state of L. To achieve this, the UAV network adopts the DFM protocol to support the exchange of relevant information between the parties. The DFM communication protocol defines the communication rules for the information exchange between nodes F and L. It provides two communication modes: broadcast mode and request mode. The broadcast mode requires the node L to actively broadcast its own position and flight status information. The node F determines whether to adjust its own flight status after receiving this information. Proactive request mode requires the node F to actively send an information request to L according to the model requirements. After receiving the request, it must immediately acknowledge its current location and flight status information to the requester.

Since bee colony applications also depend on peer-to-peer communication between nodes, to save valuable channel bandwidth resources, the communication resources required for maintaining the bee model of the bee colony network need to be kept as low as possible. How can we meet the needs of network clusters and keep a smaller communication load simultaneously?

Let T_0 be the interval period for node L to broadcast. L broadcasts a message to F for every T_0 period. As long as the L status changes (that is, when $\omega_L \neq 0$ or $\alpha_L \neq 0$), the message is immediately broadcast, so that F receives immediately. The state change amount, F will be adjusted according to the DFM; if the L state changes need a period of time to complete, the broadcast interval will change to T_1, where $T_1 < T_0$. However, when the L status does not change, the L broadcast interval is still restored as T_0.

When F determines that it needs to be adjusted according to the DFM, F sends an active request packet to L immediately, so that a packet including the current state of L can be obtained as soon as possible.

When F determines that it needs to be adjusted according to the DFM, F sends an active request packet to L immediately, so that a packet including the current state of L can be obtained as soon as possible.

It can be easily find that there are three main objectives for designing the DFM communication protocol: First, to enable F to infer the position of L, whenever F needs to adjust according to DFM, it will immediately send a request packet to L, and L immediately sends the message including its own status. The second is to ensure the alignment between network nodes, whenever the L state changes, it will take the initiative to push the message to F including its own position, speed and direction angle. The third is to pursue the efficient use of Bandwidth, whenever L's speed and direction change, its broadcast frequency increases.

Therefore, the DFM communication control Algorithm 1 is described as follows:

Algorithm 1 DFM Communication Control Algorithm

```
Leader:                //when node acts as Leader
Step 1:
    initialize periodic time T = T0
    Goto 2:
Step 2:
    broadcast status message
    timeout(T)
    Goto 3:
Step 3:
    IF ωL ≠ 0 or αL ≠ 0
        update T = T1
        Goto 2:
    ELSE
        update T = T0
        Goto 2:
    ENDIF
Follower:              // when node acts as Follower
Step 1:
    Receiving message from Leader
    IF msg_recieved  //receive message from Leader
        Goto 2:
    ELSE Goto 3:
    ENDIF
Step 2:
  IF need_adjust     //node needs to adjust its path
    adjust()
    Goto 3:
  ENDIF
Step 3:
  IF location_deviated //when location is deviated
    send(request)
    Goto 1:
  ENDIF
```

V. SIMULATION RESULTS AND ANALYSIS

A. THE PROTOTYPE SYSTEM

In order to verify the feasibility of the proposed model and algorithm, this section builds a simulation environment for UAV network based on OMNeT++ simulator. The physical layer of this model mainly uses the Radio model and the Medium model. In the MAC layer, the Ad Hoc model is mainly used and the routing is provided by the OLSR protocol, and the DFM model we developed is added. The network layer mainly uses the IMobility model. The network consists of 7 UAVs, and Wi-Fi communication is used between the nodes (maximum communication radius is set to 100m). 1 UAV is used as the master node L, and 2 UAVs are used as its F; each F is followed by 2 UAVs. In DFM, $r_1 = 2m$, $r_2 = 100m$, $r_3 = 130m$, the UAV initial speed is set to 10m/s, and the network movement range is 3km∗3km. During the movement of the UAVs, there exists wireless communication interference and random wind disturbance.

To evaluate the simulation results, we defined the following evaluation indicators.

Average Departure Distance (ADD): ADD between L and F in network is defined as:

$$ADD = \frac{\sum_{i=i}^{N} (d_{t_{i+1}} - d_{t_i})}{N \Delta t} \tag{7}$$

where $d_{t_{i+1}}$ is the distance between F and L at time t_{i+1}, d_{t_i} is the distance between F and L at time t_i, Δt is the time interval between t_{i+1} and t_i, N is the total number of time intervals, and the unit of ADD is m/s. Obviously, the more frequently the distance between two UAVs changes, the larger the ADD value, and the more dynamic of the network topology change.

Network Goodput (NG): The NG of a unit time at time t in the network is defined as:

$$NG(t) = \sum_{i=1}^{m} \frac{Goodput_i(t - \Delta t, t)}{\Delta t} \tag{8}$$

where, $Goodput_i(t - \Delta t, t)$ is the Goodput of ith data flow from $t - \Delta t$ to t, m is the total number of flows, and the unit of NG is Mbps. Obviously, in the case of the same routing protocol and communication standard, NG can be maximized when the network topology always maintains good connectivity, that is, nodes always satisfy the relation of Formula (1).

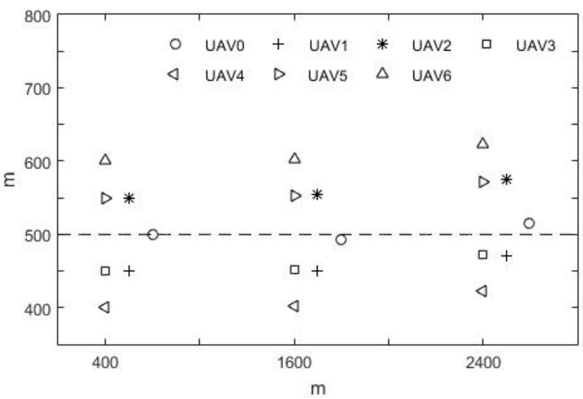

FIGURE 4. **The network topology changes when the master node flies along a straight trajectory.**

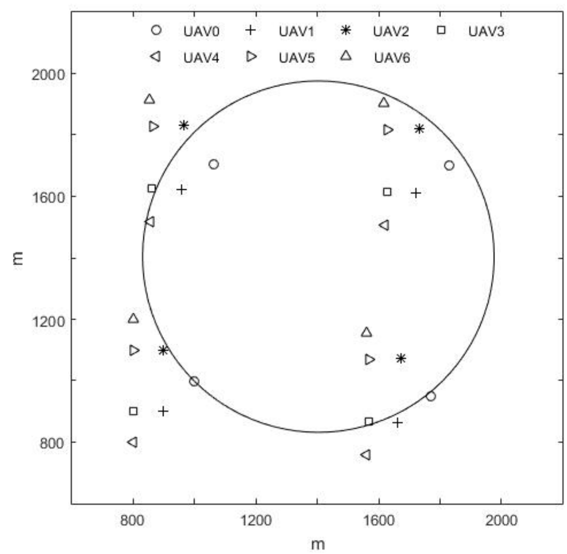

FIGURE 5. **The network topology changes when the master node flies along a circular trajectory.**

B. EXPERIMENTS AND ANALYSIS

In order to verify the effectiveness of our algorithm in different scenarios, we conducted the following experiments: Let the master node fly in straight and round flight paths to observe the behavior of the network.

Fig.4 and Fig.5 show the UAV network composed of 7 UAV nodes alignment and arrange in a circle, respectively. UAV0 follows a straight line and a circular track, UAV1 and UAV2 follow UAV0, UAV3 and UAV4 follow UAV1, UAV5 and UAV6 follow UAV2. All UAVs may deviate from their current position during flight because of ran-

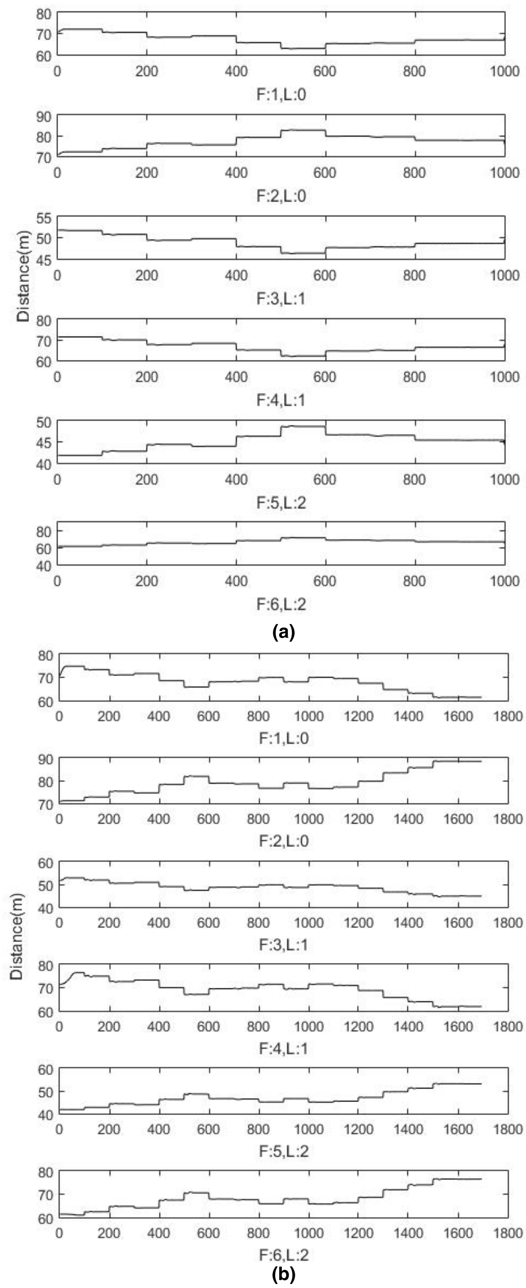

FIGURE 6. **Change of the distance between each L-F pair at different trajectories. (a) Straight trajectory. (b) Circular trajectory**

dom disturbance. It can be found from Fig.4 and Fig.5 that during the fly progress, the actual flight trajectory and network topology of the UAV node have some deviation due to random interference. But they can basically fly along the predetermined trajectory and maintain the topological stability.

Fig.6a and Fig.6b show the change of the distance between each Follower-Leader pair under the straight line and the round track, respectively. The network is composed of 7 UAV nodes. The following relationship is consistent with Fig.4 and Fig.5. From Fig.6, we can see that the distance between any Follower and its Leader node will fluctuate due to interference, self-adjustment and other factors. However, the distance between the Follower and the Leader can always meet the requirements of Formula (1) and ensure that the communication link is not interrupted. In addition, the distance between Follower and Leader fluctuates infrequently, which indicates that the entire UAV network topology is relatively stable during the operation. As shown in Table 1, the value of ADD under different Leader-Follower pairs for UAV networks composed of 7 UAV nodes in straight and round tracks, respectively. From Table 1, it can be found that the value of ADD under different Follower-Leaders pair is less than 0.25 m/s, which means each UAV deviates by an average of less than 0.25 m/s during the flight. Compared with the communication range ($r_2 = 100m$) between UAVs, under the control of the DFM algorithm, the UAV network can maintain a stable topology flight, thus ensuring the reliability of the communication link.

TABLE 1. ADD values between L-F pairs under different trajectories.

Follower-Leader	ADD of Line trajectory（m/s）	ADD of Round trajectory（m/s）
F:1, L:0	0.204	0.214
F:2, L:0	0.239	0.237
F:3, L:1	0.125	0.147
F:4,L:1	0.212	0.252
F:5,L:2	0.154	0.165
F:6,L:2	0.233	0.237

In the experiment, we also measured the network Goodput (NG). Since the peak network bandwidth based on the IEEE 802.11g standard is about 5.8 Mbps [15], we set up four nodes in the third stage of the UAV network of this experiment and send a stream of 0.48 Mbps between each pair of fi ($i = 1,\ldots, 12$).The total flow speed is 5.76 Mbps, and the NG is calculated in real time. For comparison, we conducted the experiments under three different scenarios: 1) the network topology is stationary; 2) the network node sets do linear motion and are subjected to random interference; 3) the network node sets do linear motion and are subjected to random interference, but the DFM model is simultaneously applied. Where the nodes may be offset due to the influence of the wind that obeys the Poisson distribution when the network nodes move. Fig.7 shows the variation of NG over a simulation time of 100 s (multiple averaged results).

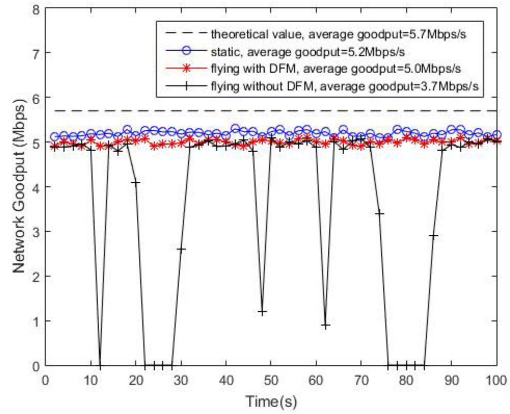

FIGURE 7. The variation of NG under different scenarios.

It can be found from Fig.7: a) under three different scenarios, NG is all lower than the theoretical value. This is because the network still has the influence of routing, control messages between F and L, and other disturbances in the simulation experiment. b) Compared with the static scenario 1, the NG value of the DFM model is slightly lower. This is because the DFM method needs to send a certain number of control messages, which reduces the overall network throughput. c) In scenario 2 (Ad Hoc model directly used by the network without DFM), due to the interference and the random influence of wind power, the network topology and the communication links between the nodes are difficult to be stable, which results the value of NG value fluctuating. When there is a large deviation from some nodes, even if all nodes are disconnected, the NG will be reduced to zero. On average, UAV networks with DFM have 1.4 times on NG than UAV networks without DFM, and the worse the environment, the greater the gap of NG. In some swarm applications, short-term and random communication interruptions cannot be tolerated, and the system cannot be adjusted in real time.

During the execution of the DFM algorithm, the value of the time period T_1 during which the leader broadcasts the state information when its motion is changing directly affects the effectiveness of the algorithm and the performance of the network. If T_1 is chosen too small, although the granularity of topology control can be improved, it may cause great interference to network data transmission. If T_1 is selected too large, although the network load can be reduced, it may not be able to effectively control network swarming. Obviously, there is a better value for T_1. Therefore, this paper measured the relationship between the NG and T_1. The results are shown in Fig.8.

Fig.8 shows that the leader broadcast period time T_1 continuously increases from 0.1s in the case of a network with a straight motion speed of 10 m/s, and the NG mean value changes. The time of the simulation is 100s. It can be found from Fig.8 that as T_1 increases, the number of control packets decreases, which leads to the increasing of average NG. When T_1 is greater than a certain value (e.g., greater than 3.2s),

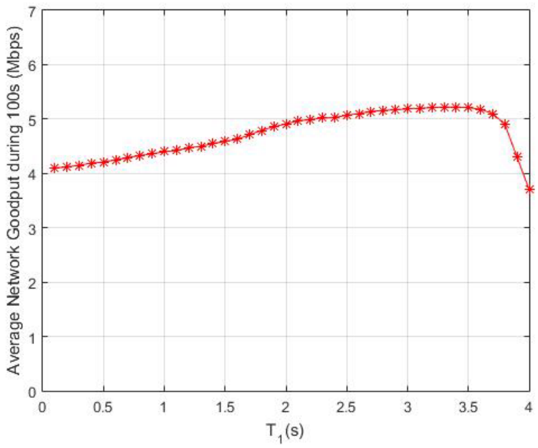

FIGURE 8. NG changes under different T_1.

the flocking of network cannot be maintained effectively, in which some nodes in the network may be disconnected with a small probability and average NG value decreases. The average NG value may decrease, while further increase the T_1 value greatly. In addition, the value of T_1 is related to the motion speed of the network node. When the speed is large, T_1 must be reduced to maintain the alignment of network nodes.

VI. RELATED WORKS

Reynolds [11] proposed the flocking model in his pioneering work in 1986, which has three heuristic rules that led to creation of the first computer animation of flocking. Reynolds' three flocking rules include: 1) Cohesion: attempt to stay close to nearby nodes; 2) Separation: avoid collisions with nearby nodes; 3) Alignment: attempt to match velocity with nearby nodes. This has motivated and guided many flocking theoretical models. For example, Vicsek *et al.* [16] focused on emergence of alignment in self-driven particle systems while Toner and Tu [17] adopted a continuum mechanics approach. Levine *et al.* [18] created rotating swarms using a particle-based model with all-to-all interactions. Recently, there has been a surge of interest in consensus problems due to [19], [20], and so on. Although the objectives that these theories aim at are different, the flocking, with its simplistic and effective framework, has been widely adopted as the coordination scheme in multi-agent systems [8], [21].

There has been a lot of research on the trajectory control of single UAV, such as applying neural networks to mobile robot manipulators [22]–[24]. From the control structure perspective for multi UAVs, the existing flocking control approaches can be classified into the centralized method, where a single controller is used to control the whole team based on the information from the whole team [25] and the distributed/decentralized method, where each team member generates its own control based on local information from its neighbors [26]–[29]. The centralized flocking control can be a good strategy for a small team of UAVs. When considering a team with a large number of UAVs, the need for greater computational capacity and a large communication bandwidth would mandate a distributed/decentralized control. From the control mechanism perspective, flocking control approaches can be classified into consensus-based approaches [30], [31], artificial potential function-based approaches [32], [33], and leader–follower approaches [34], [35]. Consensus-based approaches convert the flocking control problem into the consensus (or stability) problem of relative positions and velocities of multi-agents. They achieve formation stability based on graph theory and consensus. However, inter-vehicle collisions are not considered. Artificial potential function-based approaches apply the negative gradient of a mixture of attractive and repulsive potential functions as control inputs to satisfy the convergence and non-collision properties, respectively. The main drawback of this type of approaches is the appearance of equilibrate, where the composite vector field vanishes and the UAVs can get trapped at undesired equilibrium points. Leader–follower approaches simplify the formation problem into individual tracking problems. The main disadvantage is that the leader is a single point of failure for the formation. Moreover, it is difficult for leader–follower approaches to realize formation reconfiguration.

As described in the section of problem statement, in order to guarantee the basic QoS of UAV network, leader–follower approach was used to realize the flocking model. Many researches for UAV flocking based on leader–follower topology have been proposed. Gurfil [36] used Dudek's taxonomy to investigate the performance of UAV swarm and concentrated on the four main parameters: System size, communication range, and communication bandwidth and system composition. Quintero *et al.* [37] addressed the UAV flock in a leader-follower fashion and restrained each follower with stochastic optimal control. This flocking algorithm is solved offline via dynamic programming to minimize the expected cost over a finite horizon and three camera-equipped UAVs flocked together to perform vision-based target tracking. Hafez1 and Kamel [38] proposed a decentralized linear model with fuzzy logic control to solve the problem of formation reconfiguration for an autonomous team of UAVs in the presences of faults. Benedetti *et al.* [39] gave an algorithm aiming at coordinating of a set of multiple UAVs to self-organize in order to create a flock performing a monitoring mission. The approach is based on two algorithms that use same rules. The first one drives agents to form a flock with certain given characteristics. The second one allows agents to follow a certain path which ensures the overall coverage of the area to be monitored. Tang *et al.* [40] presented a sophisticated vision-aided UAV flocking system, which has successfully integrated various advanced technologies, including LiDAR-based SLAM, and a visual system for sensing in both of day and night without continuous wireless communication and GPS signals. But these advanced technologies make the system expensive. Hung and Givigi [41] formulated a model-free RL flocking framework for fixed-wing UAVs in a simulated non-stationary stochastic environment and proposed an algorithm called Q-flocking to solve the RL problem. The agents applied the Q-flocking algorithm to learn control policies that facilitate flocking in a leader–follower topology. However, how to speed up the learning process is a problem. Therefore, how to design the distributed algorithms that can run on the UAVs with inexpensive off-the-self equipment is still a technique challenge.

VII. CONCLUSION

The Boid principle inspired by the behavior of biological groups can be applied to satisfy flocking for UAV networks using master-slave transmission mode. However, at present, the algorithm for implementing this model is still more complicated, and there are higher requirements for the computing power, sensing capability, and communication capability of UAV agent. The distributed flocking model proposed in this paper has the characteristics of simplicity and efficiency. It can make the network possess flocking, and provide support for simplifying the upper layer swarm application design. The proposed method based on cheap commercial equipment, and can effectively reduce the cost of multiple UAV systems. The simulation results show that our model can guarantee connectivity between nodes and have better bandwidth benefits. We demonstrated that UAV networks with flocking can provide a reliable information exchange platform for intelligent applications, which can simplify the design of multiple UAV systems. In our future work, we will study the optimization model of DFM to optimize the operating parameters in the environments with large numbers of nodes, and apply the DFM model and technology in the actual UAV network system.

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