Diffusion Target Tracking Based on Software-Defined Multi-UAV Network: A Cooperative Autonomous Clustering Approach

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Abstract

This paper is centered on enhancing the efficiency of collaborative tracking and minimizing energy consumption within the framework of multi-Unmanned Aerial Vehicle (UAV) collaborative tracking, particularly for diffusion targets. This paper utilizes the software-defined networking (SDN) technique and proposes the concept of UAV-based SDN-enabled Wireless Network (SDWN). In order to collaboratively track the diffusion target in a fixed environmental field, this paper, grounded in the artificial potential field theory, puts forward a multi-UAV collaborative tracking strategy with autonomous clustering capabilities. Under the governance of the proposed strategy, the UAV-based SDWN initially tracks the target environmental field values by means of a proposed inverse-distance-weighting method. Subsequently, once the UAV-based SDWN reaches the target environmental field values, a contour tracking algorithm based on multi-UAV autonomous clustering is utilized to yield the collaborative tracking of the environmental field. Simulation results reveal that the proposed approach can precisely detect target contours. Moreover, the proposed method shows great potential in practical complex scenarios, e.g., the scenarios with multiple diffusion sources.

Keywords: SDN, Artificial potential field, Multi-UAV, Collaborative tracking, Inverse-distance-weighting

1 Introduction

In the contemporary era, Unmanned Aerial Vehicles (UAVs) have revolutionized numerous industries, with their application in environmental monitoring via multi-UAV systems showing great potential [1-4]. Tracking diffusion targets, such as airborne particulate matter, volatile organic compounds, and industrial emissions, is critical for ecological balance and public health. However, this task is fraught with challenges. Complex atmospheric turbulence and wind shear can disperse pollutants unpredictably, making it difficult for UAVs to accurately delineate pollution boundaries. Moreover, rapid changes in emission sources demand real-time trajectory adjustments from UAVs, straining their communication and coordination capabilities.

Beyond atmospheric pollutants, other diffusion targets introduce unique difficulties. In chemical leakage incidents, corrosive and toxic substances can damage UAV sensors, leading to inaccurate data collection. The terrain's influence further complicates the prediction of the chemical plume's movement. For forest fire smoke, the high-temperature environment can reduce UAV battery life and impair sensor performance. Additionally, the smoke's irregular density distribution requires UAVs to dynamically adjust their flight altitudes and sampling strategies to ensure comprehensive monitoring. Addressing these multifaceted challenges in multi-UAV cooperative tracking is essential for effective environmental management [5-6].

Traditional methods for monitoring diffusion targets in the atmosphere have long been fraught with difficulties. Single-UAV operations are severely limited in their coverage area and data collection capabilities [7-9]. They often require substantial time to survey large regions, leading to low-efficiency monitoring. Moreover, due to their limited payload and energy capacity, single UAVs may need to frequently return to the base for recharging or refueling, further reducing the overall monitoring efficiency. Non-collaborative multi-UAV approaches, although having more resources in aggregate, lack the coordinated interaction necessary to track the complex and dynamic diffusion patterns of pollutants in a fixed environmental field [10-11]. These approaches struggle to adapt to the ever-changing nature of the target, such as the wind-driven spread of pollutants, and fail to comprehensively capture the spatial and temporal distribution of the diffusion target [12].

To surmount these challenges, collaborative tracking strategies have emerged as a viable and highly promising solution [13-14]. The concept of multi-UAV collaborative tracking is based on the principle of distributed intelligence, where multiple UAVs work in tandem, sharing information and coordinating their actions [15]. This collaborative approach enables the system to cover a larger area, collect more comprehensive data, and adapt

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more effectively to the dynamic nature of diffusion targets [16-17].

This paper is dedicated to the pursuit of enhancing the efficiency of multi-UAV collaborative tracking and minimizing energy consumption specifically when dealing with diffusion targets. Rooted in the well-established artificial potential field theory, we introduce a novel multi-UAV collaborative tracking strategy that incorporates autonomous clustering capabilities. This strategy allows the UAVs to self-organize based on the characteristics of the target field, optimizing their coverage and tracking performance.

In the initial stage of the tracking process, we employ a proposed inverse-distance-weighting method. This method enables the multi-UAV system to accurately identify the target environmental field values, providing a solid foundation for subsequent tracking operations. Once the system reaches the target environmental field values, a contour tracking algorithm based on multi-UAV autonomous clustering is activated. This algorithm ensures that the UAVs can collaboratively track the environmental field, precisely detecting the contours of the diffusion target.

The following of this paper can be summarized by the following: Sec. 2 presents the system model of this work. In Sec. 3, it showcases the estimation of environmental field values by UAV-based SDWN; Sec. 4 presents the proposed cooperative tracking strategy with autonomous clustering; Sec. 5 gives the evaluation results of the proposed approaches; Sec. 6 concludes the paper.

2 System Model

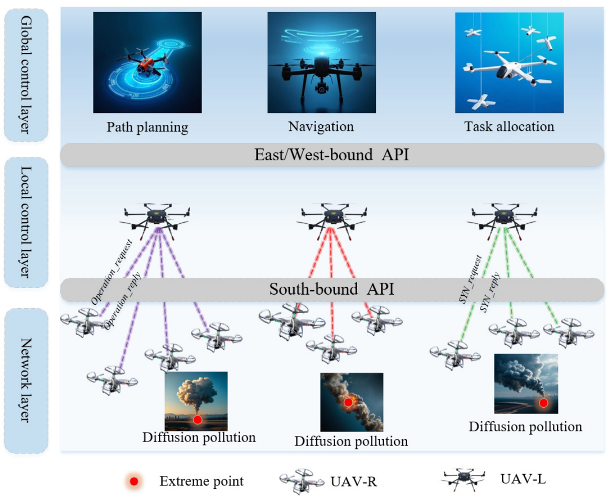


Figure 1. UAV-based SDWN

By referring to the work in [18], in this paper, the multi-UAV system is organized as a network, the software-defined networking (SDN) technique is utilzied to re-define the architecture of multi-UAV system [19-20]. Thus, the UAV-based SDN-enabled Wireless Network (SDWN) is proposed in Figure 1 where the UAV-R is dedicated to tracking the target and UAV-L controls/schedules the operation of UAV-R by following the pre-defined south-bound API (e.g., the *Operation_request* /*Operation_reply* messages). Note that the south-bound API provides as well the standard to synchroniz the information between UAV-L and UAV-R by *SYN_request* / *SYN_reply* messages.

2.1 Contour Line in Environmental Field

In this paper, the tracking environmental field is determined by its regional field quantities. Under normal circumstances, the field quantity is a function related to time and space, which can be expressed as $f(\mathrm{x}, t)$, $\mathrm{x} \in \mathrm{Z}$. According to the distribution of Z, the environmental field can be divided into a spatial field and a horizontal plane field, that is $Z \in \mathbb{R}^m (m = 2, 3)$. At the same time, if $f(\mathrm{x}, t) \equiv f(\mathrm{x})$, then $f(\mathrm{x}, t)$ represents a stable field, that is, it does not change with the passage of time. On the contrary, it is an unstable field.

In this paper, the tracking problem of pollution concentration in a two-dimensional horizontal plane is studied. And, the pollution concentration and its contour lines are stable, that is, they do not change with time or the change is so small that it can be ignored, expressed as $f(\mathrm{x}, t) \equiv f(\mathrm{x})$, $\mathrm{x} \in \mathbb{R}^2$, where $f(\mathrm{x}, t)$ is unknown.

At present, the protection of the atmospheric ecological environment has attracted the attention of countries around the world. In particular, atmospheric pollution incidents have received extensive attention, and many experimental studies have been carried out simultaneously.

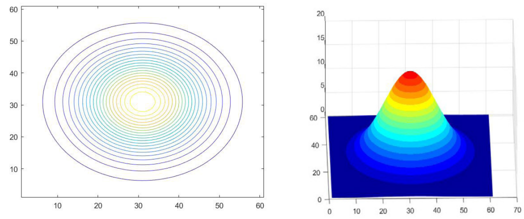


Figure 2. 2D/3D pollution concentration contour lines

In Figure 2, we present two types of pollution concentration contour lines in 2D and 3D scenarios, respectively.

2.2 Tracking Model

In this paper, the considered environmental field contour line tracking model is mainly for tracking the diffusion of atmospheric pollution concentration. As shown in Figure 3, when multiple UAVs track the contour line, the system will preset a target value:

$$\begin{aligned} y_{\text{target}} &= y_{\text{constant}} \\ y_{\text{direction}} &= \nabla y^{\perp} \end{aligned} \tag{1}$$

where y_{target} represents the target contour line tracked by the UAV; y_{constant} is the value of the concentration contour line; $y_{\text{direction}}$ is the direction of the target contour line. Therefore, the tracking of pollution concentration contour lines based on a multi-UAV system is mainly divided into two stages. The first stage is the process in which the

UAV moves towards the target contour line. The second stage is when the UAV sails to the target contour line and moves along the trajectory of the contour line. Therefore, the multi-UAV monitoring platform reaches the tracked contour line according to the gradient of the pollution concentration field, and then adopts a certain control strategy to make the multi-UAV formation move along the target concentration contour line to complete the tracking task.

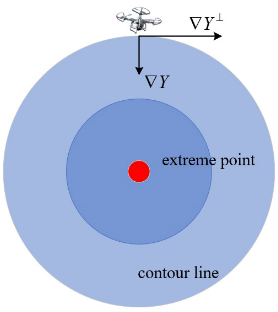


Figure 3. Tracking extreme point and contour line

3 Estimation of Environmental Field Values by UAV-based SDWN

In a two-dimensional horizontal plane area, $y(p)$ is used to represent the pollution concentration value at a certain position p, and the target environmental field contour line that the system requires to track is expressed as

$$Y = \left\{ p | \, y_{\text{constant}}\left(p\right) = y_{\text{target}} \right\} \tag{2}$$

where y_{target} is a constant greater than 0, which is the preset target contour line to be tracked by the system.

In particular, the pollution concentration field area mentioned in this paper is simply-connected. Therefore, the constructed pollution concentration field contour line $Y = \{p \mid y(p) = y_{\text{target}}\}$ is a closed curve.

Using the sampling value of a single UAV to estimate the true value and gradient of the atmospheric environmental field will bring relatively large errors. This is because during the sampling process, the UAV's detection value is affected by the noise of its sensor equipment. Therefore, in order to reduce the impact of noise, in UAV-based SDWN, we use a unified control plane to estimate the concentration value by collecting the detection results of each UAV, as shown in Figure 4.

In Figure 4, UAV-R detects a concentration value at its position at each moment. UAV-R sends the detection result to UAV-L on the control plane in the form of an *Operation_request* message. UAV-L calculates a final pollution concentration value based on multiple detections it has collected. In this paper, based on the principle of proximity similarity, we use the inverse-distance-weighting method to calculate the measurement results and finally obtain a concentration value at the current position. It should be noted that the principle of proximity similarity means that the closer two adjacent UAVs are, the more similar the concentration values at their positions are, and the higher their natural correlation is compared to those that are farther apart. Conversely, for adjacent UAVs that are far apart, their similarity is lower and their correlation is also low.

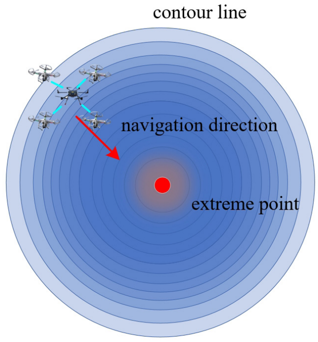


Figure 4. Diffusion atmospheric pollution contour line tracking based on UAV-based SDWN

In summary, the calculation formula for estimating the pollution concentration value based on inverse-distance-weighting adopted in this paper can be summarized as follows:

$$y_{\text{constant}} = \theta * y\left(p_i\right) + \left(1-\theta\right)P \tag{3}$$

where P represents the sum of the measured values after inverse distance weighting, which is expressed as:

$$P = \sum_{j \in N_i} \frac{1/dis}{\sum_{j \in N_i} 1/dis} y\left(p_j\right) \tag{4}$$

where dis represents the distance from the UAV to its neighbor, and $y(p_j)$ is the detection value of its neighbor.

By using the inverse-distance-weighting method, we can reduce the impact of the sampling values of UAV-Rs that are relatively far from UAV-L on the environmental field estimation and obtain more accurate concentration values estimated by multiple UAVs. Meanwhile, the sampling values of multiple UAVs are more accurate than those of a single UAV.

4 Proposed Cooperative Tracking Strategy with Autonomous Clustering

4.1 Cooperatively Tracking the Contour Lines in Environmental Field

Tracking the environmental field contour lines based on UAV-based SDWN is actually an autonomous atmospheric observation application system. It mainly uses multiple UAVs as observation platforms, combines the environmental data collected by the sensors carried by the UAVs themselves, and estimates the data to obtain information about the atmospheric environmental field. Then, in combination with the detected target value, a cooperative tracking decision is made.

This paper proposes the following steps to determine the cooperative control strategy among UAVs for using multi-UAV cooperation to track environmental contour lines:

(1) The UAV-based SDWN formation still follows the multi-UAV formation control model based on network topology proposed in [21].

(2) Under the control of the UAV-based SDWN, adjust the UAV formation to the same direction as the target environmental field concentration value.

(3) When the UAV reaches the target concentration contour line, keep the UAV moving along the concentration contour line to complete the task of multi-UAVs cooperatively tracking the target environmental field.

In this paper, n UAVs perform tasks in a given area. Considering a discrete-time control mechanism, the second-order dynamic model of the UAV is as follows:

$$\begin{cases} p_i(t+1)=p_i(t)+\mu v_i(t) \\ v_i(t+1)=v_i(t)+\mu F_i(t) \end{cases} \tag{5}$$

In this paper, n UAVs perform tasks in a given area. Considering a discrete-time control mechanism, the second-order dynamic model

In formula (5), $p_i(t)$, $v_i(t)$, and $F_i(t)$ represent the position, velocity, and control input term of UAVi at time t, respectively, and μ is the iteration step size. It should be noted that in this chapter, the control input term of the UAV is expressed as:

$$F_i(t) = f_i^g + f_i^v + f_i^c \tag{6}$$

where f_i^g is the gradient term of the potential field function related to distance, f_i^v is the consensus term based on velocity, which ensures the velocity consistency among UAVs, f_i^c is the leading term of the UAV, which enables the UAV to move towards the target.

Under the SD-UWN architecture proposed in Figure 1, this system realizes unified decision-making and deployment through the control plane. The UAV sends the collected concentration values (related to the position) to the control plane via the *Operation_request* message. The control unit on the control plane collects the concentration values collected by each UAV and estimates the gradient vector, enabling multiple UAVs to collaboratively complete the tracking task.

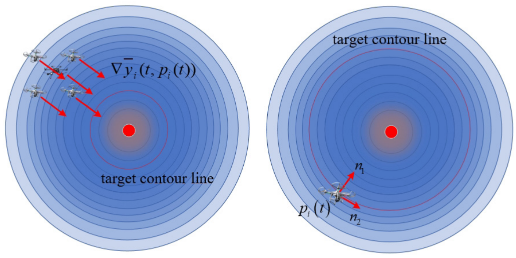
In this paper, the environmental field concentration function of the specific task area where the UAV operates is unknown. However, the UAV can detect the concentration sampling values $y(p_i(t))$ at different positions through its on-board sensor devices. Based on the sampling values, the directional derivative of the concentration value in the direction $p_j(t)-p_i(t)$ can be estimated using formula (7):

$$\frac{\partial y}{\partial(p(t))} = \frac{y(p_j(t)) - y(p_i(t))}{\|p_j(t) - p_i(t)\|} \tag{7}$$

In this paper, UAV-based SDWN is used to collaboratively perform the task of tracking environmental field contour lines. Therefore, on the control plane, the control unit uses the method of linear addition to obtain the system-estimated gradient vector $\nabla\bar{y}_i(t, p_i(t))$ from the sampling values of multiple UAVs:

$$\nabla\bar{y}_i(t, p_i(t)) = \sum_{j\in N_i} \frac{y(p_j(t)) - y(p_i(t))}{\|p_j(t) - p_i(t)\|}(p_j(t) - p_i(t)) \tag{8}$$

From formula (8), we can clearly see that when $y(p_j(t)) > y(p_i(t))$, the estimated gradient direction is approximately $p_j(t)-p_i(t)$, that is, the direction from $p_i(t)$ to $p_j(t)$. Conversely, if the current situation is $y(p_j(t)) < y(p_i(t))$, then the estimated gradient direction is approximately $p_i(t)-p_j(t)$, that is, the direction from $p_j(t)$ to $p_i(t)$. Through the above steps, the gradient vector estimated by the control unit is approximately consistent with the direction of increasing pollution concentration. As shown in Figure 5(a), the direction of increasing pollution concentration is from the outside to the inside.



(a) Approximated gradient (b) Normal and tangent vectors of a contour line at $p_i(t)$

Figure 5. Cooperative tracking model

Referring to Figure 5(b), for a certain position $p_i(t)$ in the pollution concentration area (represented by the green solid circle), the purple curve represents the contour line passing through $p_i(t)$, and its normal vector is represented by the unit vector n_1 of $\nabla\bar{y}(t, p_i(t))$. The formula is calculated as follows:

$$n_1 = \frac{\nabla\bar{y}_i(t, p_i(t))}{\|\nabla\bar{y}_i(t, p_i(t))\|} \tag{9}$$

Then, let $\vec{n}_2$ denote the tangent vector of the contour line, which is expressed as:

$$n_2 = \begin{bmatrix} 0 & -1 \\ 1 & 0 \end{bmatrix} n_1 = \begin{bmatrix} 0 & -1 \\ 1 & 0 \end{bmatrix} \frac{\nabla\bar{y}_i(t, p_i(t))}{\|\nabla\bar{y}_i(t, p_i(t))\|} \tag{10}$$

Therefore, in this paper, the UAV is designed to follow the direction of n_2 to track the concentration contour line, that is, the counter-clockwise direction of the contour line.

For each time instant t, the system can calculate the measured value of the environmental field contour line using the inverse-distance-weighting method, and plan the tracking trajectory of the UAV-based SDWN with reference to the target field value preset by the system. If the UAV-based SDWN reaches the designated area of the environmental field, the UAV-based SDWN will cruise along the contour line in the direction of the orthogonal vector of the gradient vector. Otherwise, the UAV-based SDWN will cruise again in the direction of the gradient vector calculated according to formula (8).

In summary, based on the numerical value of the target environmental field and the concentration values detected by the UAV-based SDWN, the process of tracking the environmental field concentration contour line using the UAV-based SDWN can be divided into stages. For each of these two stages, specific control input functions are designated:

(1) Stage 1: In the initial stage of the network, when the concentration value detected by the UAV is less than the target concentration value that the system needs to track, i.e., $y_{\text{constant}} < y_{\text{target}}$, at this time, the UAV needs to sail towards the target concentration value. Therefore, for the UAV at the position $p_i(t)$, the input function of each control term is:

$$\begin{cases} f_i^{\alpha} = \sum_{j \in N_i} \phi_{\alpha}\left(\left\|p_j - p_i\right\|\right) n_{i,j} \\ f_i^{v} = \sum_{j \in N_i} a_{ij}\left(v_i - v_j\right) \\ f_i^{c} = \left(\mathrm{P}(t) \otimes \mathrm{I}_2\right) \nabla \overline{y}_i\left(t, p_i(t)\right) - v_i(t) \end{cases} \tag{11}$$

In formula (11), I_2 is the second-order identity matrix, and $\otimes$ represents the Kronecker product. The consensus matrix $\mathrm{P}(t) \in \mathrm{R}^{n \times n}$, where each element P_{ij} can be calculated and expressed by the following formula:

$$\begin{cases} \dfrac{d_j}{d_i + \sum_{j \in N_i} d_j}, i \neq j \\ \dfrac{d_i}{d_i + \sum_{j \in N_i} d_j}, i = j \end{cases} \tag{12}$$

Tracking the environmental field contour lines based on UAV-based SDWN is actually an application system for autonomous atmospheric observation. It mainly uses multiple UAVs as observation platforms, combines the environmental data collected by the sensors carried by the UAVs themselves, and estimates the data to obtain information about the atmospheric environmental field. Then, in combination with the detected target value, a cooperative tracking decision is made.

(2) Stage 2: During the cruising process, when the concentration value detected by the UAV approaches the target environmental field value given by the system for tracking, that is, $y_{\text{constant}} \geq y_{\text{target}}$. At this time, for the UAV in this state $p_i(t)$, it needs to start the tracking task along the concentration contour line and adjust the UAV-based SDWN to move in the tangential direction of the target concentration contour line. Therefore, the navigation control function is

$$f_i^{c} = \left(\mathrm{P}(t) \otimes \mathrm{I}_2\right) \nabla \overline{y}_i\left(t, p_i(t)\right) n_2 - v_i(t) \tag{13}$$

4.2 Contour Line Tracking Based on Autonomous Clustering

In the case where the system's environmental field model is unknown, based on the above-mentioned multi-UAV cooperative tracking method for environmental field concentration contour lines, the system updates the estimated environmental field gradient, enabling the UAV-based SDWN to move towards the target environmental field value and making the UAV-based SDWN move along the environmental field value to complete the tracking task. To further improve the efficiency of the UAV-based SDWN in tracking environmental field contour lines and save the energy consumption of UAVs, we propose a contour line tracking strategy based on UAV-based SDWN, which allows the UAV-based SDWN to complete the tracking task from both sides of the equipotential line curve.

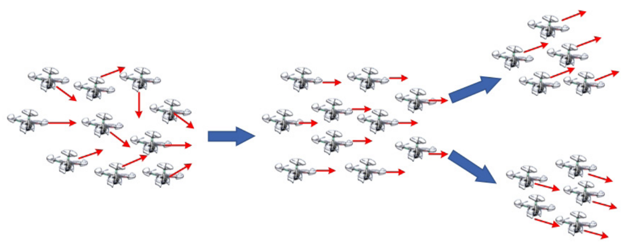


Figure 6. UAV clustering

Firstly, clustering behavior is a type of group movement. As shown in Figure 6, through the system's coordination, groups adopt different movement patterns according to the characteristics and requirements of the task. In fact, clustering behavior is widespread in nature. For example, when migrating, an ant colony splits into multiple subgroups; sheep herds also show a clustering phenomenon when looking for food on the grassland; herds will use clustering to avoid the threat of predators. Clustering behavior can help groups complete relevant tasks more effectively. Therefore, in this paper, we draw on the clustering behavior of natural groups to design a clustering tracking strategy to help the UAV-based SDWN improve its performance in tracking the contour lines of environmental field pollution concentration.

When UAV-based SDWN detects the target pollution concentration value, the UAVs only need to follow the direction of the tangent vector n_2 of the contour line to track the concentration contour line. During the process of tracking the contour line, the new direction of the tangent vector can be obtained by continuously updating and calculating the gradient vector. The UAVs can complete the task of tracking the environmental field contour line by traveling in the direction of the tangent vector.

$$n_2 = \begin{bmatrix} 0 & -1 \\ 1 & 0 \end{bmatrix} n_1 = \begin{bmatrix} 0 & -1 \\ 1 & 0 \end{bmatrix} \frac{\nabla \overline{y}_i\left(t, p_i\left(t\right)\right)}{\left\|\nabla \overline{y}_i\left(t, p_i\left(t\right)\right)\right\|} \quad \textbf{(14)}$$

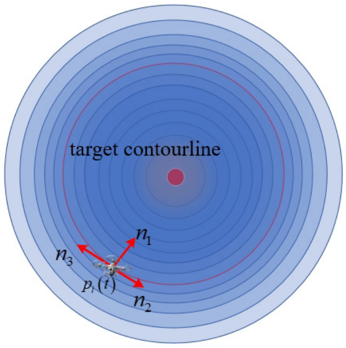


Figure 7. Normal and tangent (with the left and right sides) vectors of a contour line at $p_i(t)$

When using UAV-based SDWN to perform the task of tracking environmental field contour lines, when the preset target environmental field pollution concentration value of the system is detected, the UAV-based SDWN should be divided along the tangent vectors on the left and right sides of the tangent vector of the contour line, as shown in Figure 7. In this way, the UAV-based SDWN is divided into two multi-UAV sub-network systems, which can complete the tracking of the pollution concentration contour line in two directions. Therefore, it can be concluded that the two UAV sub-network systems track the target environmental field pollution concentration contour line along the tangent vectors in the left and right directions of the contour line respectively, that is, the clockwise direction (formula (15)) and the counter-clockwise direction of the contour line.

$$n_3 = n_1 \begin{bmatrix} 0 & 1 \\ -1 & 0 \end{bmatrix} = \frac{\nabla \overline{y}_i\left(t, p_i\left(t\right)\right)}{\left\|\nabla \overline{y}_i\left(t, p_i\left(t\right)\right)\right\|} \begin{bmatrix} 0 & 1 \\ -1 & 0 \end{bmatrix} \quad \textbf{(15)}$$

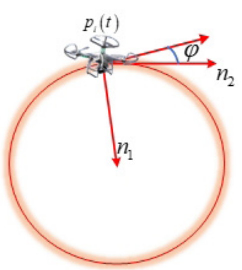


Figure 8. Tracking with opposite direction of gradient

Furthermore, we hope to reduce the deflection angle from the target concentration contour line and improve the smoothness of the tracking path during the process of UAV-based SDWN and collaborative tracking of contour lines. Therefore, this paper designs an adaptive heading adjustment mechanism. Specifically, when calculating the tracking direction of the UAV at time $t + 1$, we first determine the cruising direction of the UAV at time t. If the angle φ formed by the current heading of the UAV and the positive direction of the x-axis is smaller than a given threshold, as shown in Figure 8, then at time $t + 1$, the tracking direction of the UAV no longer uses the tangent direction of the gradient direction. Instead, the opposite direction is adjusted so that the cruising direction of the UAV at time $t + 1$ does not deviate too much from the estimated gradient, making the path smoother.

Therefore, when the above-mentioned situation is met, the cruising direction of the UAV needs to be adjusted by referring to formula (16):

$$n_4 = \begin{bmatrix} \cos\gamma & -\sin\gamma \\ \sin\gamma & \cos\gamma \end{bmatrix} n_1 \quad \textbf{(16)}$$

In summary, based on the aforementioned multi-UAV cooperative environmental field tracking, by comparing the target value set by the system with the environmental field detected by multiple UAVs, for the UAV-based SDWN to perform the tracking task in a clustered manner, the control input terms for multi-UAV sub-group 1 and multi-UAV sub-group 2 under two scenarios are $F_{1i}(t)$ and $F_{2i}(t)$ respectively, which are presented in two stages as follows:

(1) Stage 1: When $y_{\text{constant}} < y_{\text{target}}$, $t \in (0, t_{\text{target}})$, the control input of the entire multi-UAV system is:

$$F_i^t = f_i^\alpha + f_i^v + f_i^c \quad \textbf{(17)}$$

(2) Stage 2: Until $y_{\text{constant}} \geq y_{\text{target}}$, $t \in (t_{\text{target}}, t_{\text{end}})$, the control input terms $F_{1i}(t)$ and $F_{2i}(t)$ of the UAV subgroups are respectively expressed as:

$$F_{1i}^t = f_i^\alpha + f_i^v + \left(\mathrm{P}\left(t\right) \otimes \mathrm{I}_2\right) \nabla \overline{y}_i\left(t, p_i\left(t\right)\right) n_1 - v_i\left(t\right) \quad \textbf{(18)}$$

$$F_{2i}^t = f_i^\alpha + f_i^v + \left(\mathrm{P}\left(t\right) \otimes \mathrm{I}_2\right) \nabla \overline{y}_i\left(t, p_i\left(t\right)\right) n_2 - v_i\left(t\right) \quad \textbf{(19)}$$

Particularly, in this paper, t_{target} represents the moment when the UAV detects the target contour line, and t_{end} is the system time set in this paper. It should be noted that if a check on φ is carried out at time t, and it exceeds the given threshold, then at time $t + 1$, an adjustment needs to be made with reference to formula (16).

4.3 Selection and Update Mechanism of Clustering Controllers Based on The Dual-controller Model

To enhance the performance of clustered tracking, we designed a dual-controller model, in which each multi-UAV formation has only one main controller (Main Control, MC) and one assistant controller (Assistant Control, AC) at the same time. In this paper, UAVs are classified into different types according to their functional characteristics. For example, some UAVs are equipped with high-precision navigation instruments for search or surveillance, while others are equipped with high-performance storage devices only for collecting data from UAVs performing search tasks. It should be noted that in UAV-based SDWN, broadcasting any control messages between UAVs is not allowed. All UAVs are centrally managed by the control layer, and a unified open interface (following the open south-bound API) is designed and programmed by the control layer. Therefore, UAVs can retrieve unified control messages from the control layer to deploy a collaborative tracking strategy.

The clustering controller selection mechanism designed in this paper mainly involves two stages, including the state collection stage and the selection stage. We describe these two stages respectively to select appropriate clustering controllers.

UAV State Collection Stage: At the initial stage of the network, the system broadcasts a beacon message *SYN_request* to request the synchronization of UAV information. After receiving the *SYN_request* message, the UAV sends a *SYN_reply* message to the system to respond to the status request. Based on the collected information, the system establishes a network status table to maintain the operating status of the entire multi-UAV network.

Group Controller Selection Stage: This stage is implemented on the basis of the UAV state collection stage. Through the network status table generated in the first stage, the formation members are evaluated to select appropriate clustering control UAVs. Therefore, the selection of clustering controllers is an important consideration criterion.

In this paper, we take into account the positions of UAVs within the formation and their performance differences. By integrating important evaluation indicators such as real-time performance, network lifespan, and energy consumption, we design an evaluation mechanism for clustering controllers that is suitable for multi-UAV network systems to carry out tracking tasks (see formula (20)). Subsequently, we rank the UAVs in terms of priority to select the optimal MC and the sub-optimal AC.

$$T_m = k_1 V + k_2 \frac{E_{res}}{E_{in}} + k_3 P \tag{20}$$

where k_1, k_2, and k_3 are the weights of the corresponding indicators. In formula (20), V is obtained by calculating the centroid of multiple points and then getting the distance between each UAV and the centroid. In this paper, we hope that the closer the leader is to the centroid, the better. E_{res} is the remaining energy of the UAV, and E_{in} is the initial energy of UAV. In this paper, we use the length of the path traveled by the UAV to represent its energy consumption. In formula (20), P represents the performance difference of the UAV. For example, if some UAVs are equipped with high-precision navigation equipment, the final value of P will be larger.

After the target concentration contour line is tracked, the UAV-based SDWN needs to be divided into two tracking sub-networks. Therefore, during the tracking process, there is naturally a controller in each sub-formation. The MC and the AC lead their respective formations to complete the tracking of the target concentration contour line. In addition, since the MC and the AC consume more energy than ordinary UAVs during the tracking process, we re-rank all nodes in each control cycle to select new MCs and ACs, so as to maintain the energy consumption balance of the network.

In summary, we present the framework of the environmental field concentration contour line tracking strategy based on multi-UAV clustering proposed in this paper in Algorithm 1.

Algorithm 1. Multi-UAV clustering tracking algorithm

Input: Randomly generate the position p_i, velocitie v_i, and communication radius r of n nodes.
Output: updated p_i and v_i
for each control period **do**
    js_1, js_2;
    for UAV i = 1: n **do**
        Rank the priorities of all UAVs with reference to formula formula (12);
        Divide the UAVs into two groups based on the distances from UAVs to the MC and the AC, and denote them as js_1 and js_2;
    end for
    for UAV i = 1: n **do**
        if $i \in js_1$ **then**
            i detects the concentration value and calculate y_{constant} with reference to formula (3);
            if $y_{\text{constant}} \geq y_{\text{target}}$ **then**
                if flag1==0 **then**
                    flag1 = 1;
                end
                if $\varphi_1 < \varphi_{\text{safe}}$ **then**
                    Update the control input terms of the corresponding group js_1 with reference to formula (18);
                else
                    Adjust the control input for one time step with reference to formula (16);
                end if
            else
                Update the control input of the UAV with reference to formula (17);
            end if
        else if $i \in js_2$ **then**
            i detects the concentration value and calculate it by referring to formula (3);
            if $y_{\text{constant}} \geq y_{\text{target}}$ **then**
                if flag2==0 **then**
                    flag2 = 1;
                end
                if $\varphi_2 < \varphi_{\text{safe}}$ **then**
                    Adjust the control input at a certain moment by referring to formula (19);
                else

```
                    Update the control input of group
                    js_2 by referring to formula (16);
                end if
            else
                Update the control input of the UAV
                by referring to formula (17).
            end if
end for
```

5 Evaluation

5.1 Evaluation Setting

We utilize Matlab 2022b to simulate a two-dimensional atmospheric plane environment for evaluating the multi-UAV clustering cooperative tracking strategy proposed in this paper. During this simulation process, we initially consider an UAV-based SDWN comprising eight UAVs as the subject of the simulation experiments. To simplify the simulation, we represent each UAV as a mass point, as illustrated in Figure 8. The dark blue circles depict the UAVs, the red stars signify the primary control UAV and the auxiliary control UAV, the green dashed lines represent the trajectories of the UAV formation tracking the contours of the atmospheric environmental field, and the black lines with arrows indicate the velocity directions of the UAVs. It is important to note that the numbers along the contours represent the values of the environmental field. In our simulation experiments, our objective is to utilize the algorithm we propose to coordinate the multi-UAV formation to track the contour with a target environmental field value of 3. Table 1 presents some basic parameters for this simulation experiment:

Table 1. Parameter setting

Parameter	Value
number of UAV n	8
Communication range r	5
initial position p_i of UAV	(0,2)
initial velocity v_i of UAV	0m/s
target contour line	3
execution time	5000
environment scale	10m*10m
μ	0.1
initial energy	200J

5.2 Results

In Figure 9(a) to Figure 9(f), we present the test results demonstrating the effectiveness of the proposed algorithm. It should be noted that, for the sake of a more intuitive representation of the algorithm's performance, we have omitted some experimental images of the tracking process and only presented a portion of the tracking effects here. Under the guidance of the controller, after a period of time, the velocity vectors of the UAVs converge, and the UAV-based SDWN becomes more ordered according to the grid geometry structure.

Specifically, Figure 9(a) already illustrates multiple UAVs navigating along the estimated environmental field gradient. From Figure 9, we can clearly observe that Figure 9(b) shows the detection of the contour with a target value of 3. In Figure 9(c), the UAV-based SDWN adopts a clustering strategy to track the contour, and in Figure 9(e), the task of clustered contour tracking is completed. Finally, Figure 9(f) demonstrates that our proposed algorithm can achieve stable tracking results.

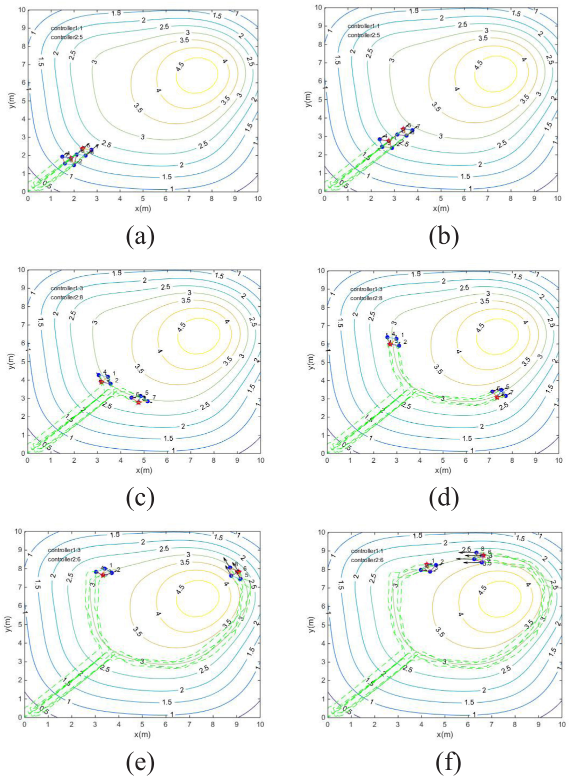


Figure 9. Test for the effectiveness of the proposed approach

To further demonstrate the execution efficiency of the algorithm proposed in this paper, we adopt numerical statistics to record the average task completion time taken by the multi-UAV system to complete the task of tracking the target contour. Here, the time recorded for completing the task of tracking the target contour refers to the duration from the initial state of the UAV-based SDWN to the point when the UAV-based SDWN have traveled one full circle along the target contour. To eliminate the influence of the randomness in UAV positions, we conducted a total of 50 experiments and calculated the average value for every 10 experiments. The experimental results are presented in Figure 10. It is clearly evident that, compared to 'one group tracking' strategy, e.g. the proposal in [22], the proposed clustering tracking strategy in this paper can reduce the running time by at least half, significantly enhancing the execution efficiency of the system.

Concurrently, we also collected statistics on the path lengths traveled by the UAVs when completing the tracking tasks under different schemes. A total of 50 path length recordings were collected, with results averaged every 10 recordings, yielding the experimental results shown in Figure 11. From the figure, we can observe that compared to the one group tracking strategy, the proposed clustering tracking strategy in this paper can reduce the path length traveled by the UAVs to complete the task. Similarly, considering the path length traveled by the UAVs as a representation of their energy consumption, it implies that the scheme proposed in this paper can conserve energy for UAVs when tracking target contours.

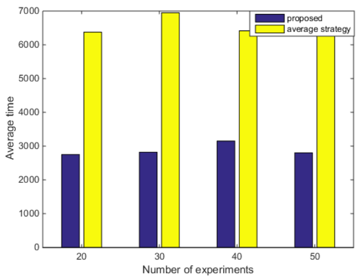


Figure 10. Test for the task completion time

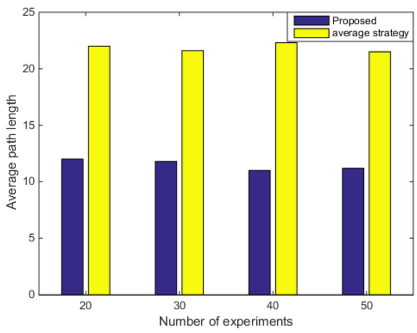


Figure 11. Test for the average path length

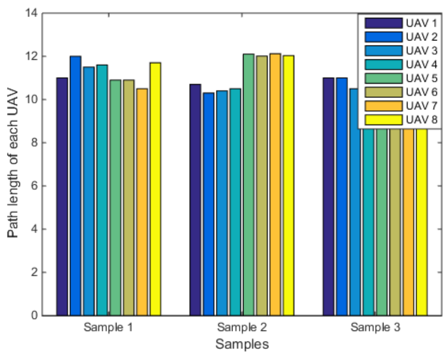


Figure 12. Test for the path length of each UAV

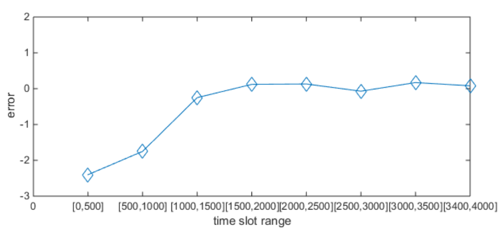


Figure 13. Test for the tracking error

To demonstrate the effectiveness of the selection and update mechanism of clustering controllers based on the dual-controller model, we collected statistics on the path lengths traveled by each UAV during the task of tracking target concentration contours. These path lengths also represent the energy consumed by the UAVs. Due to space limitations, we randomly selected three data sets, as illustrated in Figure 12. It can be observed that under our algorithm, the energy consumption of the UAVs is relatively balanced and maintained within the range of length 10-15 (Here, we asume the energy consumption of UAV has linear relationship with the path length). Further, we take a statistics about the tracking error, to demonstrate the accuracy of the proposed approach. As shown in Figure 13, the average error in each time slot range is very small.

6 Conclusion

This paper proposed a multi-UAV collaborative tracking strategy with autonomous clustering for diffusion targets. By leveraging SDN technique to build the UAV-based SDWN, the multi-AUV system can estimate the environmental field gradient at the current location to obtain the control input for the AUVs. Furthermore, to reduce tracking errors, an inverse-distance-weighting calculation method is proposed, where AUVs send their detection results to the control plane via beacon messages for unified calculation. Finally, when reaching the preset target contour, a multi-AUV clustering strategy is adopted for cooperative tracking. Simulation results show that the proposed approach can accurately detect target contours. It significantly improves the tracking efficiency of the UAV-based SDWN and reduces UAV energy consumption. The dual-controller model and its selection and update mechanism help balance the energy consumption among UAVs. Future work could focus on enhancing adaptability to dynamic environments, optimizing clustering strategies for complex target distributions, and verifying the strategy's effectiveness in real-world scenarios.

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