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RESEARCH ON MULTI-UAV AIR POLLUTION SOURCE LOCALIZATION ALGORITHM BASED ON EMOTIONAL QUANTITY

With the advancement of industrialization, the problem of atmospheric environmental pollution is becoming more and more prominent. To solve this problem, an unmanned aerial vehicle (UAV) as an airborne platform was used to design an air pollution source localization method based on an anxiety-auction algorithm and verify the feasibility of the algorithm through simulation analysis and indoor source localization experiments. The algorithm innovatively introduces the concept of anxiety in psychology into the traditional auction algorithm. By enabling each drone to make a "rational" auction time decision based on its emotional state, team resources can be conserved, and overall source localization efficiency can be enhanced. Based on different environmental factors and conditions, the number of drones and other multi-perspective comparison analyses with the traditional auction algorithm, the analysis results show that the anxiety-auction algorithm performs better in terms of success rate and distance ratio. This paper also built a set of atmospheric pollutant source localization platforms, consisting of an ultra-wideband (UWB) indoor positioning device, UAV platform, source localization monitoring and control module, and the indoor source localization experiment of atmospheric pollutants based on multiple UAVs was successfully designed and carried out.

1. INTRODUCTION

While industrial civilization and urban development have created significant wealth for humanity, they have also brought about serious environmental problems, and air pollution has become an inevitable reality in the lives of urban dwellers worldwide [1]. In daily life and industrial production processes, toxic and harmful air pollution gas emissions, and leakage phenomena are repeatedly prohibited, causing great harm to human health. Therefore, the accurate positioning of air pollution sources is essential to

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human life and production. As early as the 1990s, some researchers started to use mobile robots to track odors and locate pollution sources. After more than 20 years of robotics and sensor technology development, the active olfactory of robots has become one of the research hotspots [2]. However, the ground robot is limited by the ground conditions in the source localization process. It can achieve good results in the ideal indoor space environment. However, it is difficult to achieve the purpose of accurate and efficient positioning of pollution sources in an extensive range and complex environment. Drones have attracted much attention compared to mobile robots because of their high mobility, rapid response ability, low cost, and flexibility. Research on drones has become more and more popular [3]. Multiple drones have more advantages than single drones, significantly improving mission execution efficiency, durability, and overall robustness [4].

In solving the practical problem, the critical problem is to design a practical and effective algorithm to ensure information interaction and efficient collaboration between various drones. The auction algorithm is mainly applied to the multi-robot system task allocation problem, and the basic principles of its team collaboration and communication approach and its auction process are also applicable to the field of air pollutant source localization monitoring. However, little literature has discussed whether the timing of unmanned aerial vehicle (UAV) participation in the auction is appropriate, resulting in more unhelpful auction behavior in the process of multi-UAV collaboration, which reduced search efficiency. Therefore, this paper proposes a multi-UAV air pollution source localization algorithm based on emotional quantity. Based on the traditional auction algorithm, this algorithm introduces the psychological concept of anxiety into the multi-UAV source localization task cooperative strategy. Each UAV can make itself "rationally" choose the auction time by evaluating itself, its teammates, and the surrounding environment, and cancel the unnecessary auction before starting to avoid the waste of public resources and improve the efficiency of group source localization. This paper simulates the method by multi-UAV cooperative pollutant source localization task. The experimental results show that the algorithm has a higher success rate and source localization efficiency than the traditional auction algorithm.

2. RESEARCH STATUS OF ATMOSPHERIC SOURCE LOCALIZATION

In recent years, UAV-based active olfactory localization methods developed rapidly. The most current search strategies include concentration gradient strategies, biological heuristic algorithms, constructing probabilistic maps, and swarm intelligence algorithms. The concentration gradient strategy uses the vector difference of pollutant concentration information between different locations as the direction to guide the next flight of the UAV to quickly determine the pollution source location information, which is one of the most commonly used methods in the UAV source localization process. Rossi et al. [5] proposed an autonomous mobile gas detection system. The system uses a UAV as a carrier, equipped with gas sensors and a GPS positioning module, and adopts a search strategy of the "mountain climbing algorithm" to compare the concentration information of gas samples before and after, and guide the UAV to move in the direction of high gas concentration until the concentration is found to decrease. At this point, the current position is marked as the minimum value, the speed of the UAV is halved, and the movement direction is reversed to continue iteration. If the distance between two consecutive minimum positions is less than a fixed threshold, the highest point of the current concentration value is determined to be the source of gas leakage. Croize et al. [6] proposed a single UAV gas pollution source localization algorithm using the beetle antennae search algorithm as a source of inspiration. The principle of the algorithm is that after the UAV takes a gas sample at the current location, it randomly goes to a new location (no more than 10 m) nearby for a new sample and then determines the location of the next point by the coordinates of the current two points so that its three points form an equilateral triangle, and finally by comparing the three locations of concentration information, selects the highest concentration value location information as the starting point of the next UAV flight.

The biological heuristic algorithm is a method in which researchers are inspired by natural phenomena or processes in the biological world during the research process, abstract and simplify the biological tracking method of odor sources, and then simulate the biological search for odor sources by robots. Neumann et al. [7] proposed a plume tracking algorithm based on a pseudo-concentration gradient, in which the UAV is used to model the gas distribution using an artificial potential field method by taking measurements of concentration data at two spatially separated locations as a concentration gradient and adjusting the UAV search direction angle according to the real-time wind field. Montes et al. [8] described the idea and theory of a bionic plume tracking algorithm inspired by observing moths in flight, proposed a memory and gradient-based approach and compared it with other plume-tracking algorithms. The results show that the algorithm can track the plume in a two-dimensional and three-dimensional spatial range. Ferri et al. [9] proposed a spiral algorithm in which the robot collects gas along a spiral path and calculates a proximity index to assess the proximity of the odor source, which does not rely on any information about the airflow. Yungaicela-Naula et al. [10] proposed a gas pollution source localization algorithm combining concentration gradient search and probability map. Firstly, the area explored is gridded. Using the data already collected by the UAV and wind speed and direction information, Bayes' theorem is used to evaluate the probability that each grid is a pollution source and construct a probability distribution map of suspected pollution sources. The purpose is to plan a new course for the UAV based on the probability distribution map when the UAV falls into a local optimum or loses its forward direction during the search process to realize the localization of leaking gas sources.

Passino et al. [11] adopted a search method based on the target probability map by establishing a rational collaborative search framework to update exploration results dynamically. Peng et al. [12] proposed an extended search method based on a digital hormone mechanism and probability map, which enabled the UAV swarm to coordinate search behavior with other UAVs in the immediate vicinity through hormone information and improved target search efficiency.

The swarm intelligence algorithm is a new type of evolutionary computing technology. Swarm intelligence is an intelligent behavior exhibited by unintelligent or simply intelligent individuals through aggregation collaboration. It provides the basis for finding solutions to complex distributed problems without centralized control and without providing a global model [13]. Braga et al. [14] proposed a strategy for locating the source of gas leaks using the idea of behavioral rules and particle swarm optimization algorithms, designed to use rules such as separation, calibration, coalescence, and gas tracking to achieve information exchange between groups, adjustment of UAV heading, and obstacle avoidance functions between UAVs. Chen et al. [15] proposed a hybrid auction algorithm based on a market-based auction algorithm for studying multi-robot collaborative exploration of unknown environments. Murphy et al. [16] constructed an emotional, cognitive model to break the deadlock state in multi-robot collaborative tasks due to the cyclic dependency phenomenon.

In general, different search strategies can achieve the localization of gas sources. However, compared with other search strategies, the swarm intelligent optimization algorithm uses a collective, collaborative approach to search through information exchange between groups, which has a more extensive search area, is less likely to fall into local optimum, and improves the robustness of the whole system compared with single UAVs that do not rely on concentration gradient search. Therefore, in recent years, more and more researchers have tried to use swarm intelligence algorithms to solve the gas source localization problem and have achieved many significant research results.

3. MULTI-UAV SOURCE LOCALIZATION ALGORITHM BASED ON ANXIETY DEGREE/AUCTION

3.1. BASIC STEPS OF THE AUCTION

In the process of cooperative multi-UAV source localization, the auction algorithm is a more intensively studied and widely used method. The dynamic task in the multi-UAV collaborative source localization process is the current location point information that is randomly monitored by UAVs. Among them, those drones that detect high-value target point information and issue auction invitations are called tenderer drones, and those drones that accept and compete in bidding are bidder drones. The specific steps of a round of auction are as follows:

Step 1. To invite bids or tenders. Each UAV can store information on two different target points that exceed a pre-set threshold concentration. When a UAV detects information on two different target points, it automatically becomes a tenderer drone and broadcasts the information regarding the target point with the second-highest concentration value.

Step 2. To enter a bid. After receiving the broadcast message, the other drones will compare the concentration information of the tender point with the highest concentration target point they have stored at the current moment. If the tender point's concentration information is the highest among all the stored targets, the drones will agree to participate in the auction process and automatically become bidder drones.

Step 3. Competitive bidding. The tenderer UAV will aggregate the bid information collected from all the bidder drones, calculate the bid value of each bidder UAV, and finally determine the winner of this round of the auction process.

3.2. CALCULATION METHOD OF BID VALUE

When a UAV detects information on a target point that it does not require but may be valuable for other teammates, it broadcasts a bidding message. The rest of the UAVs decide whether to participate in this auction process by comparing the target point concentration information released by the bidder UAV with their target point concentration information stored at the current moment in the following manner:

Let the set consisting of all drones other than the tenderer drones in the *m*th auction denote as *R*, and its specific representation is given by

$$R = I + \overline{I} \tag{1}$$

$$I = \left\{ i \middle| N_i - F_k \geq 0 \right\} \tag{2}$$

$$\overline{I} = \left\{ i \middle| N_i - F_k < 0 \right\} \tag{3}$$

where N_i is the highest concentration value information stored by the *i*th UAV itself at the current moment, F_k is the target point concentration information released by the tenderer UAV in the *k*th auction.

The drones in collection *R* bid according to the following rules:

1. The UAV in the collection $\overline{I}$ does not participate in the bidding.

2. The UAV in the collection *I* determines the final winner according to the size of its bid value.

The size of each UAV's bid value is determined primarily by its two calculated metrics of revenue value (t_{rev}) and cost value (t_{cost}):

$$t_{\text{rev}} = \begin{cases} 1 \text{ for } Q > \sigma_1 \\ \dfrac{Q}{\sigma_1} \text{ for } 0 < Q < \sigma_1 \end{cases} \tag{4}$$

$$Q = \left| N - F \right| \tag{5}$$

$$t_{\text{cost}} = \delta L \tag{6}$$

where N is the maximum concentration value stored by a bidder UAV itself, F is the target point concentration information released by the tenderer UAV, L is the distance between a bidder UAV and the tender point, σ_1 and δ are constants.

The UAV i^* with the highest t_{rev} in the collection I is the first to receive the bid.

$$i^* = \arg\max_{i \in I}(F_m - N_i) \tag{7}$$

If there are two or more UAVs with the same highest t_{rev} in a collection I, their cost values t_{cost} are compared, and the drone with the lowest t_{cost} is the first to get the bid.

Here, the bidding rules based on revenue value (t_{rev}) and cost value (t_{cost}) are noted as P-value-based bidding and C-value-based bidding, respectively.

3.3. CALCULATION METHOD OF ANXIETY DEGREE

Based on the basic steps of the auction algorithm described above, when a certain tenderer UAV releases the tendering information by broadcasting, other UAVs must judge whether they agree to participate in the bidding. Little consideration has been given in the existing literature to the appropriateness of the timing of participation in auctions. This paper proposes a method for judging whether one agrees to participate in a bid based on a measure of anxiety level. According to the principle of psychology, anxiety refers to a psychological state of anxiety and worry that individuals are frustrated by their inability to achieve their goals or poor completion of tasks compared to teammates under the same conditions, resulting in frustration of self-confidence. The amount of anxiety proposed in this paper is the quantitative result of the anxiety level generated by the UAV's "rational" assessment of the environment, its teammates, and its situation, and the anxiety degree is the ratio of the UAV's current anxiety to benchmark anxiety.

Before responding to a teammate's auction invitation, the drone first makes a judgment about the situation, including the environment, teammates, and itself, to form a certain amount of emotion. The drone then decides whether to become a bidder UAV based on its subjective response generated through objective reality judgment. Because the drone may easily monitor high-value locations even if it does not respond to its teammates' auction invitations during the initial extensive search, when the "rational" drone should have a low anxiety degree and can cancel unnecessary bidding behavior before it starts, thus avoiding the waste of resources.

In the source localization task, the anxiety level of the UAV is mainly determined by both its remaining power and the difficulty of the source localization task at the current moment. The amount of anxiety of the UAV at time t can be expressed as

$$A_i(t) = \frac{c_2 D_i(t)}{c_1\left(\omega_0 - \omega_i(t)\right)} \tag{8}$$

where c_1 and c_2 are weight coefficients, ω_0 is the initial power of the UAV, $\omega_i(t)$ is the power already consumed by the ith UAV at the moment t, $\omega_0 - \omega_i(t)$ is the remaining power of the ith UAV at moment t, $D_i(t)$ is the difficulty of assessing the source localization task of the ith UAV at moment t.

The equation for the power consumption of the drone at time t is

$$\omega_i(t) = \omega_l \sum s_i(t) \tag{9}$$

where ω_l is the empirical value, $\sum s_i(t)$ is the actual distance of the UAV movement up to moment t.

The difficulty of the UAV t-moment assessment of the source localization task is

$$D_i(t) = \begin{cases} 375 V_i(t)^{1/2} \text{ for } 0 < V_i \le 0.3 \\ 925 V_i(t) - 72.105 \qquad 0.3 < V_i \le 0.65 \\ 37.64 \log_{10}(100 + 0.05\zeta_i(t)) \mathrm{e}^{3V_i(t)} \quad 0.65 < V_i \le 1 \end{cases} \tag{10}$$

$$V_i(t) = \frac{1}{n} \sum_{j=1}^{n} \zeta_j(t) \tag{11}$$

$V_i(t)$ is the average difficulty coefficient of the ith UAV at moment t, n is the number of historical UAV searches, and $\zeta_j(t)$ is the difficulty factor of the UAV at moment t.

Table 1

Difficulty coefficient mapping criterion

Concentration (C)	0	1	2	…	$C_{max} - 2$	$C_{max} - 1$	C_{max}
Difficulty coefficient (ζ)	1	$\frac{C_{max} - 1}{C_{max}}$	$\frac{C_{max} - 2}{C_{max}}$	…	$\frac{2}{C_{max}}$	$\frac{1}{C_{max}}$	0

The guidelines for the value of the difficulty factor ζ are:

1. Estimation of maximum atmospheric pollutant concentration C_{max} based on a priori experience.

2. Mapping the difficulty coefficient to the [0, 1] interval based on the concentration interval [0, C_{max}].

3. The mapping rules (Table 1) are: the lower concentration C of atmospheric pollutants, the smaller the searchable value is considered to be and the difficulty coefficient ζ is larger, the higher C of atmospheric pollutants, the larger the searchable value is considered to be and the difficulty coefficient is smaller.

To facilitate subsequent calculations and a more intuitive comparison of each UAV's anxiety level, this paper normalizes each UAV's anxiety at the current moment through a pre-set benchmark anxiety amount and then introduces a concept of anxiety degree:

$$\tau_i(t) = \frac{A_i(t)}{A_c} \tag{12}$$

where A_c is the benchmark anxiety amount, which is the value of the anxiety amount taken when the specified drone is in the highest anxiety state, expressed as

$$A_c = \frac{D_{\max}}{\omega_{\min}} \tag{13}$$

where $D_{\max}$ is the value taken in the state of the greatest difficulty of the source localization task, $\omega_{\min}$ is the value taken in the state of the minimum allowed remaining power of the UAV.

Bringing Eqs. (8), (9), and (13) into (10) gives

$$\tau_i(t) = \frac{\omega_{\min} c_2 D_i(t)}{c_1 \left(\omega_0 - \omega_l \sum s_i(t)\right) D_{\max}} \tag{14}$$

Equation (14) gives the anxiety degree of the range of values for [0, 1] but due to the existence of empirical values in the formula, to avoid the problem of its calculation results out of the range of values due to improper values in the operation process, the anxiety degree $\tau_i(t)$ is specified to satisfy:

$$\tau_i(t) = \begin{cases} \dfrac{A_i(t)}{A_c} & \text{for } A_i(t) \le A_c \\ 1 & \text{for } A_i(t) > A_c \end{cases} \tag{15}$$

After each drone calculates its value of anxiety degree based on the above formula, it determines whether it responds to the auction invitation of its teammates and becomes a bidder UAV according to the equation

$$B_i = \begin{cases} 0 \text{ for } 0 \le \tau_i(t) < \varepsilon_1 \\ \tau_i(t) \text{ for } \varepsilon_1 \le \tau_i(t) \le \varepsilon_2 \\ 1 \text{ for } \varepsilon_2 < \tau_i(t) \le 1 \end{cases} \tag{16}$$

where B_i is the probability that the ith UAV decides to bid, ε_1 and ε_2 are positive real numbers with $0 < \varepsilon_1 < \varepsilon_2 < 1$.

3.4. ANXIETY DEGREE/AUCTION METHOD

The paper introduces the anxiety and anxiety degree calculation method into the multi-UAV cooperative method based on the traditional auction. It proposes a multi-UAV collaborative source localization method based on anxiety-auction.

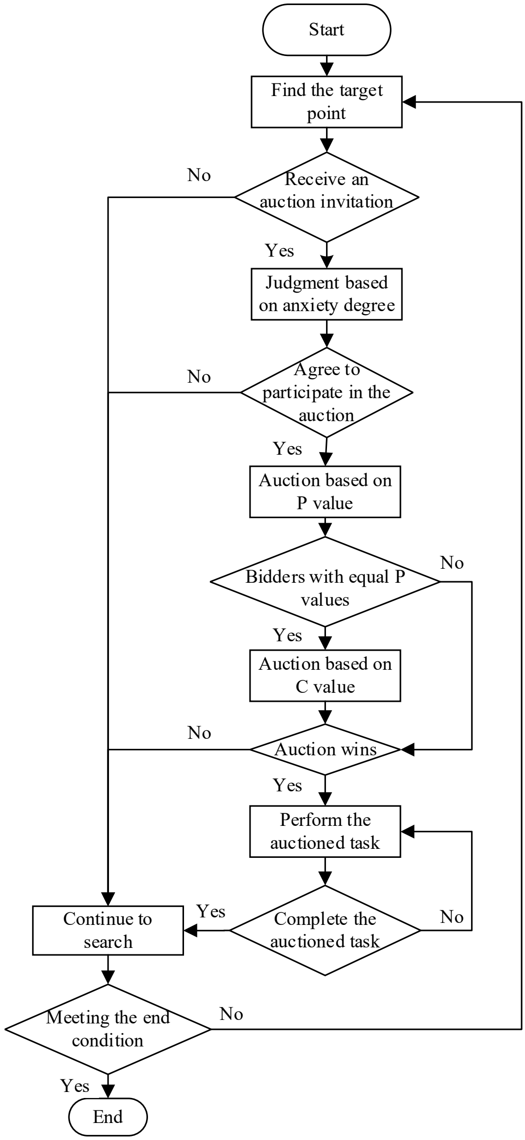

Fig. 1. Flowchart of anxiety-auction algorithm

Figure 1 shows a diagram of a complete auction process for a UAV. The auction process can be continued several times as long as the remaining power allows, and a completed auction process is equivalent to one iteration, and the UAV group updates its group extremes after each iteration until the group extremes change less than the set threshold or reach the specified number of iterations within the specified number of iterations, and the whole multi-UAV system stops the source localization mission and returns.

4. RESULT OF 2D ENVIRONMENT SIMULATION EXPERIMENT

4.1. SIMULATION OF THE STEADY-STATE CONTINUOUS POLLUTANT DISPERSION MODEL

The Gaussian plume model is relatively mature and widely used, which is general and simple to calculate, and can simulate the continuous diffusion of a gas. Because the Gaussian model ignores the effect of gravity, it is only suitable for simulation analysis in an ideal diffusion environment. The diffusion equation is as follows

$$C(x, y, z, H) = \frac{Q}{2\pi u \sigma_y \sigma_z} \exp\left(-\frac{y^2}{2\sigma_y^2}\right)\left(\exp\left(-\frac{(z-H)^2}{2\sigma_z^2}\right) + \exp\left(-\frac{(z+H)^2}{2\sigma_z^2}\right)\right) \tag{17}$$

where Q is the leakage rate of the air pollution source, kg/s, u is the average wind speed in the horizontal direction, m/s, H is the effective height of the air pollution source, m, σ_y and σ_z are the diffusion coefficients of crosswind and vertical wind, respectively, m, C is the concentration of air pollutants at any point in space, mg/m^3.

The parameters of the Gaussian plume diffusion model obtain its simulation diagram: set the range of the simulation area environment to 150 m long and 80 m wide, the diffusion coefficient in the y-axis direction under class D neutral meteorological conditions, $\sigma = 0.08x/(1 + 0.0001x)^{0.5}$, the diffusion coefficient in the z-axis direction under class D neutral meteorological conditions, $\sigma_z = 0.06x/(1 + 0.0001x)^{0.5}$, sectional height, $z = 1.5$ m, the source point coordinates of pollutants are (20, 0), the odor source height, $H = 2$ m, the wind direction is parallel to the x-axis, and the concentration distribution under different conditions is simulated by setting different wind speeds and pollution source release intensities. Figure 2 shows the simulation of the Gaussian plume dispersion model with the wind speed $u = 0.5$ m/s and the release intensity $Q = 1$ g/s from the pollution source. The analysis of the data derived from Matlab simulation shows that, under the premise of maintaining the effective height of the pollution source $H = 2$ m, the distribution of atmospheric pollutants with cross-section $z = 1.5$ m decreases gradually with the wind direction after diffusion, and the maximum value of gas concentration is 330 mg/m^3.

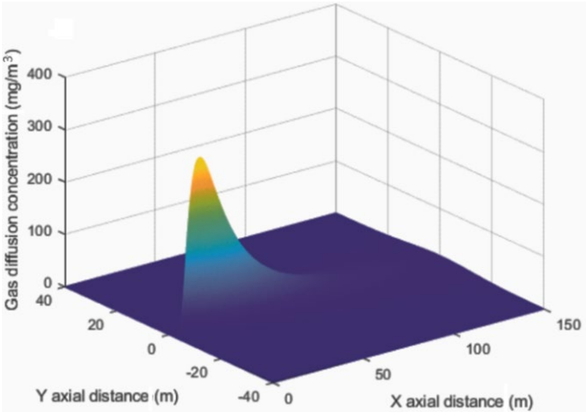

Fig. 2. Results of the Gaussian plume diffusion model simulation

The effect of different factors on the robustness of the proposed algorithm is analyzed by varying the environmental conditions such as wind speed, the intensity of pollutant release, and the number of UAV swarms, and the resulting results are presented in box plots and histograms. The box plot represents the distance ratio d_0, which is the ratio of the actual flight distance dt of each UAV to the shortest distance d_u between the initial position of each UAV and the location of the pollution source. The distance ratio is used because it can indirectly reflect the time spent in the experiment, which can represent the source localization efficiency of the algorithm to some extent. The lower d_0, the better the algorithm's performance is, when $d_0 = 1$, the algorithm achieves the best performance. Its specific expression formula is:

$$d_0 = \frac{\sum_{i=1}^{N} \frac{d_{it}}{d_{iu}}}{N} \tag{18}$$

where N denotes the number of UAVs, d_{it} denotes the distance flown by the ith UAV, d_{iu} denotes the shortest distance from the initial position of the ith UAV to the location of the pollution source.

The bar chart represents the success rate, the ratio of successful source localization to the total number of experiments within a specified time or number of iterations. Successful simulation experiments are determined by whether the global optimum of the population exceeds a threshold concentration σ at the end of the optimization iteration. If it does, it is recorded as one successful instance.

1. Effects of environmental factors on the source localization of air pollutants. Keep the number of UAVs $N = 5$ constant. The release intensity of the pollution source is set as 1 g/s, and the wind speed is 0.5, 0.75, and 1 m/s. The release intensity of the pollution source is set as 5 g/s, the wind speed as 0.5, 0.75, and 1 m/s. The release intensity of the pollution source is set as 10 g/s, and the wind speed as 0.5 m/s, 0.6, 0.9, and 1 m/s. Ten groups of simulation experiments with different environmental factors ran the anxiety auction and traditional auction algorithms 20 times.

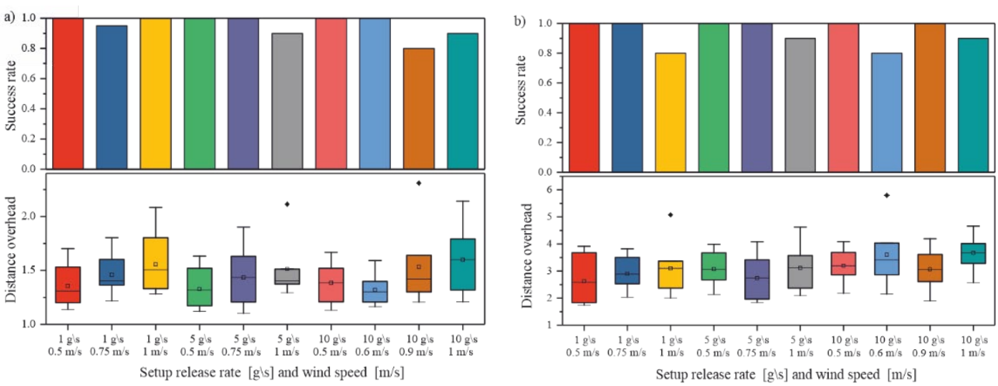

Fig. 3. Effect analysis of different environmental conditions on simulation results: a) anxiety auction algorithm, b) traditional auction algorithm

Figure 3 shows that the success rates of both algorithms are relatively high under various environmental conditions. However, the overall distribution of the distance ratio in the proposed algorithm is in the interval of [1, 2] with a median of around 1.5, while the overall distribution of the distance ratio in the traditional auction algorithm is in the interval of [2, 4]. This reveals that the anxiety-auction algorithm is less volatile under steady-state conditions in comparison with the traditional auction algorithm, resulting in stronger robustness and higher overall source localization efficiency.

2. Effects of the number of UAVs on the source localization of air pollutants. Keep the release intensity of the pollutant source constant at Q = 5 g/s and the wind speed constant at u = 0.75 m/s.

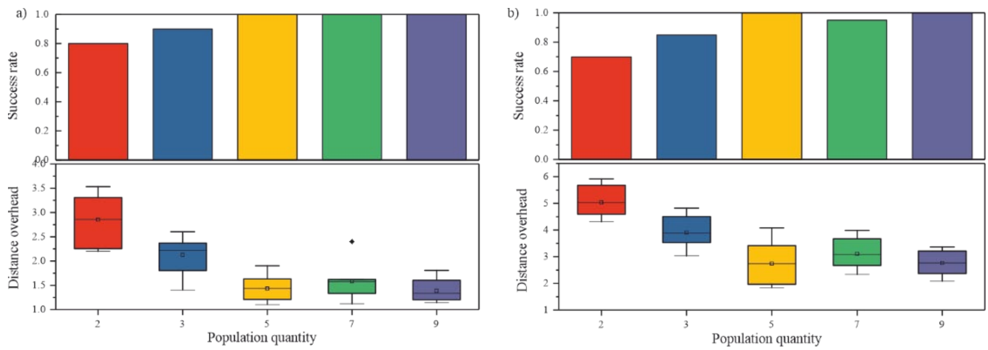

Fig. 4. Effect analysis of the number of UAVs on simulation results: a) anxiety auction algorithm, b) traditional auction algorithm

Five groups of simulation experiments set up the number of UAV swarms of $N = 2$, 3, 5, 7, and 9. In each group, the anxiety auction algorithm and the traditional auction algorithm ran 20 times. The success rate and the average distance are shown in Fig. 4.

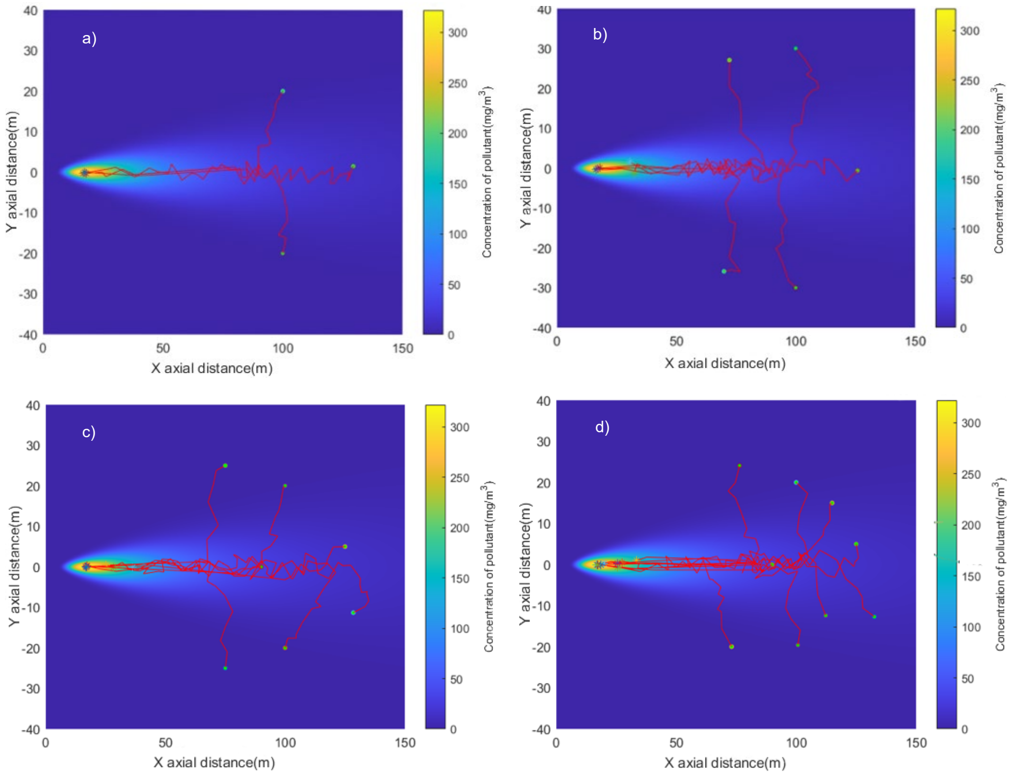

Fig. 5. Simulation path diagram of different numbers of UAVs under 2D ideal condition: a) $N = 3$, b) $N = 5$, c) $N = 7$, d) $N = 9$

Figure 5 illustrates that the number of UAVs has a significant impact on source localization efficiency. As the number of UAVs increases, the success rate gradually increases, the distance ratio gradually decreases, and the source localization efficiency continuously improves. However, when the number of UAVs exceeds 5, the distance ratio does not change significantly. This reveals that an appropriate number of UAV populations can significantly enhance source localization efficiency. With the increase in population size, the distance ratio of the source localization strategy based on the anxiety-auction algorithm is distributed in the interval of [1, 2], while the distance ratio in the traditional auction algorithm is distributed within the interval of [2, 6]. This demonstrates that the anxiety-auction algorithm proposed in this study outperforms the traditional auction algorithm in terms of source localization performance. Figure 5 presents the path diagram of atmospheric pollutant source localization based on the anxiety-auction algorithm under 2D ideal conditions for multi-UAVs with $N = 3$, 5, 7, and 9, respectively.

4.2. SIMULATION OF COMPLEX TURBULENT FLOW POLLUTANT DISPERSION MODEL

Turbulent gas diffusion model simulation of ANSYS Workbench's own DesignModeler software to establish the atmospheric pollutant leakage dispersion scene, set a vast space of 100 m long, 50 m wide, and 20 m high. The pollution source type is an elevated point source, set at the central position 10 m from the left boundary, the height of the elevated point source is set to 10 m, and the radius length is 2 m.

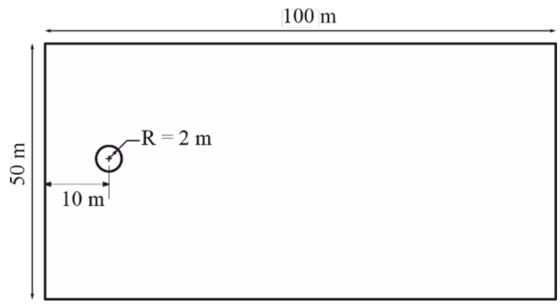

Fig. 6. Plan view of atmospheric pollutant leakage diffusion scene

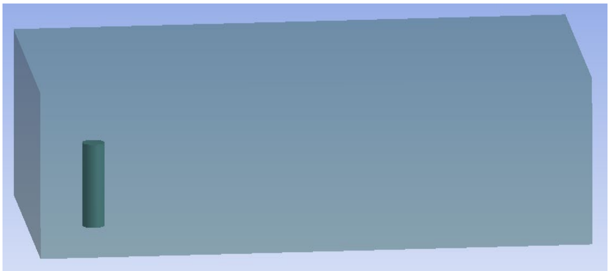

Fig. 7. 3D diagram of the atmospheric pollutant leakage diffusion scene

Figures 6 and 7 show the plan view and three-dimensional diagram of the built atmospheric pollutant leakage dispersion scene, respectively. This paper adopts tetrahedral non-uniform grid division, and the grid cell size is set to 1 m. The grid near the leakage surface of the air pollution source is divided more carefully, and the grid cell size is set to 0.5 m. The final generated grid model is shown in Fig. 8. The constructed network model file was imported into Fluent, and parameters such as turbulence model, temperature, pollutant release intensity, air inlet, pressure outlet, and atmospheric wind speed were set, as shown in Table 2. After the simulation results are stable, a cross-section 10 m high is taken as the background concentration field for the subsequent algorithm verification. The atmospheric pollutant diffusion concentration distribution maps of 1, 50, 200, and 350 s on the plane are selected, as shown in Fig. 9. When t = 350 s, the concentration dispersion distribution of atmospheric pollutants is stable.

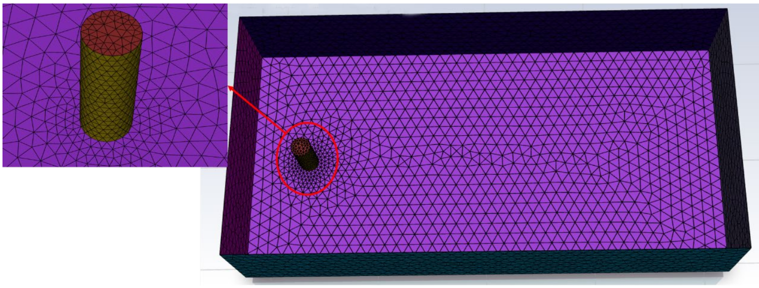

Fig. 8. Atmospheric pollutant leakage dispersion model meshing

Table 2

Fluent parameters setting

Parameter	3D environment
Dimensions, m	100×50×20
Turbulent flow model	k-ε model
Composition of pollutant gas, %	CH_4 94, H_2S 6
Temperature, K	300
Pollutant gas emission rate, g/s	1–10
Atmospheric wind speed, m/s	0.5–1
Atmospheric wind speed inlet	the left wall of the scene model
Atmospheric pressure outlet	the right wall of the scene model
Wall	The rest of the sides (except the bottom)

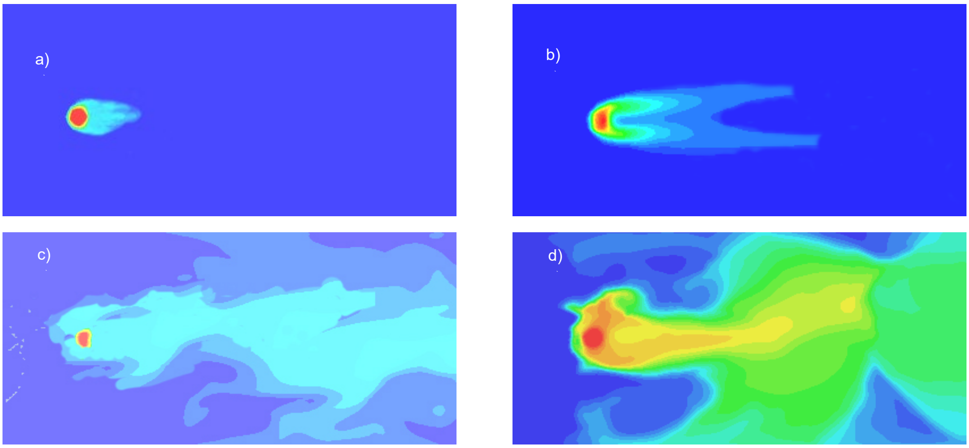

Fig. 9. Numerical simulation of pollution gas diffusion, gas diffusion simulation at: a) t = 1 s, b) t = 50 s, c) t = 200 s, d) t = 350 s

The effect of different factors on the robustness of the proposed algorithm has been analyzed by varying the wind speed, intensity of the pollutant release, and the number of UAV groups. Box plots and histograms represent the results.

1. *Effects of environmental factors on the source localization of air pollutants.* Under the two-dimensional turbulent flow conditions, the number of UAV swarms $N = 5$ is kept constant. The release intensity of the pollution source is set as 1 g/s, and the wind speed is 0.5, 0.75, and 1 m/s, respectively. The release intensity of the pollution source is set as 5 g/s, and the wind speed as 0.5, 0.75, and 1 m/s. The release intensity of the pollution source is set as 10 g/s, and the wind speed as 0.5, 0.6, 0.9, and 1 m/s, respectively. Ten groups of simulation experiments with different environmental factors ran anxiety-auction and traditional auction algorithms 20 times, respectively.

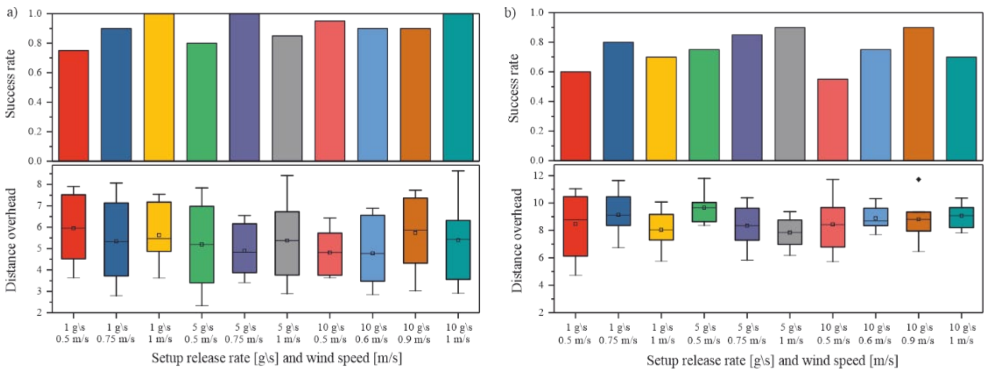

Fig. 10. Effect analysis of different environmental conditions on simulation results:
a) anxiety-auction algorithm, b) traditional auction algorithm

Figure 10 shows that under different environmental conditions, the success rate of the anxiety-auction algorithm is lower than that under the steady-state conditions. However, the overall remains above 80%, and its success rate is more excellent than the traditional auction algorithm when changing different environmental conditions. From the distance ratio, it can be seen that the median of the anxiety-auction algorithm is around 5, the highest value of the traditional auction algorithm reaches 12, and the median is also around 8.5, which fluctuates more and has lower source localization efficiency. It shows that the source localization efficiency in a turbulent flow environment decreases compared with the steady-state environment due to the complexity and discontinuity of the background concentration field. However, the anxiety-auction algorithm maintains a high success rate and a relatively efficient search. The influence of different environments on the algorithm is small, indicating that the algorithm has better robustness than the traditional algorithm.

2. Effects of the number of UAVs on the source localization of air pollutants. The two-dimensional turbulent flow conditions also keep the pollutant source's release intensity constant at $Q = 5$ g/s and the wind speed at $u = 0.75$ m/s. Five groups of simulation experiments set up the number of UAV swarms of $N = 2$, 3, 5, 7, and 9. In each group of experiments, the anxiety-auction algorithm and the traditional auction algorithm were run 20 times, respectively. The success rate and the average distance are counted as shown in the following figure.

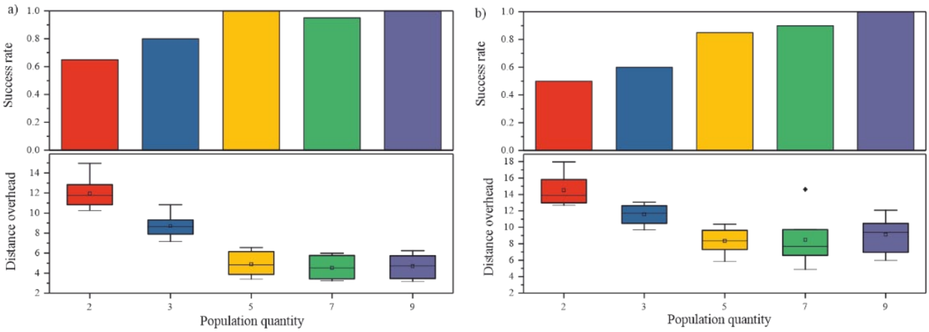

Fig. 11. Effect analysis of the number of UAVs on simulation results:
a) anxiety-auction algorithm, b) traditional auction algorithm

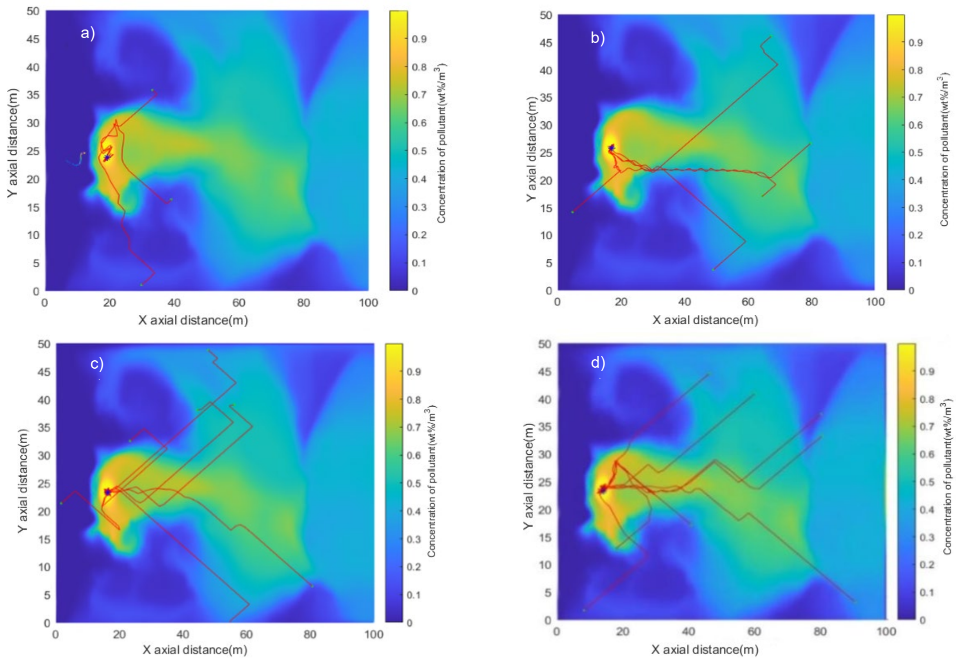

Fig. 12. Simulation path diagram of different numbers of UAV groups
under 2D turbulent flow condition: a) $N = 3$, b) $N = 5$, c) $N = 7$, d) $N = 9$

It can be intuitively seen from Fig. 11 that the distance ratio distributions of both source localization strategies become more concentrated with the increase of UAVs. When the number of UAVs reaches saturation, source localization strategies' distance ratio distribution intervals based on the anxiety-auction algorithm and the traditional auction algorithm are [3.5, 6] and [5, 10.5], and the medians remain around 4.5 and 8, respectively. Therefore, from comparing the simulation results of the two different algorithms, the overall anxiety-auction algorithm is better than the traditional auction algorithm regarding both success rate and distance ratio. Figure 12 shows the path diagram of atmospheric pollutant source localization based on the anxiety-auction algorithm under two--dimensional turbulent flow conditions for a multi-UAV with the number of UAV swarms of $N = 3, 5, 7$, and 9.

5. 3D ENVIRONMENT SIMULATION EXPERIMENTS AND ANALYSIS

AirSim is an open-source cross-platform simulator based on the game engine developed by Microsoft. It adapts to the environment built based on an unreal engine. It can be used for controllability and safety testing of UAV systems and provide realistic visual effects during physical simulation. It is suitable for visual AI simulation verification based on deep learning. In addition, AirSim provides many application programming interfaces (APIs) for reading data, controlling drones, and controlling the weather, which provides relevant researchers for deep learning, robot vision, reinforcement learning, and other artificial intelligence-related research. Based on the UE4 virtual engine development tool, this paper designs and constructs a three-dimensional atmospheric source localization simulation environment, imports the 3D simulation map into Airsim for the simulation experiment, and verifies the subsequent source localization algorithm. As shown in Fig. 13, the theme space is a 30×15 m factory building. The gas tank equipped with pollutants is set up as a pollution source and a fan for pollutant diffusion to simulate the diffusion of air pollution sources in the real environment.

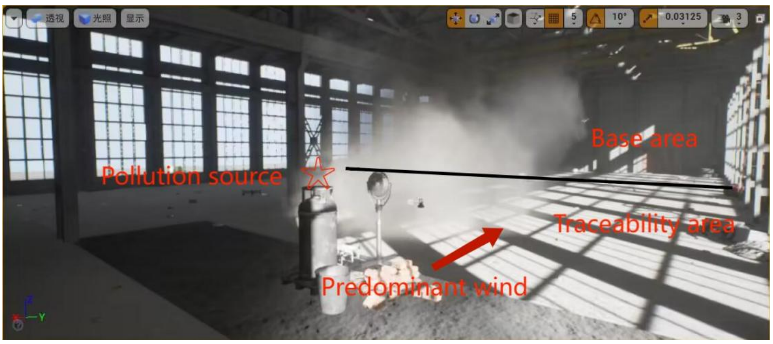

Fig. 13. Construction of 3D indoor air pollutant diffusion concentration field in UE4 environment

In the 3D experimental scene in Fig. 13, the black line divides the overall experimental area into source localization and base ones. The task of the multi-UAV experimental system is to update its position by the anxiety-auction algorithm within a specified number of iterations and finally to determine the location of the pollution source. At the beginning of the source localization task, the initial positions of the five UAVs are randomly initialized in the base area and the parameters $\varepsilon_1 = 0.3$ and $\varepsilon_2 = 0.7$ in the source localization method based on the anxiety-auction algorithm. When the anxiety degree $\tau(t) = [0, 0.3)$, the UAVs believe they are confident in completing the source localization task independently and should reject the auction invitation from their teammates. When the anxiety degree $\tau(t) = [0.7, 1]$, the UAV may lose confidence in completing the source localization task independently due to its insufficient power or the source localization task has greater difficulty and should accept the invitation from its teammates. At the anxiety degree $\tau(t) = [0.3, 0.7)$, the UAV rejects the auction invitation from the teammate according to the probability of $1 - \tau(t)$.

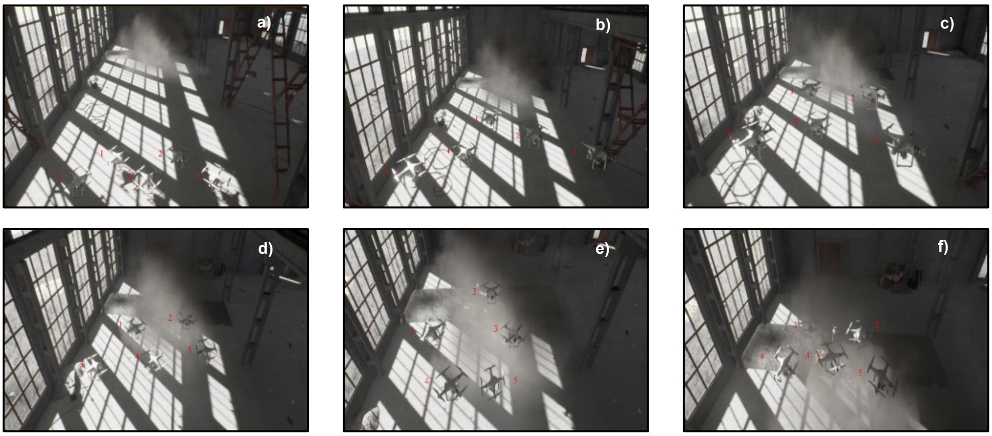

Fig. 14. Multi-UAV source localization experiment scene diagram
(details in the text)

A screenshot of the video during a source localization mission experiment is shown in Fig. 14. As shown in Fig. 14a, the initial position of the UAV group is allocated in the base area immediately before the source localization task is started. Figures 14b, c show the schematic diagram of the UAV swarm location updates before and after the primary auction process of the UAV swarm at the beginning of the process. In Figure 14b, UAV No. 1 first discovered the plume and stored the information of two locations that exceed the threshold concentration, so it makes a mission statement with the information of the location of the next largest value point and issues an auction invitation. The remaining UAVs get $\tau_2(t) = 0.15$, $\tau_3(t) = 0.25$, $\tau_4(t) = 0.2$, and $\tau_5(t) = 0.2$, all within the [0, 0.3) interval, through anxiety calculation. All decide not to accept this auction invitation and go to find the pollution source by themselves. Figure 14c shows the remaining UAVs updating their next location according to the concentration gradient of the scenario. At the early stage of the source localization task, when the UAVs have sufficient power, and the task is less difficult, it is easier for the UAVs to search for the location of high--value target points. Thus, it is reasonable to tend to reject the auction invitation from teammates. Figures 14d, e show the schematic diagram of the UAV swarm location update before and after the auction process at the late stage of the source localization task. In Figure 14d, UAV No. 2 searches for the location of the high-value target point and issues a mission statement with an auction invitation. The remaining UAVs obtain $\tau_1(t) = 0.25$, $\tau_3(t) = 0.8$, $\tau_4(t) = 0.75$, and $\tau_5(t) = 0.6$ by anxiety calculation. UAV No. 1 with a high concentration value of its storage location, considered its current area to be of high search value, so it had a low anxiety level and refused the auction invitation from its teammates, choosing to find the target on its own. With high anxiety levels, UAVs Nos. 3 and 4 accepted the auction invitation. Similarly, UAV No. 5, with a probability of 0.6, chose to accept the auction invitation and entered the auction process. According to Eqs. (1) and (2), the bidding value based on the P-value auction is calculated, and finally, UAV No. 3 is awarded. As shown in Fig. 14e, UAV No. 3 performs the auction task of flying to the tender point location and storing the current location point information. The remaining unsuccessful UAVs continue the search according to the concentration gradient strategy. At the later stage of the source localization task, when the UAV power is low and the difficulty of the source localization task is serious, the UAVs tend to accept the auction invitation from their teammates, and it is reasonable to make full use of the collaboration among the UAVs, which can improve the system search efficiency. Figure 14f shows a screenshot of the final position of each UAV at the end of the source localization mission. The positions of each UAV have gathered in the vicinity of the pollution source and the error between the population extremes and the concentration of the pollution source is small, which proves that the UAV swarm has successfully found the pollution source.

Twenty experiments based on the traditional auction algorithm and the anxiety-auction algorithm proposed in this paper were conducted, respectively. The average values of the concentration extremes monitored by the multi-UAV population in the source localization task experiments were recorded with the number of iterations, as shown in Fig. 15. From the figure, it can be seen that the traditional auction algorithm has higher search efficiency in the early iteration. In contrast, the anxiety-auction algorithm has a higher convergence speed in the late iteration. Because the anxiety-auction algorithm has sufficient power for the UAVs in the early iteration, the difficulty level of the source localization task is low, and the anxiety level of each UAV is low, thus prompting each UAV to tend to search independently, resulting in less cooperation between teams less. The search efficiency is lower compared with the traditional auction algorithm. However, as the number of iterations increases, the useless bidding behavior in the traditional auction algorithm also increases, which leads to a significant decrease in source localization efficiency. The anxiety-auction algorithm proposed in this paper enables UAVs to flexibly decide whether they should accept auction invitations from teammates according to the characteristics of the environment, that is, to rationally judge whether the cooperation between UAVs is beneficial, thus ensuring the overall performance of the system.

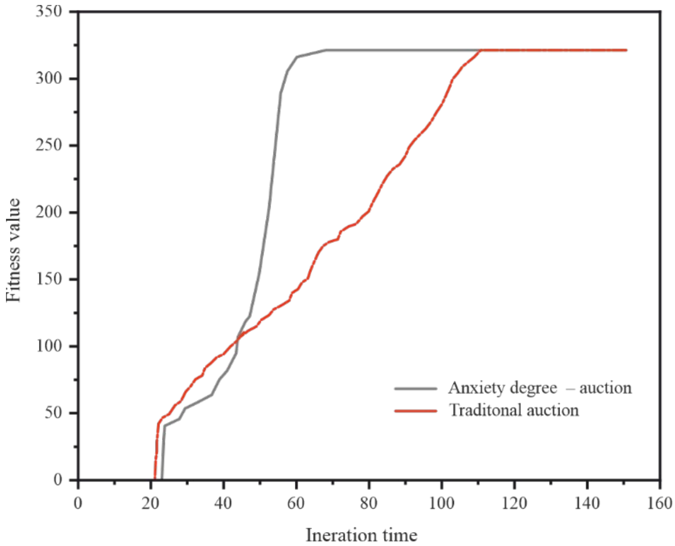

Fig. 15. Source localization efficiency for the two methods

6. CONCLUSION

This article analyzes the shortcomings of applying traditional auction algorithms to the multi-robot source localization strategy, innovatively proposes a multi-UAV air pollutant source localization algorithm based on the amount of emotion, and gives each drone the concept of anxiety to simulate the anxiety degree in human emotion, which effectively solves the problems of more useless bidding behavior and lower utilization of public resources caused by the mechanized judgment of bidding time of UAV in the traditional auction algorithm. At the same time, based on the 2D and 3D background concentration fields built above, simulation experiments are carried out, and the results are analyzed. The results show that the proposed anxiety-auction algorithm can make each UAV choose the auction timing more “rationally” than the traditional auction algorithm, which can effectively improve the efficiency of collaborative group tracing and greatly enhance the robustness of the multi-UAV system.

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