Research Article

Adaptive Weight Adjustment and Searching Perception Strategy for Multivariate Complex Environments

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Affected by the complex environment and the destruction of communication infrastructure in the disaster-stricken area, it has brought great challenges to the search and rescue team. The use of small unmanned aerial vehicles (UAVs) for search tasks can minimize casualties. Therefore, in order to avoid any possible collision and search for unknown targets in the shortest time, it is necessary to design a multi-UAV cooperative target search strategy. In this paper, we analyze the unknown target search problem of multi-UAVs under random dynamic topology and propose an adaptive target search strategy based on the whale algorithm. First of all, each UAV detects the environmental information of its current area and uses the probability map search algorithm to gain the target existence probability map in the task area. Then, the whale optimization search method of shrinking circle or spiral is selected to update the position of the UAV to continuously approach the target. Finally, the obstacle avoidance strategy based on artificial potential field is designed to solve any collision problems that may be encountered during the flight of UAVs. Simulations on multi-UAVs target search in different scenarios show that compared with the whale optimization algorithm, the proposed algorithm can reduce the search time by 43.1% and the total path cost by 18.1%, and it is also superior to the advanced metaheuristic optimization algorithms such as PSO and GWO.

1. Introduction

Due to its high flexibility and autonomy, UAVs can perform surveillance and search tasks in complex environments, especially in postdisaster search and rescue scenarios [1]. In search and rescue missions, to locate the missing target is usually unclear, and it is important to complete the rescue mission 72 hours after the disaster [2]. In the traditional search method, rescuers are scattered in all mission areas, which is inefficient and dangerous. Compared with traditional search methods, a postdisaster rescue based on multi-UAV search is an effective method. However, the former is more challenging. Due to the complexity and unknowability of the environment, solving the problem of crashes between UAV and UAV and UAV and obstacles during the flight has also become the key to the safe execution of multi-UAVs.

UAV path optimization is a global optimization problem [3], which aims to increase the performance indicators during the entire mission execution, including search likelihood and search time. At present, there are many methods to solve the problem of multi-UAV collaborative search, which are mainly divided into two categories. One is the graph search method based on sampling. The second is the metaheuristic optimization method based on swarm intelligence.

First, the graph search method based on sampling divides the search space into grids or hash points and expands feasible planning paths through different search mechanisms. For example, A star algorithm, Probabilistic Road Map (PRM), and Voronoi diagram search algorithm, Song et al. [4] proposed a sparse A* search algorithm, which can be applied to the obstacle avoidance scenarios in a complex environment and can effectively avoid threats and realize the search and monitoring of targets in the task area. In

order to make up for the disadvantages of traditional UAVs that take a long time to perform tasks and poor stability, Cai et al. [5] proposed a path planning strategy based on the improved A* algorithm, which improved the efficiency of UAV missions. Probabilistic Road Map (PRM) is a path planning algorithm based on random sampling strategy [6], which can solve the problem of difficulty in constructing effective paths in high-dimensional space. However, this algorithm requires a large amount of sampling data, which leads to increased calculation time and reduced efficiency. Farooq et al. [7] proposed a collision-avoidance UAV formation reconstruction and probabilistic roadmap navigation algorithm which complete UAV path planning with obstacle avoidance function. Xu et al. [8] proposed a dynamic exploration planner (DEP) based on incremental sampling and PRM to explore unknown environments. PRM allows DEP to quickly search for paths and avoid obstacles for safe exploration. In order to solve the path planning problem of multi-UAV searching for multiobjective, Chen et al. [9] used the Voronoi diagram to create the task area scene, preliminarily determined the cost of total path, and then planned the optimal path of multi-UAVs by setting up a path solving framework. To reduce the energy consumption of UAV and prolong its service life, Baek et al. [10] proposed a UAV route algorithm based on Voronoi diagram to provide a hovering position for UAV with low computational complexity. Then, the hovering position of each UAV was adjusted in turn according to the sensor energy state to obtain the optimal UAV route.

These algorithms mentioned above can solve the conventional path planning problem well. However, with the increasing complexity of the task environment in which UAVs are found, the requirements for the calculation and execution time of the algorithm are also getting higher and higher.

Second, the metaheuristic optimization method is a commonly used method in solving path planning problems, because these algorithms not only have strong robustness and good generalization but also can find possible solutions that meet the requirements in a short time. In these algorithms, the path planning task is regarded as a complex optimization problem, which is solved by intelligent algorithms such as particle swarm optimization (PSO) algorithm, ant colony optimization (ACO) algorithm, and gray wolf optimization (GWO) algorithm. PSO is one of the commonly used heuristic optimization algorithms in path planning, but it is easy to fall into local optimization. To solve this problem, Gou and Li [11] proposed a PSO algorithm based on inertia weight of logistic function. This algorithm has fast execution speed and good global optimization ability. But as the number of UAVs increases, its search accuracy will decrease accordingly. Therefore, Sánchez-García et al. [12] proposed a path planning algorithm based on Distributed Particle Swarm Optimization (DPSO) to achieve the needs of fast convergence and precise search. However, this algorithm cannot achieve a satisfactory result when the target location is unclear and there are too many obstacles in the disaster area. Zhen et al. [13] used a hybrid artificial potential field and ant colony optimization (HAPF-ACO) method to search for targets in an uncertain environment and

constructed the target attraction field and threat repulsive field, which improved the global search ability of UAVs. This scheme has advantages in task execution efficiency and collision avoidance performance, but it is not suitable for emergency environment because of high time cost. Liu et al. [14] improved the ant colony algorithm and designed a multi-UAV path planning algorithm to avoid the problem of slow optimization. But the algorithm ignores the energy waste problem when multiple drones repeatedly search the same area. Jarray and Bouallègue [15] proposed a method based on GWO for flight path planning of UAVs to ensure destination arrival and obstacle avoidance, whereas this method has slow convergence speed and high overhead. For this reason, Liu et al. [16] proposed a whale optimization algorithm, which improved the global search ability of WOA by introducing adaptive weights and nonlinear convergence factors. This method improves the ability of UAV to adapt to complex map and provides a new idea for solving the problem of UAV path planning. But this method is aimed at the known target search problem and does not consider the case of unknown target search. In recent years, deep reinforcement learning has been widely used in path planning scenarios. For single UAV path planning problem, Li et al. [17] proposed a trajectory planning algorithm based on deep reinforcement learning (DRLTP), which gradually learns the best value by training a deep neural network on the UAV to optimize the flight trajectory in real time. For multi-UAV path planning problem, Yu et al. [18] proposed an extended deep deterministic policy gradient (DDPG) algorithm to learn the control strategy of UAV in target search, which solved the problem of target assignment and path planning for multi-UAVs in complex environments. Nevertheless, the data sampling efficiency of the DRL algorithm is not ideal, and it is difficult to be competent for rescue tasks in emergency scenarios.

Motivated by this, we propose an adaptive search strategy based on a whale optimization algorithm (ASWOA) for multi-UAVs to quickly find lost persons in disaster scenarios with less energy consumption. Figure 1 clearly shows how the ASWOA is related to path planning. In particular, in the first stage, we establish the whale optimization algorithm (WOA) and add the obstacle avoidance strategy. If the position of a UAV updated by the whale algorithm is within an obstacle area, the obstacle avoidance strategy will be executed to ensure that the UAV will not collide with the obstacle. Since the target position is unknown, the traditional method of using the distance between the current position of the UAV and the target position as the fitness function is not appropriate. Therefore, in the second stage, we introduce the target probability strategy. Since the UAV flying over the task area has a certain range of sight, the closer it is to the target, the greater the target existence rate. Otherwise, the smaller the target presence rate. We restrict the flight direction of multi-UAVs in the third stage to avoid invalid search. When there is no target in an area unit searched by a UAV, the area unit is marked. The more times the target is marked, the lower the probability of the target appearing in this area unit. Since multi-UAVs are interconnected, other UAVs will no longer fly towards this area unit.

FIGURE 1: Proposed ASWOA model process.

Based on the above discussion, we consider the comprehensive design factors (e.g., the success rate of target searching, the search time, and the cost of repeated search paths) and propose the ASWOA of multi-UAVs for unknown target searching. Through our algorithm, the success rate of multi-UAVs for searching the unknown target has been significantly improved. The contributions of this work are as follows:

- (i) The obstacle avoidance strategy based on virtual forces is used to improve the flight safety of multi-UAVs and reduce repeated paths and energy consumption
- (ii) The probability map search strategy is used to update the probability of the target existence in the task area to improve the search ability of the population
- (iii) Adaptive inertia weight is introduced to balance the convergence speed of the algorithm
- (iv) The position adjacent to the UAV with the highest target existence rate is selected as the optimal solution to improve the convergence speed of the algorithm

The rest of the paper is organized as follows. Section 2 is the description and modeling of the target searching problem by multi-UAVs and discusses the path planning strategy based on the whale algorithm. Section 3 presents numerical simulation results and performance comparison with other algorithms and verifies the effectiveness of the proposed algorithm. Lastly, the conclusion and future work are drawn in Section 4 to close our paper.

2. Optimal Deployment of Multi-UAVs

2.1. System Model and Problem Formulation. In this paper, N highly manoeuvrable UAVs are used to search for lost target in an unknown environment. The specific mission requirements are as follows: in a complex mission environment, multi-UAVs need to avoid environmental obstacles, form a reasonable formation, and find the lost target as soon as possible to ensure the rescue team has enough time to carry out a rescue mission. Each UAV is regarded as a particle moving in a three-dimensional space, which make new action decision and find the target at every moment. As shown in Figure 2, each quadrotor UAV can move in

eight directions, that is, it can move from the current cell to the adjacent cell.

The mechanism of UAV for detection and data collection uses wireless communication technology [19, 20] or artificial vision technology [21, 22] and transmits monitoring information in a multihop manner [23]. The channel is determined by the line-of-sight (LOS) link and non-line-of-sight (NLOS) link [24]. Whenever a communication link can be established between two UAVs, they will exchange information about the best candidate. Lost in personnel can help themselves to be found by sending out distress signals via smart devices such as phone. Although missing persons can help themselves to be found by sending out distress signals via smart devices such as phones, sometimes, these devices cannot work or the communication base station is damaged [25]. Therefore, in the paper, we consider using multi-UAVs to search and rescue the lost person without receiving any distress signal. The strategy of using multi-UAV cooperative path planning mainly includes centralized control structure and distributed control structure [26, 27]. In the former, since the communication between UAVs is handled by a single control centre, the optimal deployment of multi-UAVs based on global information can be realized, but its expansibility is poor, and the calculation amount of the central node increases exponentially with the increase of the number of agents [28]. In the distributed control structure, a single UAV can autonomously interact with local information [29], which significantly reduces the amount of calculation in each UAV node and has better flexibility and expansibility. In consequence, compared with centralized control, most researchers choose distributed control strategy for unknown environments. Similarly, the distributed cooperative control strategy is also used in this paper to study the path planning of multi-UAVs.

The multi-UAV target searching model based on distributed control structure is shown in Figure 3. We divide a $H_x \times H_y$ rectangular task area $\mathcal{R}$ into M cells and use $[gx_j, gy_j]$ to represent the position of cell ζ_j , where $[gx_j, gy_j] \in \mathcal{R}$ and $1 \leq j \leq M$. Obstacles are randomly distributed in the task area and are represented by symbol O . The target position is denoted by $T = [tx, ty]$. The multi-UAVs are distributed over the task area, and we use $[ux_i, uy_i, uz_i]$ to represent the position of UAV i , where $[ux_i, uy_i] \in \mathcal{R}$, $1 \leq i \leq N$, N is the number of UAVs, $h_{\min} \leq z_i \leq h_{\max}$, and $h_{\min}$ and $h_{\max}$,

FIGURE 2: The direction of movement of the UAV.

respectively, represent the minimum and maximum flying height of the UAV. In Figure 3, we also see that under the premise of a certain antenna beam width, the flying height of the UAV is proportional to the coverage radius R , which can be represented by $R_i = uz_i \times \tan \theta$, where θ is the cone half angle of UAV. In this paper, the size of R_i is set to be half of the task area cell.

2.2. The Adaptive Target Searching Strategy Based on Whale Algorithm. The Whale optimization algorithm is a random swarm intelligent optimization algorithm modeled by simulating the predation mode of whales in nature. It uses individual whales to update their own position and estimate the position of the prey with a certain optimization strategy, to achieve the optimal algorithm and convergence to the optimal [30]. The strategy architecture of ASWOA is shown in Figure 4, which mainly includes several modules such as target probability graph module, fitness function module, and obstacle avoidance module.

In this paper, each UAV is regarded as a whale in the three-dimensional search space, so the ASWOA is a population composed of N whales, and the position of the i whale is $[ux_i, uy_i, uz_i]$. Each whale constantly updates its position on the signals it catches to get closer to its prey.

2.2.1. Path Marking. In order to improve the task efficiency of multi-UAVs and reduce the waste of energy caused by the repeated searches of multi-UAVs in a certain area, we have defined the concept of nontarget existence rate of regional cell.

Definition 1. The nontarget existence probability $\eta(\zeta_j)$ of the cell will increase if the position ζ_j of the area cell searched by the UAV at a certain moment is not the position of the target.

$$\eta(\zeta_j) = \eta_j(\zeta_j) + 1, \quad \zeta_j \neq T \text{ and } \zeta_j \in \{\mathcal{R} - O\}, \quad (1)$$

where $\zeta_j \in \{\mathcal{R} - O\}$ denotes the nonobstacle area in the task area. The larger the value of $\eta(\zeta_j)$, the smaller the probability of target existence in the area, and the UAV should avoid searching this area.

In addition, we record the number of area cells that each UAV has searched and the number of area cells that have been repeated searches, so as to avoid too fast convergence of UAV and provide constraints for UAV position updated

in the following ASWOA. The number of area cells SN_i that UAV _{i} has searched and the number of area cells RP_i that have been repeated searches are calculated as follows:

$$SN_i = SN_i + 1, \quad i \in N, \quad (2)$$

$$RP_i = RP_i + 1, \quad i \in N, \text{ if } [ux_i, uy_i, uz_i] \in \text{Path}_i, \quad (3)$$

where Path_i denotes the trajectory of the UAV _{i} .

2.2.2. Obstacle Avoidance. In the problem of multi-UAV path planning, once obstacles or other UAVs are predicted by the algorithm, the corresponding actions will be taken through obstacle avoidance strategy to get rid of potential threats.

(1) *Collision Avoidance between UAV and Obstacle.* We fit the obstacles in the task area as a rectangle area with threat values. If the UAV detects an obstacle in front of the flight, it will retreat to its previous position.

$$UAV_i(t+1) = \begin{cases} UAV_i(t), & R_i \geq D(UAV_i, O_j), \\ UAV'_i(t+1), & \text{else,} \end{cases} \quad (4)$$

where $UAV_i(t)$ represents the position of UAV _{i} at time t , $UAV'_i(t+1)$ represents the position of UAV _{i} at time $t+1$ obtained by the ASWOA, and $D(UAV_i, O_j)$ represents the distance between UAV _{i} and the obstacle O_j .

(2) *Collision Avoidance between UAV and UAV.* In addition to the above obstacles affecting the flight safety of UAVs, the distance between UAVs should also be considered during the formation process; otherwise, it is easy to collide. We adopt the virtual force strategy to adjust the flight direction of the UAV to avoid disasters.

Definition 2. There will be a virtual repulsion between the two UAVs if the distance between UAV _{i} and UAV _{k} is less than the coverage radius of the UAVs.

In order to reduce the energy consumption of the multi-UAVs, according to Figure 1 and Equation (1), we choose the UAV with a few searching cells to move due to virtual repulsion. For example, if $SN_i < SN_k$ is satisfied, UAV _{i} generates repulsive force F_{ik} .

$$F_{ik} = X - UAV_i(t), \quad (5)$$

where $X \in H_{UAV_i}$ and $\eta(X) = \min(\eta(H_{UAV_i}))$, H_{UAV_i} denotes the set of adjacent position units of UAV _{i} (as shown in Figure 2), and X represents the position where the nontarget existence probability is the lowest in the adjacent position unit of UAV _{i} , i.e., $\eta(X) = \min(\eta(H_{UAV_i}))$.

2.2.3. Fitness Function Setting. As mentioned above, the multi-UAVs need to avoid obstacles to find the target node. The target is said to have been detected if the position of UAV meets the following conditions.

FIGURE 3: Multi-UAV target searching model based on distributed control structure.

FIGURE 4: Architecture of ASWOA.

FIGURE 5: The strategy of UAV position update in ASWOA.

Algorithm 1 ASWOA

Input: The UAV cluster UAV, task area $\mathfrak{R}$, obstacles set $\mathcal{O}$

Output: Optimal paths for multi-UAVs Path

1 Initialize the UAV cluster $\text{UAV} = \{\text{UAV}_1, \text{UAV}_2, \dots, \text{UAV}_N\}$ and the task area set $\mathfrak{R} = \zeta \cup \mathcal{O}$

2 Calculate the fitness of each individual UAV according to Equation (6)

3 while $t < \tau$ do4 for UAV_i in UAV do5 Update the values of parameters $\alpha_1, \alpha_2, \alpha_3, \beta, A_i, l$ 6 if $\alpha_1 < 0.5$ then7 if $|A_i| < 1$ then8 Update the position of UAV_i according to Equation (8) and Equation (9)9 else if $|A_i| \geq 1$ then10 Update the position of UAV_{rand} according to Equation (11)

11 Update the individual position according to Equation (10)

12 end if

13 else if $\alpha_1 \geq 0.5$ then14 Update the position of UAV_i according to Equation (8)

15 end if

16 Determine whether the UAV_i exceeds the task area

17 Implement obstacle avoidance strategy according to Equation (3) and Equation (4)

18 Add the current position of UAV_i to the path set Path_i

19 Calculate the fitness of each UAV according to Equation (6)

20

Update the global optimal solution UAV_{best}

21 end for

22 end while

23 Return to the path planning of the UAV cluster

ALGORITHM 1: The ASWOA flow

FIGURE 6: The scene of the multi-UAV path planning space.

Definition 3. T is said to be found by UAV_i if the two-dimensional projection position of UAV_i and the position of the target T are less than or equal to the coverage radius R_i .

$$D_i = \sqrt{(ux_i - tx)^2 + (uy_i - ty)^2} \leq R_i. \quad (6)$$

It is known that the choice of fitness function can directly affect the convergence speed of the algorithm and the value of the optimal solution. The principle of path selection for multi-UAVs is to choose less repeated coverage route to find the unknown target node and save the energy consumption of multi-UAVs. We use the fitness function to evaluate the best

path of the UAV. According to Equations (1), (2), and (3), we define the fitness function as

$$\text{fitness} = \begin{cases} \lambda_1 \omega \cdot \exp(\eta(\text{UAV}_i(t)) + 1) + \lambda_2 \log_2\left(\left(\frac{\text{RP}_i}{(\text{SN}_i + 1)}\right) + 1\right), & \text{UAV}_i(t) \neq T, \\ 0, & \text{else,} \end{cases} \quad (7)$$

$$\omega = \frac{2\tau}{t + 1}, \quad (8)$$

where ω is called the adaptive inertia weight, which is used to balance the convergence speed and exploration ability of the ASWOA. λ_1 and λ_2 are constants, and $\lambda_1 = \lambda_2$. $\eta(\text{UAV}_i(t))$ represents the search times of the current position searched by UAV_i . When the value of fitness function is 0, it means that the UAV has found the target.

2.2.4. Position Update. The process of the ASWOA searching for targets is divided into the development stage and exploration stage.

(1) *Development Stage.* The UAV simulates a whale to produce a bubble network of shrinking circles to update its position to gradually approach and surround the target. The position update equation of the UAV is as follows:

$$\text{UAV}_i(t+1) = \begin{cases} \text{UAV}_{\text{best}}(t) - A_i \cdot D_{1,i}, & \alpha_1 < 0.5, \\ D_{2,i} \cdot e^{bl} \cdot \cos(2\pi l) + \text{UAV}_i(t), & \alpha_1 \geq 0.5, \end{cases} \quad (9)$$

where t is the current iteration number, UAV_{best} is the optimal solution position, and α_1 is a random variable between $[0, 1]$. When $\alpha_1 < 0.5$, we choose a shrinking circle to surround the target, as shown in Figure 5(c). $D_{1,i} = \|\text{UAV}_{\text{best}}(t) - \text{UAV}_i(t)\|$ is the contraction circle, and the values of other parameters are shown in

$$\begin{cases} A_i = 2\beta\alpha_2 - \beta, \\ C_i = 2\alpha_3, \\ \beta = 2 - \frac{2t}{\tau}, \end{cases} \quad (10)$$

where α_2 and α_3 are random variables between $[0, 1]$ and τ represents the maximum number of iterations of the algorithm.

In order to prevent the target from falling into the local optimal by using only the shrink circle search strategy, we use the logarithmic spiral search strategy to expand the optimal solution when $\alpha_1 \geq 0.5$, as shown in Figure 5(b). In Equation (9), b is the constant of the logarithmic spiral shape, and l is a random variable between $[-1, 1]$, so as to better search for the optimal solution space. $D_{2,i}$ represents the length of the i th whale from the target, and $D_{2,i} = \|\text{UAV}_{\text{best}}(t) - \text{UAV}_i(t)\|$ is the distance between the i th solution and the current optimal solution.

(2) *Exploratory Stage*. The position of the target in the whale predation is known, but in the collaborative path planning of multi-UAVs, the position of the target is unknown. In this paper, the optimal solution obtained in each iteration is set as the target position, and each UAV keeps approaching this target. $A_i \in [-\beta, \beta]$, the current whale randomly selects the position of other whales UAV_{rand} as the target position when $|A_i| \geq 1$, then the position update equation of the whale UAV_i at this time.

$$\text{UAV}_i(t+1) = \text{UAV}_{\text{rand}}(t) - A_i \|C_i \cdot \text{UAV}_{\text{rand}}(t) - \text{UAV}_i(t)\|. \quad (11)$$

2.2.5. ASWOA for Multi-UAV Path Planning. After the above description, Algorithm 1 provides the detailed implementation process of ASWOA for multi-UAVs path planning.

3. Simulation Analysis

Based on the ASWOA description, in the first part of this section, we introduce the parameter setting of the proposed algorithm in the simulation. Second, through the evaluation and comparison of a series of simulation experiments, we confirmed that ASWOA has the ability to find unknown target in emergency scenarios for multi-UAVs.

TABLE 1: List of important notations used in the paper and value of system parameters.

Symbol	Description	Value
N	The number of UAVs	10
M	The number of cells in the mission area	—
ζ_j	A cell of the mission area	—
O	The set of obstacles	—
T	The position of target, $T = [tx, ty]$	—
UAV_i	The position of UAV, $\text{UAV}_i = [ux_i, uy_i, uz_i]$	—
$h_{\min}$	Minimum height of UAVs	30 m
$h_{\max}$	Maximum height of UAVs	150 m
R_i	The radius of an area covered by UAV_i	—
θ	Detector perspective	$\frac{\pi}{9}$
τ	Simulation step size	300
t	Number of current iterations	—

TABLE 2: The performance of ASWOA with different constant values.

λ_1	λ_2	$N_{\text{iteration}}$	N_{UAVs}	N_{repeat}	L_{average}	L_{shortest}
0.1	0.9	300	0	343	189.51	—
0.2	0.8	300	0	327	271.21	—
0.3	0.7	222	4	295	313.72	136.36
0.4	0.6	150	6	266	252.23	184.16
0.5	0.5	141	6	129	220.11	158.92
0.6	0.4	120	6	117	212.55	144.18
0.7	0.3	132	6	213	227.99	166.0
0.8	0.2	195	6	433	238.96	222.12
0.9	0.1	240	3	486	316.24	275.05

3.1. Parameter Setting. First, we set the size of the task area R to 50×50 . Then, we divide R evenly into 1×1 cells and randomly mark the position of obstacles in R . Finally, the position of multi-UAVs and target node is initialized. In this paper, the UAVs do not know the terrain (including the position of obstacles and target). The terrain is modeled through simulation, and the altitude of multi-UAVs during the flight is uniform and unchanged. The path planning environment of multi-UAVs is shown in Figure 6, where obstacles are modeled as black areas.

The important notations of related sets, variables, and parameters, as well as main parameter values in this paper, are summarized in Table 1. In addition, as in Equation (7), the values of the constants λ_1 and λ_2 affect the rate of population convergence and the selection of the optimal solution, and $\lambda_1 + \lambda_2 = 1$. If λ_1 is too small, the population convergence rate is slow and it is easy to fall into local optimum. If λ_2 is too small, the population cannot guarantee whether the route it takes has been searched, which increases repeated paths and waste resources. After several experiments, the average

FIGURE 7: Path planning and shortest route results for multi-UAVs in the same location.

performance of the ASWOA with different constant values is shown in Table 2, where κ is the number of iterations when the first UAV finds the target node. If the UAV cluster fails to find the target before the maximum number of iterations of the program, $N_{\text{iteration}}$ is set to the value of τ . N_{UAVs} refers to the total number of UAVs that found the target node. N_{repeat} represents the total number of repeated search cells. L_{average} denotes the average path of the multi-UAVs, and

L_{shortest} represents the shortest path of the UAV from the starting point to the target node. In Table 2, we can see that if λ_1 is too small, the time $N_{\text{iteration}}$ it takes for the UAV to find the target node is correspondingly longer, which is not suitable for emergency environments. Besides, with the decrease of λ_2 , the number N_{repeat} of area cells repeatedly searched by multi-UAVs and the average path length L_{average} of multi-UAVs also increase. In consequence, we set $\lambda_1 = 0.6$ and

FIGURE 8: Path planning and shortest route results for multi-UAVs in the different locations.

$\lambda_2 = 0.4$; in this case, the algorithm can achieve the best performance, that is, it takes less time for the UAV to find the target and the path it takes is shorter.

3.2. Analysis of Experimental Results. To confirm the reliability of ASWOA, we carried out simulations of different starting points and ending points and conducted extensive simulations, comparisons, and experiments.

3.2.1. Simulation of ASWOA

(1) *Dispatching of UAVs from the Same Position.* Figure 7 shows the path planning for dispatching multi-UAVs at the same position. In different unknown position target scenarios, ASWOA enables each UAV to avoid obstacles and find target. Moreover, after the first UAV finds the target, the other UAVs can also find the target in a short time. Further, we can see the shortest route taken by the multi-UAVs in Figure 7.

FIGURE 9: Comparison of the number of UAVs and the time cost that use four algorithms to find unknown target.

(2) *Dispatching of UAVs from Different Positions.* When a major disaster occurs, it is usually to dispatch multiple rescue teams from different directions to search for targets at the same time. Figure 8 shows the path planning for dispatching multi-UAVs from different positions. Without knowing the specific position of the missing person, ASWOA allows each UAV to avoid obstacles and share information until it finds the target. Compared with Figure 7, it is obvious that dispatching multi-UAVs from different positions takes shorter time and has a relatively lower path cost than dispatching multi-UAVs from the same position.

3.2.2. Comparison with Other Optimization Algorithms. To further evaluate the performance of ASWOA, we compared it with other heuristic optimization algorithms, including the WOA [16], PSO [11], and GWO [15] algorithms. Considering the randomness of the heuristic algorithm, each test algorithm is executed 30 times independently.

Figure 9 plots the speed comparison of six UAVs searching for unknown target node under the same initial position. The convergence speed of the PSO algorithm is relatively fast. When the number of iterations is 66, the UAV cluster finds the target node for the first time, whereas only three UAVs find target, and the remaining three UAVs stagnate around the obstacle, falling into the local optimum. Although the GWO algorithm has more UAVs to find the target node than the PSO algorithm, the convergence speed is slower. When the number of iterations is 227, the UAVs find the target node for the first time, which takes too long to be suitable for emergency scenarios. The WOA can satisfy all UAVs to search for unknown target, but the convergence speed is still slower than that of the ASWOA. The ASWOA can complete the task in only 20 iterations, which is 4.75 times faster than the WOA.

Due to the limited energy of UAVs, it is necessary to reduce path costs in a limited time. Figure 10 shows the comparison of repeated paths, average paths, and shortest paths of the four algorithms. Although the PSO algorithm

FIGURE 10: The path cost comparison with WOA, PSO, and GWO algorithms.

has better performance in average path consumption, it can be seen from Figure 9 that the PSO algorithm has three UAVs falling into the local optimal and fails to find the target node, so the total path cost is relatively low. The GWO algorithm has high cost of repeated search and path, which is not suitable for emergency scenarios with limited energy resources. Since the ASWOA incorporates strategy to reduce repeated paths, the cost of both repeated paths and average paths is less.

4. Conclusions

In this paper, an adaptive target searching strategy based on the whale algorithm has been successfully applied to solve the multi-UAV search unknown target. We first design a probability map algorithm to calculate the target existence probability map, then use the whale optimization algorithm to optimize the search paths of multi-UAVs. In addition, we design an obstacle avoidance strategy based on virtual repulsion force to avoid any collision problems that may be encountered during the flight of UAVs. In this paper, practical constraints are considered to define various flight scenarios of the UAV. Simulation results show that, compared with other algorithms, the AWOA algorithm has the advantages of high search efficiency and low path cost.

Data Availability

All the data can be generated according to the steps described in our paper, and readers can also ask for the data by contacting wangwenshan@hrbeu.edu.cn.

Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

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