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Pollution Source Localization Based on Multi-UAV Cooperative Communication

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ABSTRACT Harmful gas leakage accidents in chemical plants have occurred from time to time. The application of mobile robots to find odor source has become one of the hottest research topics. Compared to traditional robots, unmanned aerial vehicle (UAV) is more flexible and safer. Therefore, using multi-UAV to solve pollution source tracking is a meaningful study. In this paper, an air pollution source tracking algorithm based on artificial potential field and particle swarm optimization is proposed. The particle swarm optimization algorithm combined with artificial potential field method is used to guide the UAVs to track the plume and avoid the collisions among them. At the same time, adaptive inertia weights are used to help improve the convergence and the searchability of particles. We not only evaluated this algorithm in simulation experiments but also designed a multi-UAV pollution source tracking platform for real-world experiments. The experimental results show that the algorithm can accurately find the pollution source in a short time.

INDEX TERMS Artificial potential field, multi-UAV, particle swarm optimization, odor source localization, encrypted communication.

I. INTRODUCTION

While industrial civilization and urban development have created enormous wealth for mankind, they have also brought serious environmental problems. Air pollution has become an inescapable reality in the lives of urban residents around the world. In the real life and industrial production process, toxic and harmful gas leakage accidents often occur, which cause great harm to human health. Therefore, the accurate localization of pollution sources is of great significance to human life and production.

As early as the 1990s, researchers began to use mobile robots for odor detection [1]–[5]. After more than two decades of robot and sensor technology development, robotic active olfaction has become one of the hot research topics. Concentration gradient drive [2], bio-bionic algorithm [4]–[6], group intelligent optimization algorithm [7], [8], probability and information theory [9], [10] are the main solutions to solve the odor source localization.

Compared with previous mobile robots, UAV has attracted much attention due to its high mobility, flexibility, low cost and "zero casualties", and researchs on UAV have become more and more popular [11], [12]. Multi-UAV have a greater advantage than a single UAV and they have a huge improvement in task execution efficiency, endurance and overall robustness. Therefore, Multi-UAV cooperate to perform tasks has become a trend of development in the future. Using Multi-UAV to solve the pollution source tracking problem can effectively reduce the tracking time and improve the accuracy of pollution source localization. At the same time, the application of Multi-UAV has brought new challenges. How to solve the communication and data transmission among UAVs has become the key to the problem. VANET (Vehicular Ad-hoc NETwork) [13] is an emerging mobile ad hoc network that has been widely used in intelligent transportation systems in recent years [14].

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Communication problems can be effectively solved by VANET among UAVs.

Some works have used UAV to solve gas source localization. Soares *et al.* [10] found the odor source by integrating three behaviors-upwind movement, plume centering, and Laplacian feedback formation control. Neumann *et al*. [15] considered the influence of wind. He proposed a pseudo-concentration gradient algorithm to track plume and improved particle filter algorithm to confirm the odor source. But he only used a single UAV. Scheutz *et al*. [16] proposed a simple heterogeneous UAV proxy model that can locate and track target chemical clouds. But the model is limited to simulation experiments.

In this paper, we propose a hybrid particle swarm optimization algorithm to track the odor source. The main contributions of our works are as follows:

1. Based on the particle swarm optimization algorithm, we introduce the artificial potential field method to solve the problem of collision among particles when the particle positions are updated. In addition, adaptive inertia weight parameters are used to control the convergence and divergence of the particle swarm.

2. We design and implement a Multi-UAV pollution source location platform. Communication among UAVs and secure data transmission are possible in real time.

3. We perform comparison experiments with other algorithms in the simulation experiment and apply our algorithm to the real environment. The results show that our algorithm can accurately find the source of pollution and is suitable for small-scale UAV group.

The structure of this paper is as follows. Section II introduces the work related to odor source localization. Section III explains our pollution source tracking algorithm. Section IV describes the experiments we have done in the simulation environment and analyzes the final results. Section V describes the Multi-UAV pollution source tracking platform and discusses the results of the actual experiments. Section VI summarizes our work and determines the direction of future work.

II. RELATED WORK

In recent years, the olfactory source localization method based on robot olfaction has been rapidly developed. According to the different search basis of the robot, the proposed algorithm can be roughly divided into three categories. One is bio-inspired algorithm, the second is engineering strategy algorithm, and the last one is swarm intelligence optimization algorithm.

A. BIO-INSPIRED ALGORITHM

Researchers are inspired by natural phenomena or processes of the biological world during the research process to abstract and simplify the methods of bio-tracking odor sources. Then, they use robots to mimic biological search odor sources.

Neumann *et al*. [15] proposed a plume tracking algorithm based on pseudo-concentration gradient. The UAV measures the concentration data at two spatially separated measurement locations as a concentration gradient and adjusts the search direction angle based on the real-time wind field.

Shigaki *et al*. [17] proposed a time-varying moth-inspired algorithm. Silkworm is used as a model for chemical plume tracing. The robot changes behavior adaptively or time-varying depending on the environment. The response of the silkworm moth to the stimulus was analyzed based on the discrimination index and the estimator, and the behavioral model was estimated using the support vector machine.

Ferri *et al*. [18] proposed a spiral algorithm. The robot collects gas along a spiral path and calculates the Proximity Index to assess the proximity of the odor source. The algorithm does not rely on any information about the airflow.

B. ENGINEERED STRATEGIES ALGORITHM

Wu *et al*. [19] proposed a plume tracking method for mobile sensor networks with fixed topologies. The direction of motion of the robot is determined by the probability of a concentration detection event and does not require an anemometer.

Sinha *et al*. [20] proposed a heterogeneous multi-agent system to solve the problem of unknown odor source localization. The system uses a three-layer hierarchical collaborative control scheme. The first layer obtains instantaneous plume induction and population concentration and wind information. The second layer is designed to manipulate agents through traditional surging, casting, and searching methods. The third layer is the collaborative control layer, which uses the sliding mode control to pass the information obtained in the first layer as a reference to the tracking controller.

C. SWARM INTELLIGENCE ALGORITHM

Marques *et al*. [21] proposed an odor source localization method based on genetic algorithm. In this algorithm, the odor concentration collected by the robot is taken as the fitness value of the genetic algorithm individual, and the odor source localization is completed by the crossover and mutating steps according to the target robot position. The method can find the global optimal value without prior information of the odor concentration region, and does not need to calculate the odor concentration gradient.

Feng *et al*. [22] proposed an improved PSO (particle swarm optimization) algorithm for identifying sources of periodicity or decay in a room. The algorithm adds a new headwind item to the standard PSO algorithm, which combines the concentration with the airflow speed to improve the search ability of the robot and prevent them from falling into local optimum. Dadgar *et al*. [23] proposed an adaptive robot PSO algorithm, which avoids falling into local optimum by adjusting parameters, and uses a robot equipped with a sensor to avoid obstacles. Compared with other methods, this method is more significant in large environments and a small number of robots.

Che *et al*. [24] proposed an improved ant colony algorithm. The algorithm uses the gas concentration value as the value of the pheromone, and the update of pheromone takes the historical pheromone value into account. The robot shares the global pheromone distribution map and considers the influence of the wind field on the plume and the obstacle avoidance among the robots.

In general, odor sources can be found using different algorithms. However, compared with the traditional single robot biological heuristic calculation and engineering strategy algorithm, the group intelligent optimization algorithm uses the collective cooperation method to search. The search area is larger, and it is not easy to fall into the local optimal position. However, it is necessary to consider the coordination and obstacle avoidance issues between group robots. In addition, most of the research was limited to simulation experiments and was not verified in the real-word.

III. POLLUTION SOURCE TRACKING ALGORITHM

In general, the odor source localization problem can be divided into three sub-problems [25]. (1) Plume acquisition. (2) Plume tracking. (3) Odor source declaration. Finally, the odor source declaration refers to the use of some source declaration algorithm to determine whether the location is a true source of odor when the robot arrives at a location that may be an odor source. This paper focuses on the plume tracking phase.

A. PLUME ACQUISITION

The plume Acquisition is the beginning of the mission. The robot quickly contacts the plume without any prior information on the search area. Robot plume acquisition can be divided into two modes, active mode and passive mode. Passive discovery means that the robot waits for the plume information in place, which saves energy, but for high-powered UAVs, the efficiency is very low, so an active search strategy must be used. Active search strategies include random search, system search, Zigzag search [26] and Outward Spiral search [25].

Z-shaped search covers a large area in a short time. So in our work, we use zigzag search in three-dimensional space as a plume discovery strategy. The UAV group starts at a certain starting position at the downwind, and starts to search against the wind at different angles from the wind direction. The UAVs continues to search when they reach the boundary. When a UAV finds a plume, the plume discovery phase ends and all UAVs enter the plume tracking phase.

B. PLUME TRACKING

Plume tracking is the act of using odor information and wind field information to approximate the odor source along the plume after the robot discovers the plume information.

1) ARTIFICIAL POTENTIAL FIELD ALGORITHM

In order to complete the multi-UAV odor source positioning task, we must first solve the problem of obstacle avoidance among UAVS. The APF (artificial potential field) method has been widely used in the field of robot path plan because of its simple implementation, high efficiency and smooth generation path. The paths APF generated are not necessarily the shortest, but is the safest and smoothest, especially for UAVs which require high security.

The APF method is a virtual force method proposed by Khatib [27] and has been widely used in robot path planning. The basic idea is to abstract the motion of the robot into particles moving in a virtual artificial gravitational field. Robot is attracted by the mission target, and the closer to the target, the smaller the gravity. At the same time, the robot is repelled by obstacles. The closer the obstacles are, the greater the repulsive force. The resultant force of gravity and repulsion will control the motion of the robot. However, this method has the disadvantage that it is easy to fall into the local optimum. In addition, when there are obstacles near the target, the mobile robot may never reach the destination.

APF includes a gravitational field function and a repulsive field function. The basic gravitational field function is:

$$U_{att}(X) = \frac{1}{2}k_{att}\left(X - X_g\right)^2 \tag{1}$$

where k_{att} is the gain factor, X is the current position of the robot, X_g is the target point position, and $X - X_g$ is the distance between the robot and the target point.

The gravitational force generated by the gravitational field on the robot is a negative gradient of gravitational potential energy:

$$F_{att}(X) = -\nabla U_{att}(X) = -k_{att}\left|X - X_g\right| \tag{2}$$

The basic repulsion field function is:

$$U_{rep}(X) = \begin{cases} \frac{1}{2}k_{rep}\left(\frac{1}{X - X_{obs}} - \frac{1}{\rho_0}\right)^2 & X - X_{obs} \leq \rho_0 \\ 0 & X - X_{obs} > \rho_0 \end{cases} \tag{3}$$

where k_{rep} is the gain factor, X_{obs} is the position of the obstacle, $X - X_{obs}$ is the distance between the robot and the obstacle, and ρ_0 is the distance of the obstacle. If the robot is within the influence of the obstacle, the repulsion increases as the distance between the robot and the target point decreases. When the robot is outside the range of obstacles, the robot is not affected by obstacles.

The repulsion of the robot generated by the repulsion field is the negative gradient of the repulsion potential:

$$\begin{aligned} F_{rep}(X) &= -\nabla U_{rep}(X) \\ &= \begin{cases} k_{rep}\left(\frac{1}{X - X_{obs}} - \frac{1}{\rho_0}\right)\frac{1}{(X - X_{obs})^2}\frac{\partial(X - X_{obs})}{\partial X} & X - X_{obs} \leq \rho_0 \\ 0 & X - X_{obs} > \rho_0 \end{cases} \end{aligned} \tag{4}$$

The resultant force field and resultant force of the robot in the virtual artificial force field are:

$$U_{total}(X) = U_{att}(X) + U_{rep}(X) \tag{5}$$

$$F_{total}(X) = F_{att}(X) + F_{rep}(X) \tag{6}$$

2) HYBRID PARTICLE SWARM OPTIMIZATION

This section first introduces the standard particle swarm optimization algorithm, and then describes our proposed APF-PSO algorithm.

a: STANDARD PARTICLE SWARM OPTIMIZATION

Particle Swarm Optimization is a biological heuristic algorithm developed in 1995 by Kennedy [28]. PSO has attracted the attention of the academic community because of its advantages of easy implementation, high precision and fast convergence. It performs well when applied to the robotics field. Recently, many researchers have used PSO to solve the odor source localization problem of multiple robots.

In PSO, each UAV is abstracted into a single particle. In a D-dimensional target search space, N particles form a population. The position of the i-th particle is represented as a D-dimensional vector $X_i = (x_{i1}, x_{i2}, \cdots, x_{iD}), i = 1, 2, \cdots, N$, And its flight speed is also expressed as a D-dimensional vector $V_i = (v_{i1}, v_{i2}, \cdots, v_{iD}), i = 1, 2, \cdots, N$. The fitness values of all particles are calculated from the fitness function. Each particle has a memory function that records the optimal position searched so far, called the individual extremum $P_{best} = (p_{i1}, p_{i2}, \cdots, p_{iD}), i = 1, 2, \cdots, N$, representing the individual experience. In addition, the optimal position searched by the entire population is called the global extremum $g_{best} = (p_{g1}, p_{g2}, \cdots, p_{gD})$, representing the population experience. The speed update for each particle consists of three parts: the first part is the inertia speed, which represents the tendency of the particle to maintain its previous speed. The second part is the speed of cognition, which represents particles tend to the individual optimal position. The third is the social speed, which represents the trend of particles close to the optimal position of the group. The speed and position update formula is as follows:

$$v_{id} = \omega v_{id} + c_1 r_1 (p_{id} - x_{id}) + c_2 r_2 \left(p_{gd} - x_{id}\right) \quad (7)$$

$$x_{id} = x_{id} + v_{id} \quad (8)$$

where ω is the inertia weight, c_1 and c_2 are learning factors, r_1 and r_2 are random numbers in the range [0, 1], $i = 1, 2, \cdots, N$. The particle will follow the current optimal particle to search optimal solution in the target search space.

b: APF-PSO ALGORITHM

When the UAV is used as a particle of PSO, the number of UAVs will inevitably affect the accuracy of the PSO. In practical applications, the use of large-scale UAVs to search for pollution sources is high cost, so it is necessary to improve the algorithm for small-scale UAV clusters.

The inertia weight w needs to be adjusted to improve the convergence of the basic particle swarm optimization algorithm and the global search ability of the particles. The inertia weight adjustment methods mainly include linear decrement, nonlinear decrement and adaptive adjustment. In order to reduce the running time of PSO and increase the search efficiency, the population ends the iteration when it reaches the global optimum. Therefore, linear decrement and nonlinear decrement strategies according to the number of iterations are not suitable. We use adaptive dynamic adjustment of inertia weights. The adaptive value of particle i is f_i at the k_{th} iteration and the optimal particle fitness value is f_{best}. The average fitness value of the population is $f_{avg} = \frac{1}{n}\sum_{n}^{i=1} f_i$. Adaptive inertia weight adjustment is as follows:

$$\omega = \begin{cases} \omega_{max} - k_1 \cdot \dfrac{f_i}{f_{avg}} & f_i \leq f_{avg} \\ 1 - k_2 \left(\dfrac{f_i - f_{avg}}{f_{best} - f_{avg}}\right) & f_i > f_{avg} \end{cases} \quad (9)$$

where ω_{max} is the maximum inertia weight, and k_1 and k_2 are the algorithm parameters. It can be seen from (9) that the particles with higher fitness values will reduce the inertia weight and improve the local search ability of the particles. Particles with lower fitness values need to increase the inertia weight to improve the global search ability of the particles and ensure the diversity of the particles.

When the standard PSO algorithm is applied to odor source localization, the particles tend to fall into local optimum in the later stage of the algorithm, resulting in the failure to find the correct target. In order to avoid the algorithm falling into local optimum, the concept of forbidden area is introduced. When the particle reaches the local optimal position, the algorithm determines whether the location is the target location, and if not, the location is set to the exclusion zone and is added to the forbidden zone list. Then the direction of particle search should be far from the forbidden area.

In addition to the disadvantages of the PSO algorithm itself, the problem of collisions among particles should also be considered when using UAVs as particles. Therefore, when the PSO algorithm particle velocity is updated, it is necessary to combine APF to control the particle speed update to avoid collisions among particles and improve the security of the system. The new APF-PSO algorithm is affected by the resultant force of gravity and repulsive force when particle velocity is updated. Among them, gravity is the attraction of the next iteration update position calculated by the particle, and the repulsive force is the repulsive force among the particles and the forbidden area.

When the distance among particles or the distance from the forbidden areas is within the radius of influence, the particles are repulsive. Moreover, the particles are not affected by the repulsion when they are outside the radius of influence. Gravity and repulsive force are calculated by (6). The particle velocity and position update formula for APF-PSO is:

$$v_i = F_{total}(x_i) \quad (10)$$

$$x_i = x_i + v_i \quad (11)$$

Particles are affected by both gravitational and repulsive forces of APF as they are updated. Therefore, the particles will move away from the forbidden area and other particles, achieving the function of avoiding obstacles and moving away from the local optimal position.

At the same time, because of the randomness of the particle swarm algorithm, the position of each update of the particles is different, so even if the resultant force is zero, the position will change in the next iteration. In addition, as long as one UAV in the UAV group finds a source of pollution, the mission is completed. Therefore, there is no case where the repulsion in the standard APF algorithm is much larger than the target gravity and the target cannot be reached. The steps of our proposed algorithm are described as follows:

Step 1. Set the position of each UAV as the starting position, and initialize the position and speed of each individual in the population.

Step 2. All particles perform a zigzag search within the target search area until a plume is found and then all particles proceed to Step 3.

Step 3. Every particle takes the concentration value of the current position as its fitness value.

Step 4. The particle calculates the next position according to the PSO algorithm.

Step 5. Update the particle velocity and position according to (10) and (11) and update the local optimum and global optimal until the particle finds the local optimal value.

Step 6. Determine whether the local optimum position is a pollution source. If it is the source of pollution, the position is output and the algorithm is terminated. Otherwise, the algorithm puts the position into the forbidden area list and continues with Step 3.

The algorithm flow chart is shown in Fig. 1.

C. SOURCE DECLARARION

There have been many related studies on odor source statements in previous work. We use the method of [11], which uses a particle-based filter source declaration algorithm to locate the odor source. This method uses gas and wind measurements to reconstruct the trajectory of a gas patch and creates a patch path envelope instead of a single patch trajectory. If the position estimate is consistent for multiple iterations, the source is considered to have been found.

IV. SIMULATION EXPERIMENT

A. EXPERIMENTAL SET

In order to verify the credibility of the algorithm, we use matlab2014a to do the simulation experiment. Our implementation platform is Core i5-3330S CPU 2.70GHz Windows 10 desktop computer. The Gaussian plume diffusion model is one of the most widely used models for describing the diffusion concentration of pollutants continuously leaking into the atmosphere along the downwind direction. Therefore, the Gaussian plume diffusion model is used to evaluate the robustness of the algorithm in simulation experiments. The simulation environment is a search space of 200m×200m×50m, with the wind direction as the positive direction and the wind speed being 2m/s. The takeoff point is 50m away from the source of pollution. In our experiments, it was assumed that the UAV had found the plume and only considered the plume tracking phase.

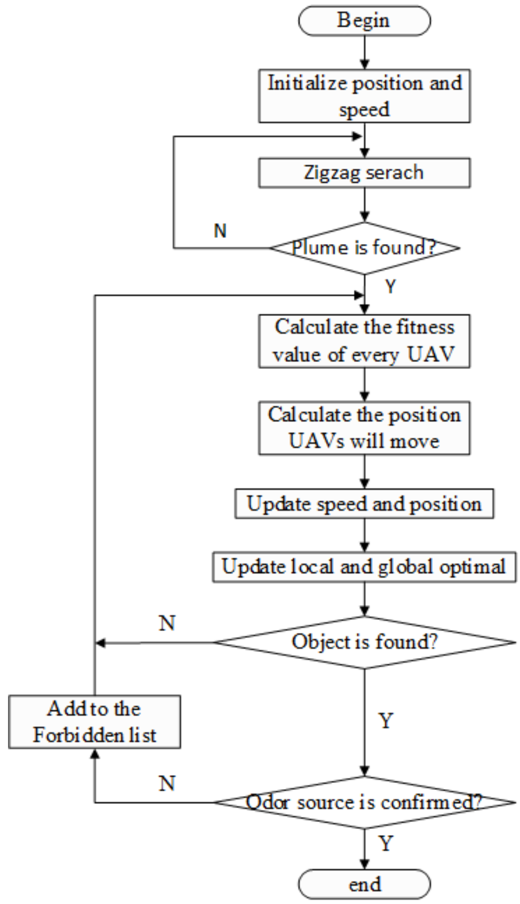

FIGURE 1. Flow chart of APF-PSO.

Related parameters are as follows. $c_1 = 2$, $c_2 = 2$, maximum number of iterations = 500, $v_{max} = 10$ and safety distance = 10.

We use the following two indicators to evaluate the performance of the algorithm. One is the success rate (SR), defined by the ratio of the number of successful odor sources to the total number of runs. The other is the average length (AL), which is the distance traveled by all UAVs when any UAV confirms the source of the scent.

B. NFLUENCE OF INERTIA WEIGHT PARAMETER

The inertia weight parameters of the particles in our proposed algorithm play an important role in the algorithm. Therefore, the effects of different ω_{max}, k_1 and k_2 on the performance of different population sizes of the algorithm are analyzed experimentally. Table 1 shows the statistical results of the success rate and average length collected by the algorithm independently running 1000 times under different population sizes and different parameters.

Table 1 shows the results of the algorithm for different population sizes in different parameters. Fig. 2 shows the effect of different parameters on SR and Fig. 3 shows the effect of different parameters on AL. It can be seen from the results that the population size has a great influence on

TABLE 1. SR and ANI of different algorithms.

parameter \ swarm size	10		7		5		3	
	SR(%)	AL(m)	SR(%)	AL(m)	SR(%)	AL(m)	SR(%)	AL(m)
$\omega_{max} = 1.2, k_1 = 0.2, k_2 = 0.2$	100	101	100	112	99.2	133	93.3	180
$\omega_{max} = 1.2, k_1 = 0.2, k_2 = 0.4$	100	81	100	89	99.6	108	87.4	177
$\omega_{max} = 1.2, k_1 = 0.2, k_2 = 0.6$	100	73	99.9	82	98.2	105	70.3	231
$\omega_{max} = 1.4, k_1 = 0.4, k_2 = 0.2$	100	104	100	118	99.8	137	93.8	178
$\omega_{max} = 1.4, k_1 = 0.4, k_2 = 0.4$	100	84	99.9	94	99.5	106	87.9	178
$\omega_{max} = 1.4, k_1 = 0.4, k_2 = 0.6$	100	73	99.9	85	98.4	106	73.9	220

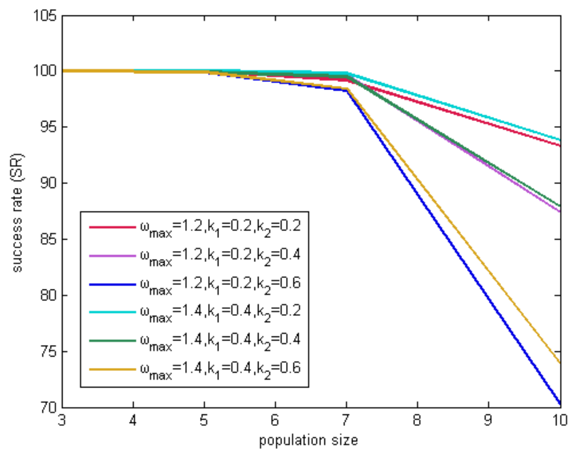

FIGURE 2. The effect of different parameters on SR.

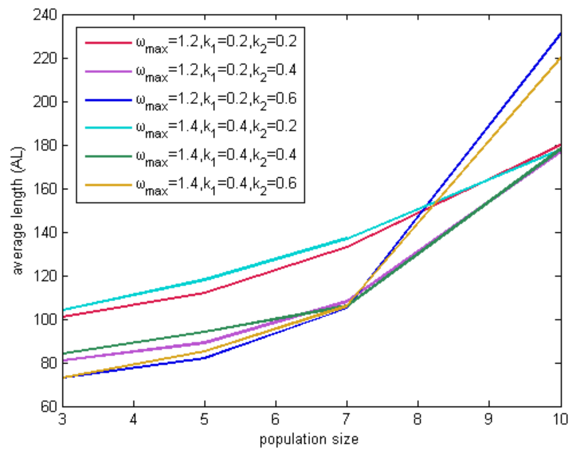

FIGURE 3. The effect of different parameters on AL.

the SR and AL of the algorithm. The larger the population size, the higher the SR and the smaller the AL. When the population size is large, choosing a larger k_2 can reduce the AL. When the population size is small, the larger k_2 will reduce the SR and increase the AL. In general, when the population size is large, a larger k_2 should be chosen. When the population size is small, we should choose a smaller k_2, ω_{max} and k_1 have little effect on the algorithm.

C. EXPERIMENTAL RESULTS AND ANALYSIS

The proposed method is an improved algorithm based on particle swarm optimization algorithm. Therefore, we choose several classical group intelligence algorithms as comparison algorithms. In this paper, we compare the success rates and the average length of different algorithms with proposed

TABLE 2. SR and ANI of different algorithms.

swarm size \ algorithm	APF-PSO		PSO		GA	
	SR(%)	AL(m)	SR(%)	AL(m)	SR(%)	AL(m)
10	100	101	95.7	183	90.1	212
7	100	112	90.6	212	87.4	222
5	99.2	133	85.3	245	81.3	269
3	93.3	180	81.7	276	78.5	287

FIGURE 4. UAV platform.

FIGURE 5. Ground station platform.

FIGURE 6. The flight path of the UAVs.

method for different population sizes of the algorithm. The simulation experiments use the same model environment and parameters for comparison experiments. The parameter selection is $\omega_{max} = 1.2$, $k_1 = 0.2$ and $k_1 = 0.2$. Table 2 shows the experimental results.

It can be seen from Table 2 that APF-PSO has a higher success rate in locating odor sources for different sizes of populations, which is much higher than standard PSO and GA. At the same time, in any population size, APF-PSO takes fewer steps than other two algorithms, which greatly saves search time and improves search efficiency. In addition, it is clear that the success rate of all algorithms is higher as the number of particles increases, but our method has a higher success rate even when the number of particles is small.

V. MULTI-UAV POLLUTION SOURCE TRACKING PLATFORM

A. EXPERIMENTAL PLATFORM

Multi-UAV pollution source tracking system consists of two parts: the UAV platform and the ground station platform. The UAV platform is mainly composed of three quadrotor UAVs (DJI-M100, DJI-In-novations Inc.). Each UAV is equipped with an onboard computer named "MANIFOLD". This computer uses a Linux system, and can connect more sensors through the USB port or serial port, including gas sensors and wireless network cards. A fully loaded UAV can fly for about 20 minutes. The Fig. 4 shows our UAV platform. The main functions of the UAV platform include real-time data acquisition, data fusion, data processing, task assignment, communication among UAVs, and communication among UAVs and ground stations.

The ground station platform consists of a mobile phone mobile terminal and a server. The mobile terminal is connected to the remote controller and can receive the data collected on the UAV in real time. The received data is forwarded directly to the server. The server processes and stores the received data, and displays the current flight trajectory and data information of all UAVs. The ground station platform is shown in the Fig. 5.

The UAVs communicate based on the configured vehicle ad hoc network. Because the obstacle avoidance of UAVs requires high communication quality, we refer to an efficient emergency-aware packet scheduling algorithm, which is called EARS [29] and a time synchronization scheme [30]. In addition, the transmitted data must be authenticated and need to be transferred quickly. Reference [31] proposed an effective VANET communication protocol, which can send encrypted data anonymously to other UAVs, and can quickly verify the transmitted information.

B. EXPERIMENTAL SET

Our experimental environment is a playground of approximately 50m×100m. Three UAVs were deployed on the ground at a distance of 3m each. The takeoff point is located at the center of the right boundary of the area, and the coordinates are (0, 0, 0), where the wind direction is the positive direction of the x-axis. Considering that it is difficult to achieve high-emission pollution sources in an open environment, and to ensure the safety of the experiment, the coordinates of the pollution source points are simulated $(-55, -5, 20)$. All UAVs take off to a certain height at the takeoff point and then execute the algorithm. Each UAV step is set to a maximum of 3m. At least one UAV finds a source of pollution and stops the algorithm.

C. EXPERIMENTAL RESULTS AND ANALYSIS

Fig. 7 shows the position when UAVs are finding the odor source. Fig. 6 shows the flight path of the UAVs. In ten flight experiments, one experiment could not find the source of pollution within 20 minutes, and the accuracy of the experiment was 90%. In nine successful experiments, the average time cost from taking off the UAV to find a source of pollution was 5 minutes and 53 seconds, with an average length of 196. The average error of positioning odor source is 2.03m. Considering the error of the UAV GPS signal and the threshold of the algorithm, the error is within an acceptable range. In addition, we also notice that wind speed has a greater impact on the position of UAVs. Faster wind speeds can cause the position of the UAV to shift, affecting the results of the experiment. In general, the experimental results of actual flight are basically consistent with the simulation experiments, which prove the feasibility and accuracy of our algorithm.

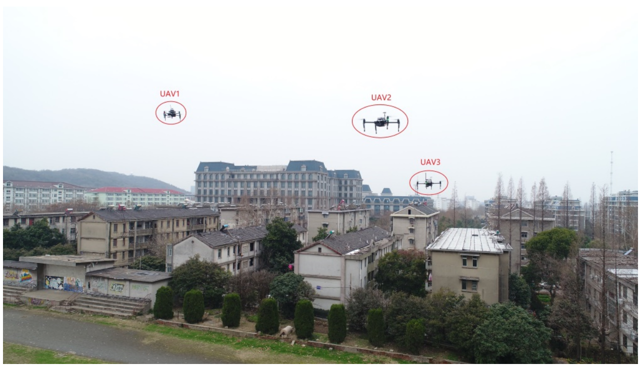

FIGURE 7. UAVs are finding the odor source.

VI. CONCLUSION

In this paper, we propose an odor source tracking algorithm based on hybrid particle swarm optimization. We prevent PSO particles into local optimization through adaptive inertia weight and forbidden area. In addition, we introduce APF to avoid particle collisions when updating particle positions, which greatly improves the security of the system. In order to verify the feasibility of the proposed algorithm, a simulation experiment is carried out. The experimental results show that the APF-PSO algorithm has a significant effect on search success rate and efficiency. At the same time, our method is also applicable to small-scale UAV groups, which can also effectively reduce costs in practical applications. Moreover, we design a multi-UAV pollution source tracking platform for managing UAVs, displaying and storing data. Our next work will consider applying the APF-PSO algorithm to a more complex multi-pollution environment.

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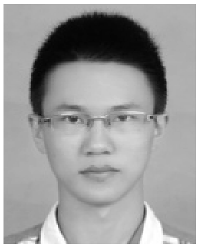

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