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Reconnaissance Mission Conducted by UAV Swarms Based on Distributed PSO Path Planning Algorithms

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ABSTRACT Reconnaissance mission has a wide application in both civil and military fields, which provides intelligence and basis for the following decision-making to accomplish certain goals. Due to numerous advantages of UAV swarms such as strong flexibility, high efficiency, and low cost, conducting reconnaissance missions by UAV swarms has become a trend of future. However, the path planning problem of UAV swarms is a key challenge in the aspect of model construction, algorithm, selection and high computational complexity, especially when the mission is complicated. In this paper, various distributed particle swarm optimization (DPSO)-based path planning algorithms are proposed for UAV swarms conducting a reconnaissance mission, in which targets are gathered in the form of clusters and different tactic needs are taken into consideration. Three algorithms named the maximum density convergence DPSO algorithm (MDC-DPSO), the fast cross-over DPSO algorithm (FCO-DPSO), and the accurate coverage exploration DPSO algorithm (ACE-DPSO) are proposed correspond to the needs of fast convergence, random cross-over, and accurate search, respectively. Different fitness functions and search strategies are specifically designed considering the mobility and communication constraints of the UAV swarms. Besides, the jump-out mechanism and revisit mechanism are designed to save invalid search efforts and avoid falling into local optimum. The simulation results demonstrate that the proposed algorithms are effective in generating paths for UAV swarms conducting a reconnaissance mission, which can be easily applied to large scale swarms.

INDEX TERMS Reconnaissance mission, path planning, distributed particle swarm optimization (DPSO), UAV swarms.

I. INTRODUCTION

The development of UAV swarms technology has drawn great attention in both civil and military applications, such as aerial mapping for terrain mapping [1], disaster search and rescue [2], surveillance and reconnaissance mission [3], [4]. UAV swarms equipped with sensors are capable of collecting and sharing information of targets in complicated and unknown environments. The path planning is a key element of UAV swarms autonomous control module, especially for a large number of UAV swarms [5]. It allows the swarms to autonomously compute the best path from start to end waypoints. The main purpose of this paper is to propose path planning algorithms for UAV swarms aiming at conducting a reconnaissance mission.

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The general path planning problem is to find the flight path from the starting point to the target point for UAV swarms under specified constraints [6]. The purpose of path planning is to find a flight path that can quickly find the target in the region with minimum cost. Path planning algorithm of UAV swarms is a NP-hard problem and a number of existing literatures have been devoted to path planning for UAV swarms [7], [8]. Usually three steps are applied to settle this problem [9]. First, a gird search map needs to be constructed, which can reflect the targets and some terrain information. Thus, the path planning problem is converted to map search problem. Second, search criterions are applied to update the search map of UAV swarms at each moment. Third, optimal paths or sub-optimal paths are calculated based on the updated search map to find target quickly. There are many optimization search algorithms for this problem, which are mainly divided into two categories: deterministic algorithms and stochastic algorithms. The deterministic algorithms include: sparse A* algorithm, D* lite algorithm, etc. Szczerba *et al*. [10] proposed the sparse A* algorithm to plan a real-time route for aircraft. The sparse A* algorithm can efficiently decrease the search space when many constraints of aircraft are taken into consideration. However, it can only be applied when prior environment information is given. To solve this problem, Koenig and Likhachev [11] studied the D* lite algorithm for shortest paths in an unknown environment. However, it spent much time to formulate paths, especially when the number of UAVs in swarm is large. The stochastic algorithms mainly includes some heuristic algorithms [12], such as genetic algorithm (GA) [13], ant colony (AC) algorithm [14], particle swarm optimization (PSO) algorithm [15], [16], and so on. These bio-inspired algorithms are mainly applied to find the solutions of objective function to solve the task assignment and waypoints of UAV swarms. High time complexity within each time step is the main drawback of these bio-inspired approaches and cannot settle down at a predictable solution. To avoid this problem, Hereford *et al.* [17], [18] firstly gave the distributed PSO (DPSO) algorithm to perform a search task of robots. Each particle (robot) was able to obtain the measurements according to its sensors and update its own position and velocity based on the evaluation of the information. Ayari and Bouamama [19] proposed the dynamic DPSO for trajectory path planning of multi-robot in order to find collision free optimal path for each robot. Stagnation and local optima problems were avoided by adding diversity in the DPSO algorithm. Spanogianopoulos [20] reviewed the various applications that use the PSO based algorithm. It shows that DPSO algorithm can be applied efficiently in multi-agents path planning algorithm such as robotics. Sánchez-García *et al.* [21] extended the DPSO algorithm for UAV swarms and to form mobile Ad hoc networks (MANET) on the disaster area.

Inspired by [17]–[21], we focus on a DPSO-based algorithm for a reconnaissance mission in a given hostile region which contains several unknown target clusters, accomplished by the UAV swarms with optical sensors and limited communication ranges.

In a reconnaissance mission, different strategies are adopted according to specific tactic needs. There are three typical applications of tactic intention in military reconnaissance mission: 1) UAV swarms convergence to the area with the maximum density of targets within each cluster in a short time, which intends for the following fire strike action; 2) UAV swarms fly cross over the target cluster in random paths, which aims at enhancing the flexibility and survival rate of themselves while realizing an fast reconnaissance of hostile targets; 3) UAV swarms search in the way of online lawn mower to accomplish full coverage and accurate reconnaissance of targets, which costs more time but obtains the highest accuracy. To cope with the different tactic needs stated above, three algorithms named the maximum density convergence DPSO algorithm (MDC-DPSO), the fast cross-over DPSO algorithm (FCO-DPSO), and the accurate coverage exploration DPSO algorithm (ACE-DPSO) are proposed in this paper to meet the needs of aforementioned missions, respectively.

Therefore, the main contributions of this paper can be concluded as follows:

- Three DPSO based algorithms are proposed for path planning of UAV swarms conducting reconnaissance mission, where targets appear in the form of clusters. Each UAV is one particle in proposed algorithms as an intelligent agent, which searches for targets, updates its own position and velocity without prior knowledge.
- To the knowledge of authors, this is the first time that DPSO is applied in three specific reconnaissance scenarios with detailed tactic needs. Specific fitness functions are designed to fit the tactic intentions in aspect of time and accuracy. The velocity updating rules of UAV swarms are composed of three phases, in which the parameter setting of inertia weight, personal best (pbest) weight and global best (gbest) weight are different to enhance the algorithm performance.
- Geofence (both dynamic and static) is applied to deal with forbidden zones, boundary solutions and collision avoidance. The jump-out mechanism and revisit mechanism are proposed to save invalid search efforts and avoid falling into local optimum.

The remainder of this paper is organized as follows. Some related work is given in Sec. II and the problem statement in our paper is given in Section III. Then, the MDC-DPSO, FCO-DPSO and ACE-DPSO algorithms are proposed in Sec. IV, Sec. V and Sec. VI, respectively. These algorithms are verified via simulations in Sec. VII, and finally Sec. VIII concludes the paper.

II. RELATED WORK

A. BASIC PSO ALGORITHM

Particle Swarm Optimization (PSO) algorithm is one of classic heuristic algorithms applied in optimization problems [22]. Each particle in swarm is defined with original position and velocity and modified by a position vector and a velocity vector, which acts independently in seeking for pbest and interacts with other particles to find out gbest. Thus, the particle swarm can be regarded as a multi-agent system [23]. For classic PSO algorithm, particles are initialized with random position and velocity values in search space, they explore and exploit in multi-dimensional search space to optimize fitness function and find the best global values of position, velocity and fitness function. During this process, the history and current values of pbest and gbest are stored in system memory to help making decision of next move in the following iteration until the global optimal point is found.

There are four important variables in PSO algorithm, the velocity of the i-th particle v_{ij}^k, position x_{ij}^k, the best position that has been found independently by itself pbest$_i$, and the best position that has been found by all the particles after interaction gbest.

During the iteration, each particle updates its position and velocity according to the following rules [24]:

$$v_{ij}^{k+1} = wv_{ij}^k + c_1 r_{1j}^k \left(pbest_{ij}^k - x_{ij}^k\right) + c_2 r_{2j}^k \left(gbest_j^k - x_{ij}^k\right), \tag{1}$$

$$x_{ij}^{k+1} = x_{ij}^k + v_{ij}^{k+1}, \tag{2}$$

where, k is the iteration number, w is the inertia weight, j is the dimension of the velocity,c_1 and c_2 are learning factors, r_{1j}^k and r_{2j}^k are two random values with uniform distribution between [0, 1]. For the whole swarm, the values of pbest and gbest are updated according to following rules:

$$pbest_i^{k+1} = \begin{cases} pbest_i^k \ if\ f\ \left(pbest_i^k\right) \le f\left(x_i^{k+1}\right) \\ x_i^{k+1}\ if\ f\ \left(pbest_i^k\right) > f\left(x_i^{k+1}\right), \end{cases} \tag{3}$$

$$gbest^{k+1} = \arg\min_{pbest_i^{k+1}} f\left(pbest_i^{k+1}\right). \tag{4}$$

B. DPSO ALGORITHM AND OUR WORK

The DPSO algorithm is based on the basic PSO algorithm formula shown in Eq. (1) but with some minor modifications [16]. In the basic PSO, the random values r_{1j}^k and r_{2j}^k are designed to expand the exploration. However, the main aim of UAVs in this paper is not to identify the global maximum, but discovering several maxima according to the specific tactic needs. Thus, these two parameters may not be necessary [17]. Moreover, taking the flight dynamics and control problem of UAVs into consideration, the trajectories with less turning are preferred. Due to this reason, the random parameters r_{1j}^k and r_{2j}^k are dismissed. Instead, we include a random component when the UAVs reach the geofence and have to make a turn mandatorily.

Our work is different from previous applications of PSO algorithm assisting UAV missions in the following aspects:

(1) The main aim is not to identify the global maximum, but finding several maxima in reconnaissance area. Moreover, different algorithms are proposed to meet the need of specific tactical intentions.

(2) Every particle in DPSO algorithm corresponds to a real UAV in reconnaissance mission rather than a fake observer. Thus, the updating of velocities and positions are based on real observation values of UAVs rather than virtual value of particles.

(3) By taking in account the flight dynamics of a UAV, the main desire is to have trajectories that are not changing the direction every now and then. Therefore, the velocity updating rules are composed of different phases, and parameter selections are determined via statistical experiment rather than totally random.

III. PROBLEM STATEMENT

This paper focuses on the path planning problem of reconnaissance mission assisted by UAV swarms without any prior knowledge of target positions, in which ground targets appear in the form of clusters. According to different tactic needs, the scenario assumptions, UAV assumptions and UAV mission assumptions are given as followings.

A. SCENARIO ASSUMPTIONS

(1) Assume that the scenario is flat. Thus, the projection of sensor detection range on the ground can be considered as a two-dimensional problem.

(2) There are few areas where the targets gather together, which are considered as targets clusters.

(3) The UAV swarms do not have any prior knowledge of target positions.

B. UAV ASSUMPTIONS

(1) UAV swarms are equipped with short-range wireless communication devices. Any pair of UAVs separated a distance smaller than range restrain will be able to establish a communication link with each other.

(2) UAV swarms are equipped with optical sensors which have the fixed detection range and circular projection on the ground.

(3) Two common types of UAV are the rotor and the fixed wing. In this paper, the rotor UAV is selected to perform reconnaissance mission. The reason is that compared with the fixed wing, the rotor UAV can hover, the turn radius is smaller and the maneuverability is better, which is more in line with the mission requirements. The kinetic characteristic of the rotor UAV is considered as dynamic constraint in problem modeling.

C. RECONNAISSANCE MISSION ASSUMPTIONS

The aims of the UAVs are to explore the hostile scenario without prior knowledge, discover as many targets as possible to meet three kinds of tactic intentions.

(1) A fast reconnaissance to prepare for fire strike: UAVs are expected to explore the hostile area, find the targets and converge to areas with the maximum destroy performance in fixed detection range and fire strike range.

(2) A fast reconnaissance to enhance the survival rate: UAVs are expected to explore the hostile area, find the target clusters and execute reconnaissance mission in a flexible path so that hostile equipment is hard to track them.

(3) The accurate reconnaissance intention: UAVs are expected to explore the hostile area, find the clusters, and execute accurate coverage exploration for all the targets within the clusters.

D. GEOFENCE CONSTRAINT

There are two types of geofence considered in this paper, which are static and dynamic geofences.

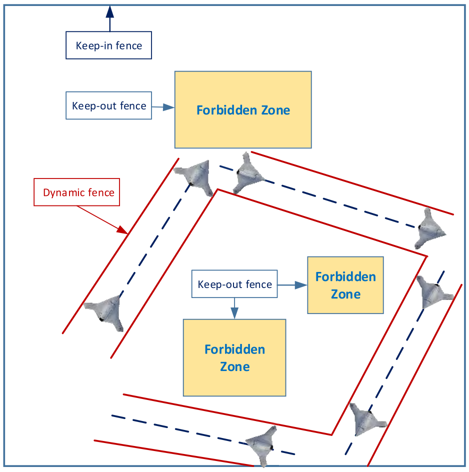


FIGURE 1. Geofence in reconnaissance mission.

Dynamic geofence aims at preventing collision between UAVs, which is defined as a certain safety range surrounds each UAV. Static geofence assigns each UAV a keep-in zone and keep-out zone, which is used as an effective mechanism to assure the authorized operation airspace for UAVs dealing with the scenario boundaries and forbidden zones respectively. In the application of geofence, there are two issues to be clarified. The first one is the definition of bounding box, and the second one is UAV's response to a geofence violation.

The definition of bounding box consists of the keep-out fence and keep-in fence, which should be considered as an airspace constraint during the reconnaissance mission. The keep-in zone represents an allowed bounded flight volume for the UAVs, and the keep-out zone represents a forbidden flight volume as a cut-out volume within a keep-in zone. In this paper, the keep-in geofence corresponds to the border of reconnaissance area, which defines the search space for UAVs. The keep-out geofence corresponds to forbidden zones which should be avoided due to the danger so as to keep UAVs safe from being attacked.

The UAV's response to a geofence violation defines the corresponding maneuvering tactics when it encounters with any geofence border [25]. In this paper, UAV swarms need to expand the exploration to find targets as soon as possible. Thus, we apply a turning around in random direction φ_f^k as the response to a geofence violation, as Fig. 1 shows.

IV. THE MAXIMUM DENSITY CONVERGENCE DPSO ALGORITHM (MDC-DPSO)

For MDC-DPSO algorithm, this strategy has significant tactic meaning of maximum destroy performance in fixed detection and fire strike range, as shown in Fig 2. Assume that each UAV is equipped with specific number of weapons, and targets in each cluster are of the same threat level, then the destroy performance is apparently better when UAVs attack the areas with the maximum density of targets other than target-sparse areas. Therefore, the fitness function can be

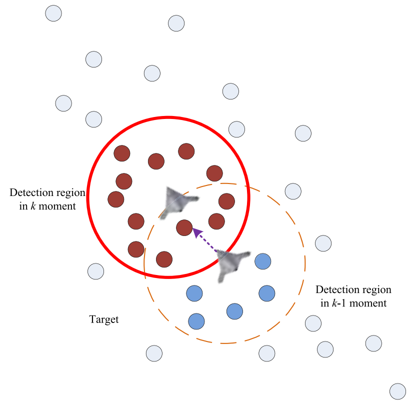


FIGURE 2. Find area with the maximum density of targets.

expressed as:

$$\begin{aligned} d &= \&\text{ground nodes discovered} \\ f(x,y) &= d \\ \mathit{find}\left(x^*,y^*\right) &\in S \in \mathbb{R}^2 \text{such that} \\ \forall (x,y) &\in S, \quad f\left(x^*,y^*\right) \geq f(x,y) \end{aligned} \tag{5}$$

Notice that our goal for UAV in this circumstance is to find the targets and convergence to area with the maximum density of them, the cost function and solutions based on DPSO should be designed accordingly, which is different from methods in reference [21] in the following aspects:

(1) In the velocity updating rule, a random value vector is added to increase the possibilities of velocity directions and values to expand the exploration area.
(2) A jump-out mechanism is proposed to avoid UAVs being trapped in specific target cluster.
(3) A return visit mechanism is proposed so that UAVs can remember the best positions ever found. In the circumstance where UAVs leave a cluster but cannot find another cluster, they can fly back to the discovered one through the return visit mechanism.
(4) Forbidden areas are set to simulate realistic situations. The geofence is proposed for UAVs to avoid entering the forbidden areas and avoid collisions.

In order to explain the MDC-DPSO more explicit, we divide the algorithm into three phases:

Inertia phase: Exploration before finding any targets. Assume that UAVs take off at the original point. Each UAV searches as a particle in DPSO algorithm independently and simultaneously, then the velocity updating of particle can be written as:

$$v_{ij}^{k+1} = w_A v_{ij}^k, \tag{6}$$

where, w_A is inertia component weight $w_A = 1$. In this phase, UAVs haven't encounter with any targets, they search in the initial direction with fixed value of speed. The parameter setting can also show the characteristic of UAVs in this phase which is to try their best in exploration to find targets as soon as possible.

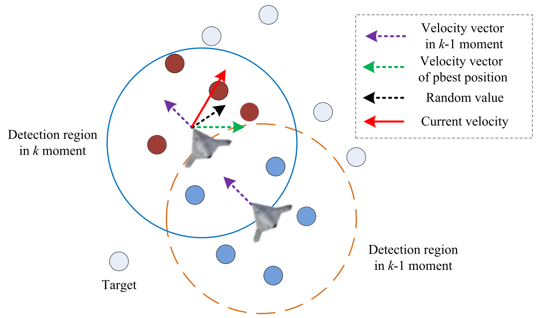


FIGURE 3. Velocity updating for single UAV.

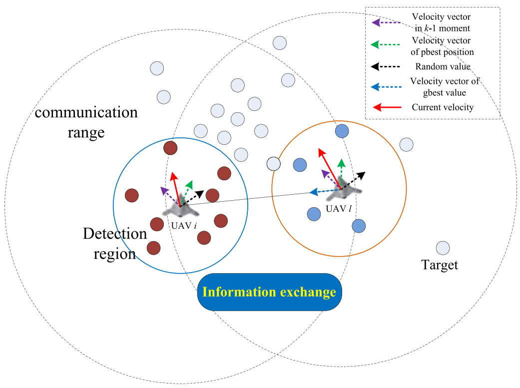


FIGURE 4. Velocity updating with communication between UAVs.

Pbest phase: Reconnaissance after finding target for single UAV without communication. Once an UAV finds any target in a certain cluster, it begins to search around this cluster hoping to find the area with most density of targets. During this process, UAV keeps updating its pbest values.

As shown in Fig 3, The velocity vector is formed by three vectors which are velocity vector in k-1 moment, velocity vector of pbest position and random value vector. At the beginning, an UAV takes off and begins the exploration in a random direction. Before discovering any targets, the UAV explores straightly in the original direction under the influence of inertia weight w_A to avoid unnecessary maneuverings. Once the UAV discovered any targets, the velocity updating goes into the second phase, where local best weight C_{p_A} increases and the inertia weight decreases. In this case, the velocity vector in k moment in determined both by inertia weight and local best weight. To avoid early convergence to local best, we also add a random value vector $\varphi_{p\_A}^k$ in this phase. Therefore, the velocity of UAV i can be expressed as:

$$v_{ij}^{k+1} = w_A v_{ij}^k + C_{p\_A}(pbest_{ij}^k - x_{ij}^k) + \varphi_{p\_A}^k, \quad (7)$$

where, C_{p_A} is the intensity of attraction of a particle towards its local best.

Gbest phase: Reconnaissance with communication between UAVs. Once the distance between UAVs satisfies the communication constrain, they can exchange the exploration information with each other to achieve cooperation and better performance. Through comparing the values of each UAV's pbest, they can obtain the gbest values at this moment.

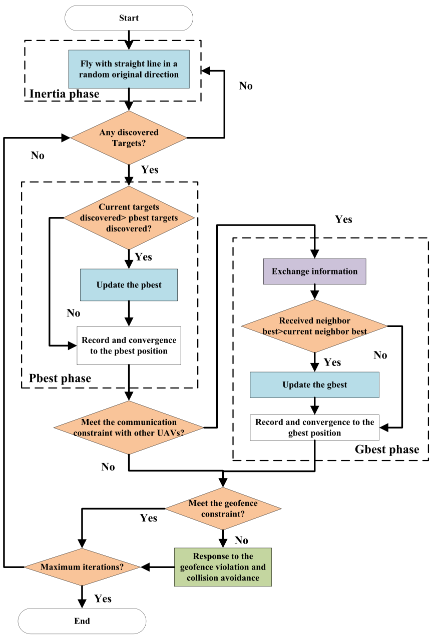


FIGURE 5. Flow diagram of MDC-DPSO.

As shown in Fig. 4, for two UAVs or multiple UAVs within communication range L_{com}, the pbest positions are exchanged to acquire a neighbor best position. The velocity vector of k moment is formed by four parts, which are velocity vector in k-1 moment, velocity vector of pbest position, velocity vector of gbest value and a random value vector. The effect of information exchange between UAVs is gathering towards the gbest position to realize fast convergence, which appears in the form of mutual attraction. The velocities of UAV i and l can be modified as

$$\begin{cases} v_{ij}^{k+1} = w_B v_{ij}^k + C_{p\_A}(pbest_{ij,\max}^k - x_{ij}^k) + C_{g\_A}(x_{lj}^k - x_{ij}^k) \\ \qquad\qquad + \varphi_{g\_A} \\ v_{lj}^{k+1} = w_B v_{lj}^k + C_{p\_A}(pbest_{lj,\max}^k - x_{lj}^k) + C_{g\_A}(x_{ij}^k - x_{lj}^k) \\ \qquad\qquad + \varphi_{g\_A} \end{cases} \quad (8)$$

where, C_{g_A} is the intensity of attraction of a particle towards its gbest; $\varphi_{g\_A}^k$ is a random value in gbest phase.

Fig. 5 shows the flow diagram of MDC-DPSO, in which the dashed boxes correspond to the stated three phases of this algorithm. The pseudocode of MDC-DPSO is as follows.

V. THE FAST CROSS-OVER DPSO ALGORITHM (FCO-DPSO)

For FCO-DPSO algorithm, this strategy aims at enhancing the searching exploration ability and improving the survival rate of UAV swarms in combat, which can realize a random fast reconnaissance. In this case, the random cross-over exploration is executed as shown in Fig.6, which has different tactic need from the MDC-DPSO obviously.

To achieve the fast cross-over reconnaissance, in each moment k, the UAV identifies newly discovered targets compared to the moment $k - 1$, and choses the position of new

Algorithm 1 MDC-DPSO Algorithm

for $k = 1, \ldots, M$ **do** (the maximum iterations)
Select initial directions of velocity for N UAVs
Compute the fitness f_k according to (5)
for $i = 1, \ldots, N$ **do**
%————————*Update the pbest information* ————
if $pbest\ (i,k) < pbest\ (i,k-1)$ and $pbest\ (i,k-1) \neq 0$
then $Max\_num\ (i,k) \leftarrow \max(pbest(i,k-10:end))$
$\boldsymbol{P_i}\ (k) \leftarrow find\ (pbest\ (i,:) == Max\_num)$
end if
if $pbest\ (i,k-1) \neq 0$
then $\boldsymbol{V\_dir} \leftarrow w_A \cdot \boldsymbol{v}\ (\boldsymbol{i},\boldsymbol{k}) + C_{p\_A} \cdot (\boldsymbol{P}_i\ (k) - x(i,k)) + randn \cdot \varphi_{p\_A}$
else $\boldsymbol{V\_dir} \leftarrow w_A \cdot \boldsymbol{v}\ (\boldsymbol{i},\boldsymbol{k})$
end if
if $length\ (unique\ (Max\_num\ (i, k-10:k))) ==1$
then $\boldsymbol{V\_dir} = w_A \cdot \boldsymbol{v}\ (\boldsymbol{i},\boldsymbol{k})$
end if
$\boldsymbol{v}\ (i,k+1) \leftarrow \boldsymbol{v}_0 \cdot \frac{\boldsymbol{V\_dir}}{norm(\boldsymbol{V\_dir})}$
%—*Gbest information exchange part between different UAVs* —
if $dis\_i, l <= L_{com}$
then compare the pbest of the i-th and l-th particles:
$Max\_pbest(i) \leftarrow \max(i,k)$
$Max\_pbest(l) \leftarrow \max(l,k)$
$\boldsymbol{gbest}\ (k) \leftarrow \max\ (Max\_pbest(i), Max\_pbest(l))$
gbest particle:$\boldsymbol{G_i}(k) \leftarrow find\ (pbest\ (i,:) \cup pbest\ (l,:) == gbest\ (k))$
end if
$\boldsymbol{V\_dir} \leftarrow w_A \cdot \boldsymbol{v}\ (\boldsymbol{i},\boldsymbol{k}) + C_{p\_A}\ (\boldsymbol{P}_i(k) - x(i,k)) + C_{g\_A}\ (\boldsymbol{G}_i(k) - x(i,k)) + randn \cdot \varphi^k_{g\_A}$
$\boldsymbol{v}\ (i,k+1) \leftarrow \boldsymbol{v}_0 \cdot \frac{\boldsymbol{V\_dir}}{norm(\boldsymbol{V\_dir})}$
%——————————*Geofence* ——————
if keep_in (i) ==1 || keep_out(i) ==0
%—(keep_in(i) is the keep-in fence function, keep_out(i) is the keep-out fence: "1" means the i-th particle reaches the outbound of the geofence; "0" means the i-th particle do not reach the outbound of the geofence).——
$\boldsymbol{V\_dir} \leftarrow -w_A \cdot \boldsymbol{v}\ (\boldsymbol{i},\boldsymbol{k}) + \varphi^k_f \cdot randn$
$\boldsymbol{v}\ (\boldsymbol{i},\boldsymbol{k}+1) \leftarrow \boldsymbol{v}_0 \cdot \frac{\boldsymbol{V\_dir}}{\boldsymbol{norm}(\boldsymbol{V\_dir})}$
end if
end for
end for

target which is furthest from UAV at moment k as the next flight direction. When an UAV finishes the cross-over reconnaissance and leaves this cluster, a revisit mechanism is set to restart another round reconnaissance with a random return value. Every UAV will record the detected targets at each moment, update the detected targets in real time and mark them. When two or more UAVs enter the communication

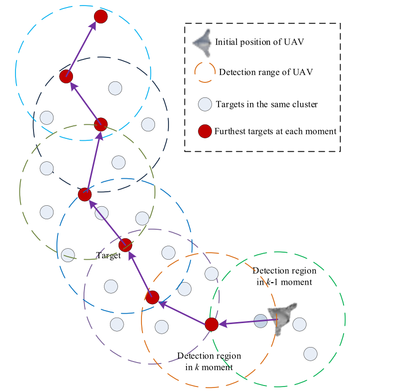


FIGURE 6. Fast cross-over reconnaissance of target cluster.

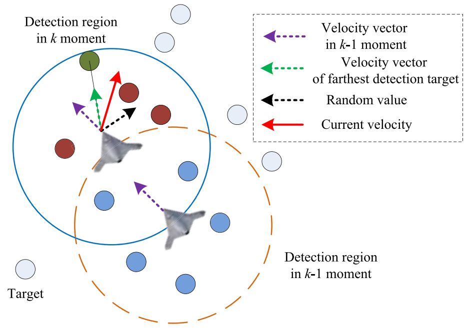


FIGURE 7. Velocity updating for single UAV.

range, these UAVs will share the information of detected targets.

Thus, the fitness function is designed by finding newly discovered target in detection range and can be represented as:

$$\begin{aligned} d_k &= \&\text{ground nodes discovered ink moment} \\ f_{k-1}(x,y) &= d_{k-1} \\ f_k\left(x^*, y^*\right) &= d_k \\ find\ \left(x^*, y^*\right) &\in S \in R^2 \text{such that} \\ \forall (x,y) &\in S, \quad f_k\left(x^*, y^*\right) \cap f_{k-1}(x,y) \neq \emptyset \end{aligned} \tag{9}$$

Similarly, the velocity updating of UAVs are divided into three phases (which are the inertia phase, the pbest phase, and the gbest phase) as in MDC-DPSO algorithm.

Inertia phase: This phase is the same as inertia phase in MDC-DPSO, and is omitted here.

Pbest phase: velocity updating for single UAV without communication and information exchange, as shown in Fig. 7. For cross-over reconnaissance, every single UAV is expected to discover new targets and fly towards the farthest one among them. Similar to the velocity updating for single UAV in MDC-DPSO, the update of velocity vector is consisted of velocity vector in k-1 moment, velocity vector of farthest detection target, the current velocity vector and a random vector.

$$v^{k+1}_{ij} = w_B v^k_{ij} + C_{p\_B}(pbest^k_{ij,\max} - x^k_{ij}) + \varphi^k_{p\_B}, \tag{10}$$

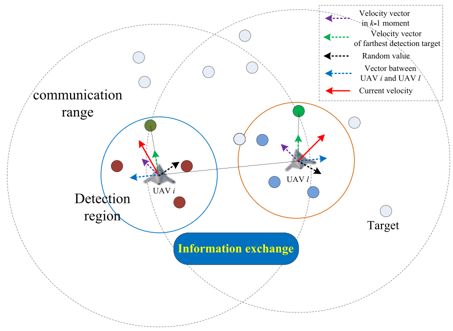


FIGURE 8. Velocity updating with communication between UAVs.

where, w_B is inertia component weight, C_{p_B} is the intensity of attraction of a particle towards its local best, $pbest_{ij,\max}^{k}$ is the farthest target within the newly detected targets, $\varphi_{p\_B}^{k}$ is a random value in pbest phase.

Gbest phase: velocity updating for two or multiple uavs with communications. As long as there are UAVs satisfying the communication constraint, they can exchange information of discovered targets to avoid repeat searches. Thus, the velocity updating with communication between UAVs is consisted of the velocity vector in k-1 moment, the velocity vector of farthest detection target, current velocity vector, the exclude vector between them, and a random value vector. Thus, the performance of information exchange appears in the form of mutual exclusion between two UAVs.

As shown in Fig. 8, this process aims at enhancing efficiency of exploration through cooperation between UAV i and UAV l. then the velocities of UAV i and UAV l can be expressed as:

$$\begin{cases} v_{ij}^{k+1} = w_B v_{ij}^{k} + C_{p\_B}(pbest_{ij,\max}^{k} - x_{ij}^{k}) + C_{g\_B}(x_{lj}^{k} - x_{lj}^{k}) \\ \qquad + \varphi_{g\_B} \\ v_{lj}^{k+1} = w_B v_{lj}^{k} + C_{p\_B}(pbest_{lj,\max}^{k} - x_{lj}^{k}) + C_{g\_B}(x_{lj}^{k} - x_{ij}^{k}) \\ \qquad + \varphi_{g\_B} \end{cases} \tag{11}$$

where, C_{g_B} is the intensity of attraction of a particle towards its gbest, φ_{g_B} is a random value in communication scenario. Moreover, a revisit mechanism is proposed to realize multiple fast searches in the same cluster.

The pseudocode of FCO-DPSO is shown below:

Algorithm 2 FCO-DPSO Algorithm

for $k = 1,\ldots,M$ **do**
  Select initial directions of velocity for N UAVs
  Compute the fitness f_k according to (9)
  for $i = 1,\ldots,N$ **do**
%————*Update the pbest information* ————
    if pbest $(i, k) \cap$ pbest $(i, k1) \neq 0$ and *pbest* $(i, k-1) \neq 0$
    then new targets: pbest $(i, k) \leftarrow$ pbest $(i, k) \cup$ pbest $(i, k-1)$
      $\boldsymbol{P_i}(k) \leftarrow$ *find* (pbest $(i, k) \cap$ pbest $(i, k1)$)
    $\boldsymbol{P_{max,i}}(k) \leftarrow$ *find* ($\boldsymbol{P_i}(k) ==$ max distance$(\boldsymbol{P_i}(k), x(i, k))$)
    end if
    if pbest(i, k − 1) $\neq$ 0pbest $(i, k1) \neq 0$
      then $\boldsymbol{V\_dir} \leftarrow w_B \cdot \boldsymbol{v}(i, k) + C_{p\_B}\left(\boldsymbol{P_{max,i}}(k) - x(i, k)\right) + randn \cdot \varphi_{p\_B}^{k}$
    else $\boldsymbol{V\_dir} \leftarrow w_B \cdot \boldsymbol{v}(i, k)$
      end if
        $\boldsymbol{v}(i, k+1) \leftarrow \boldsymbol{v}_0 \cdot \frac{\boldsymbol{V\_dir}}{norm(\boldsymbol{V\_dir})}$
%–*Gbest information exchange part between different UAVs* —
    if $dis\_i, l <= L_{com}$
      Then compare the pbest of the i-th and l-th particles:
      $\boldsymbol{gbest}(k) \leftarrow$ pbest $(i, k) \cup$ pbest (j, k)
      end if
$\boldsymbol{V\_dir} \leftarrow w_B \cdot v(i, k) + C_{p\_B}\left(\mathrm{P}_{\max,i}(k) - x(i, k)\right) + C_{g\_B}(x(i, k) - x(j, k)) + randn \cdot \varphi_{g\_B}^{k}$
    $\boldsymbol{v}(i, k+1) \leftarrow \boldsymbol{v}_0 \cdot \frac{\boldsymbol{V\_dir}}{norm(\boldsymbol{V\_dir})}$
%—-*Geofence part refers to algorithm* 1 *and is omitted here*—-
      end for
  end for

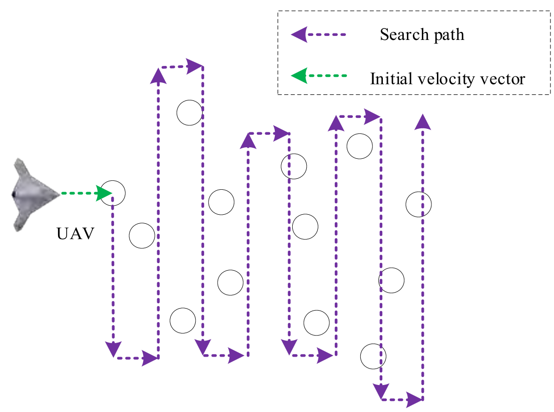


FIGURE 9. ACE-DPSO algorithm for single UAV.

VI. THE ACCURATE COVERAGE EXPLORATION DPSO ALGORITHM (ACE-DPSO)

For ACE-DPSO algorithm, the DPSO is combined with the online lawn mower algorithm to realize the accurate reconnaissance as shown in Fig. 9. Compared with MDC-DPSO and FCO-DPSO which provide two methods of rough reconnaissance with a fast speed, ACE-DPSO aims at achieving an accurate reconnaissance of all targets within a cluster. Thus, more exploration and full coverage of discovered cluster and are needed. Lawn mower algorithm is a classic method of full coverage rate. However, it would need extra time after sweeping the entire scenario for UAVs to fly to clusters discovered [26], [27]. To solve this problem, a combination of DPSO and online drawn mower algorithm called ACE-DPSO is proposed in this paper.

As Fig. 9 shows, after discovering a target, the UAV begins to explore the whole cluster in vertical direction of current velocity direction using drawn mower algorithm to guarantee the precision of contour depiction. Similarly as aforementioned algorithms, the velocity updating of UAVs are divided into three phases. However, the searching rules are different. As long as an UAV discovers a target, it begins to explore the cluster in the mode of online lawn mower. The initial search direction is vertical to the direction of discovering the first target. The trigger condition of making a turn and termination condition are determined by setting threshold values.

The rules of this combined algorithm are as followings:

A. FOR SINGLE UAV EXPLORATION

In the circumstance where a single UAV discovers a target, it begins to explore this very cluster using drawn mower algorithm. The initial searching direction is vertical to the initial velocity direction.

To determine where to turn around, a threshold value α is given. Denote the searching distance in the same direction after finding a target as d_{ij}. The rule of turning around is as follows.

$$turnaround = \begin{cases} 1 \text{ } if \text{ } \alpha < d_{ij} \\ 0 \text{ } if \text{ } \alpha > d_{ij} \end{cases} \tag{12}$$

The termination condition is also set with a threshold value β.

$$search = \begin{cases} 1 \text{ } if \text{ } \beta > d_{ij} \\ 0 \text{ } if \text{ } \beta < d_{ij} \end{cases} \tag{13}$$

B. FOR TWO OR MULTIPLE UAVS' EXPLORATION

In the situation where two UAVs discover and explore the same cluster, they work independently using the online drawn mower algorithm before satisfying the communication constraint with the other. Once they meet this constraint, the information exchange between them is executed. The serial number and positions of all discovered targets are exchanged and memorized. The corresponding solution of two (or multiple) UAVs discovering and exploring the same cluster after information exchange is shown in Fig.10. First, a comparison of which UAV has explored more targets is made. Then, this UAV keeps exploring the rest region while the other one leaves the current cluster immediately and tries to find other clusters. This process is designed to enhance the efficiency of cooperation and helps in ergodic exploration.

Therefore, the pseudocode of ACE-DPSO is as follows:

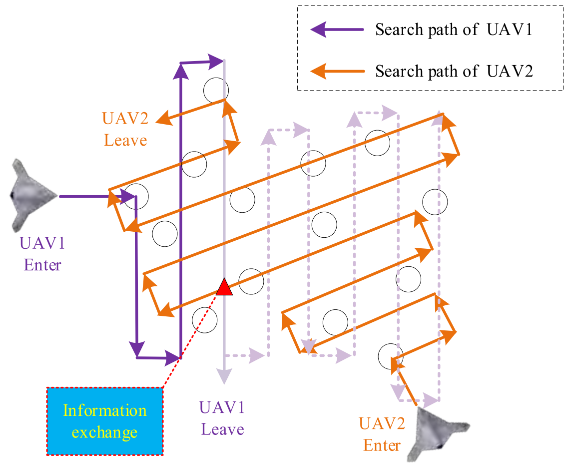


FIGURE 10. FCO-DPSO algorithm with communication between UAVs.

Algorithm 3 ACE-DPSO Algorithm

$v_{\perp}(i,k)$ *The vertical velocity of the i-th UAV in k moment*
N_c *Number of clusters*
φ_{g_C} *random value in gbest information part*
ω_C *inertia component weight*
for $k = 1,\ldots,M$ **do**
Select initial directions of velocity for N UAVs
Compute the fitness f_k according to (9)
for $i = 1,\ldots,N$ **do**
%————-*Update the pbest information*————
if *pbest* $(i, k-1) \neq 0$
new targets: pbest (i,k) = pbest $(i,k) \cup$ pbest $(i, k-1)$
$\boldsymbol{V\_dir} \leftarrow \boldsymbol{v_{\perp}(i,k)}$
then step into the lawn mower algorithm
end if
if *pbest*$(i, k-10:k) == 0$
then step out the lawn mower algorithm
end if
%–Gbest information exchange part between different UAVs —-
if $\boldsymbol{dis\_i,j <= L_{com}}$
then compare the pbest of the i-th and l-th particles:
$\boldsymbol{gbest\ (k)}$ = pbest $(i,k) \cup$ pbest (j,k)
end if
if pbest (i,k) >pbest (j,k)
then $\boldsymbol{V\_dir = v\ (i,k)}$
$\boldsymbol{V\_dir = v\ (i,k)}$ +randn $\cdot\ \varphi_{g\_C}$
end if
%—-Geofence part refers to algorithm 1 *and is omitted here—-*
end for
end for

VII. SIMULATION RESULTS

To verify the performance of proposed path planning algorithms, the simulations are conducted under different scenarios. The path planning based on MDC-DPSO, FCO-DPSO and ACE-DPSO algorithms are implemented, respectively. The characteristics of each algorithm are analyzed and good agreements between the algorithms and simulations are obtained.

A. SIMULATION SETTINGS

The basic simulation settings for path planning algorithms are shown in Table 1.

TABLE 1. Basic simulation settings.

Number of target clusters: 6
Number of UAV swarms: 6
Velocity of UAV swarms: 25m/s
Detection range of UAVs: L_{det}=200m
Communication range of UAVs:: $L_{com} = 600m$
Boundaries of geofence:
Forbidden Zone 1: [1500, 1700, 3200, 4000]
Forbidden Zone 2: [3500, 4200, 1500, 1700]
Simulation time: 1600s

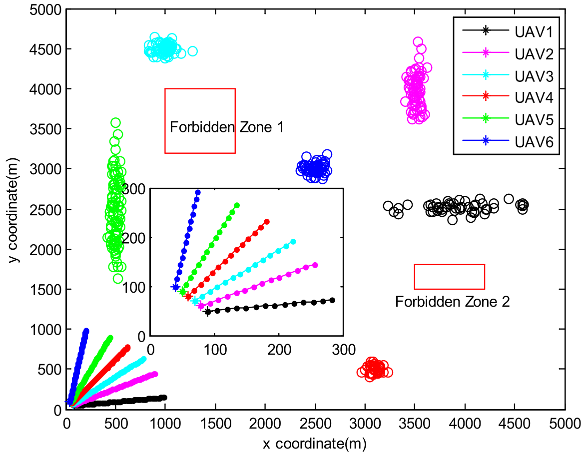


FIGURE 11. Environment setting of target clusters, forbidden zones and initial positions.

The reconnaissance region is set to be a square area of 5000×5000m shown in Fig. 11 and the UAV swarms are located in the lower left corner with different initial heading angles. There are 6 target clusters and 2 forbidden zones, randomly distributed in the search area. The shape and size of target clusters are arbitrary. Two forbidden zones are in different shape and size. The initial take-off position of UAV swarms is at the original point. Due to the random search characteristic of DPSO algorithm, the initial velocities of UAV swarms are assumed to uniformly distributed in interval [0, pi/2] to maximum search performance.

Because of the random search characteristic of DPSO algorithm, the Monte Carlo method is adopted to verify the algorithm effectiveness. Due to the communication range constraint, the UAV paths are obviously different with or without information exchange. To clarify the influence of communication between UAVs are compared.

B. THE PERFORMANCE OF MDC-DPSO

As shown in Fig. 12, after taking off from the original point, UAVs fly straight in the original direction. This phase corresponds to inertia phase which is exploration before finding any targets. For UAV1, UAV3, UAV4, and UAV6, they discover different target clusters after some time and go into pbest phase. From Fig. 12 we can clearly see that these four

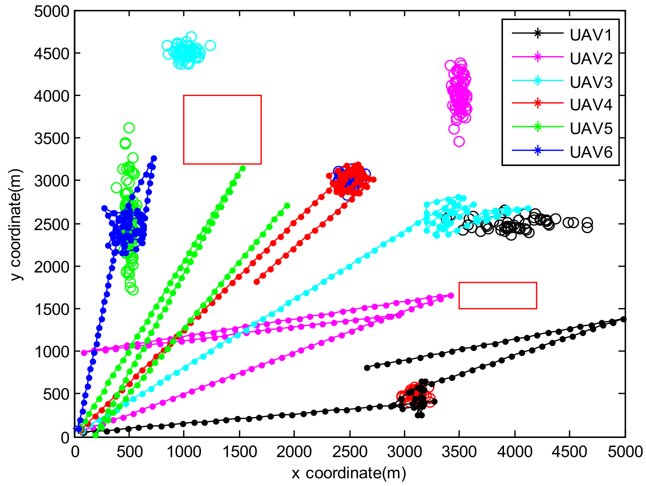


FIGURE 12. UAV paths without influence of information exchange.

UAVs convergence to the most target intensive areas after some time. For UAV 2 and UAV 5, they encounter with the forbidden zone and area boundaries, so they reenter with a random value to continue searching. Because UAVs are out of the communication range, there is no information exchange of target clusters, each UAV searches independently. We assume that each UAV can finish the reconnaissance mission for a specific target cluster after a fixed time period, in other words, each UAV spends a fixed time for a target cluster. Thus, after the fixed reconnaissance time, UAV can leave the current cluster and continue its search for other clusters. We also can see that UAV 1 and UAV 4 finally leave their discovered clusters after the set value of reconnaissance time. Note that after the UAV 3 and UAV6 successfully converging to the maximum density areas in two clusters respectively, they finally leave the clusters after 15 time steps straight forward. This is due to an intentionally designed mechanism called "jump-out mechanism", which means that after converging to certain area for certain time, i.e., 15 time steps, UAVs are set to leave the current cluster and continue to search new clusters. This design is aimed at enhancing overall performance of the UAV swarms in the whole reconnaissance area.

In other situations where UAVs satisfy the communication range constraint, they not only search the area obeying velocity updating rules, but also exchange the position information of target clusters and finding the gbest position. This case corresponds to gbest phase which is reconnaissance with communication between UAVs. For example, as Fig. 13 shows, UAV 4 is attracted by UAV 3, UAV 5 and UAV 6 are attracted by UAV 1.

Note that parameter selection is vital to PSO based algorithm performance [28]. In order to analyze and compare the performance of different parameter selections in MDC-DPSO algorithm, Fig. 14 shows the percentage of all detected targets in 100 times Monte-Carlo simulation [29], [30]. It can be seen that the maximum value can be acquired when the parameters are set to be $w_A = 0.9$, $C_{p\_A} = 0.1$,

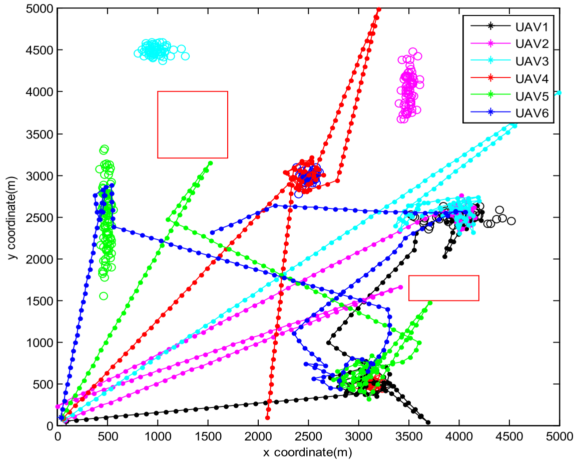


FIGURE 13. UAV paths with the influence of information exchange.

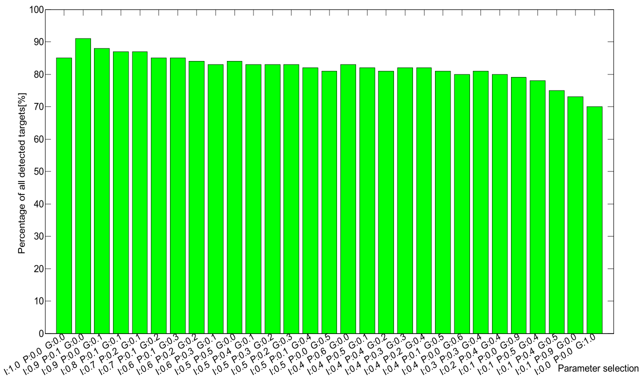


FIGURE 14. The percentage of all detected target.

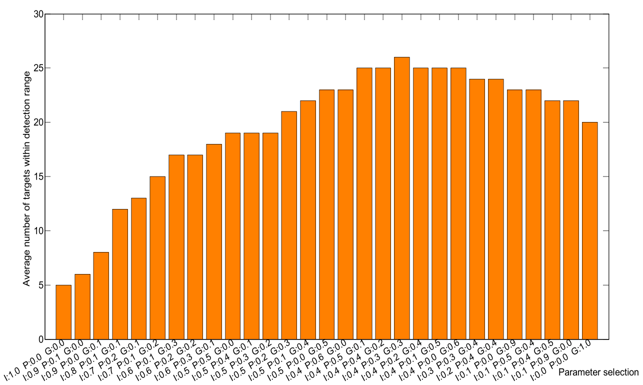


FIGURE 15. The average numbers of targets within UAV swarms detection range.

$C_{g\_A} = 0$, respectively. In this scenario, UAV swarms fly nearly in straight-line pattern with highest exploration ability. They do not converge to target clusters and are not being attracted by pbest and gbest positions. It is obvious that the value of w_A can directly impact the number of the detected targets. As the value of w_A decreases, the exploration ability decreases accordingly. Fig. 15 shows the average numbers of targets within UAV swarms detection range. We can observe that the parameters with higher values of pbest weight C_{p_A} and gbest weight C_{g_A} help UAV swarms converge to target

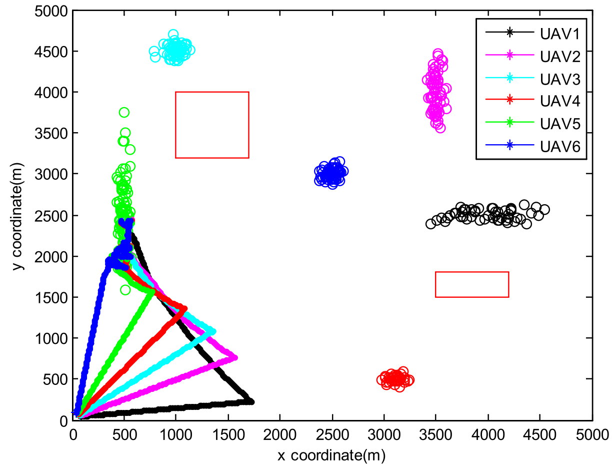


FIGURE 16. Extreme values of gbest to show the influence of parameter settings.

clusters, specifically between 0.3 and 0.6. In this scenario, each UAV tries to explore the surroundings of pbest and gbest locations in target clusters in which the maximum number of targets were detected. From Fig. 14 and Fig. 15, the parameter selection is a NP-hard problem, and we should acquire a balance between the value of inertia, pbest and gbest. Therefore, in this scenario, a suitable parameter selections are $w_A = 0.4, C_{p\_A} = 0.3$ and $C_{g\_A} = 0.3$.

To further explain the influence of parameter selections, an extreme value of $w_A = 1, C_{p\_A} = 0, C_{g\_A} = 0$ are simulated here. As Fig. 16 shows, in inertia phase every UAV moves under the influence of inertia weight and flies straight forwards. After satisfying communication constraint, the gbest weight plays the most important role in velocity updating. As a result, all the UAVs are attracted to gbest position and convergence to the same cluster. This simulation clarifies the importance of parameter selections, and provides guidance for parameter settings in this paper.

Table 2 shows the comparison between MDC-DPSO algorithm and DPSO-U algorithm [20]. The parameter selections are all set to be $w_A = 0.4$, $C_{p\_A} = 0.3$, $C_{g\_A} = 0.3$, respectively. It is obvious that the average numbers of targets within detection range in DPSO-U algorithm is the same with the numbers in MDC-DPSO algorithm. As for the time consuming for detecting the 25%, 50%, 75% and 85% of targets, it take less time for the proposed MDC-DPSO algorithm the DPSO-U algorithm. This is mainly because of the random value vector in the velocity updating rules. The random value vector shows the characteristics of PSO-based algorithm and helps to improve the flexibility and exploration ability. Since that our work focuses on the application of DPSO, the algorithm performance is compared between DPSO and other state-of -the-art PSO algorithms in this paper.

C. THE PERFORMANCE OF FCO-DPSO

Similar with the MDC-DPSO, the simulation results of FCO-DPSO can be sorted into two types: without and with theinformation exchange. The parameters are selected by

TABLE 2. The comparison between MDC-DPSO and DPSO-U.

Methods	Average numbers of targets within detection range of a UAV	Time consuming for detected target(s)			
		25%	50%	75%	85%
MDC-DPSO	27	183	345	637	1128
DPSO-U	27	195	361	656	1161

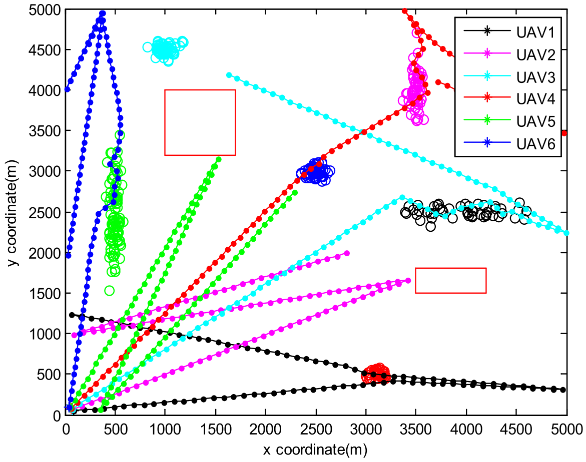
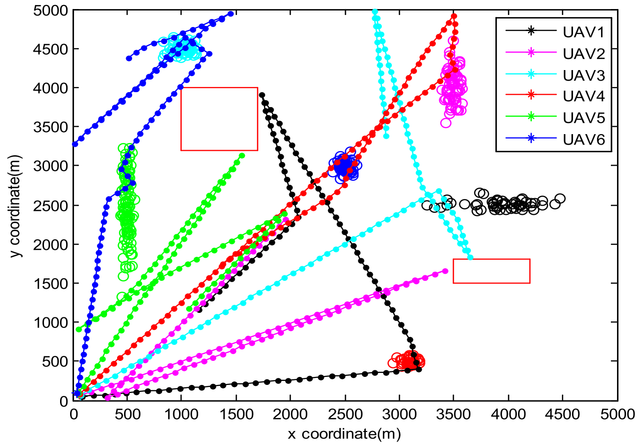


FIGURE 17. UAV paths without the influence of information exchange.

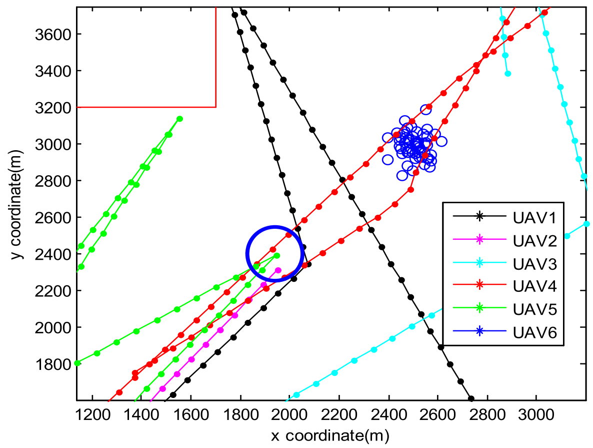
statistical experiment as in MDC-DPSO algorithm and are omitted here. The suitable parameters are $w_B = 0.4$, $C_{p\_B} = 0.4$ and $C_{g\_B} = 0.2$, respectively.

As shown in Fig. 17, after taking off from the original point, UAVs fly straight in the original direction. This phase corresponds to inertia phase which is exploration before finding any targets. For UAV 1, UAV 3, UAV 4, and UAV 6, they discover different target clusters after some time and go into pbest phase which is reconnaissance after finding target for single UAV without communication. We also can clearly see that these four UAVs fly cross-over target clusters. Especially, UAV 3 performs a typically cross-over path which verifies the proposed algorithm. For UAV 2 and UAV 5, they encounter with the forbidden zone and area boundaries, so they reenter with a random value to continue searching. Because UAVs are out of the communication range, there is no information exchange of target clusters, each UAV searches independently. Moreover, a revisit mechanism is designed in this algorithm to enable UAVs return to the same cluster in a different entering point and cross-over this cluster again, which helps in gathering more reconnaissance intelligence as well as enhancing the flexibility of UAVs. Especially when the area is equipped with hostile fire power, this cross-over tactic can enhance the survival rate of UAVs.

As shown in Fig. 18(a), once there are communications between UAVs, the path planning process turn into the gbest phase. The effect of information exchange can be descripted as mutual exclusion. For example, UAV 5 originally flies towards the blue cluster, however, after establishing communication with UAV 4, it changes the direction to find



(a)



(b)

FIGURE 18. UAV paths with the influence of information exchange.(a). The performance of FCO-DPSO the influence of information exchange. (b) Partial enlarged detail of path of UAV 5.

other clusters. To clarify the effect of information exchange more clearly, a partial enlarged drawing.

Fig. 18(b) is the partial enlarged figure of Fig. 18(a). In the blue circle, the path of UAV 5 turns around because of its communication with UAV 4. This detail verifies the effectiveness of information exchange mechanism.

The proposed algorithm can be easily applied to more complicated situations with more UAVs, which is convenient for extended application. For instance, Fig. 19 shows an application of 9 UAVs. Simulation result shows that UAVs can still realize the fast cross-over reconnaissance in proposed way.

UAV swarms are set to revisit a cluster in the situation where they fly cross over this cluster but do not find any new cluster in a certain time. As shown in Fig. 18(a), UAV 6 revisits the same cluster marked in blue several times because it does not find any new cluster in the set time after it leaves this cluster. Another example can be seen in Fig. 19, UAV 9 revisits the same cluster several times. This mechanism named revisit mechanism aims at improving the reconnaissance efficiency for the whole swarm.

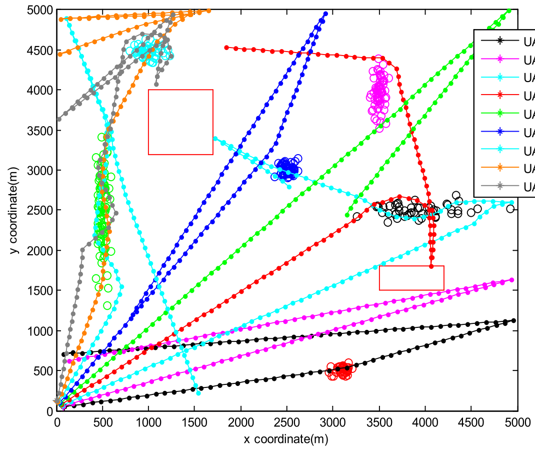


FIGURE 19. An extended application of 9 UAVs.

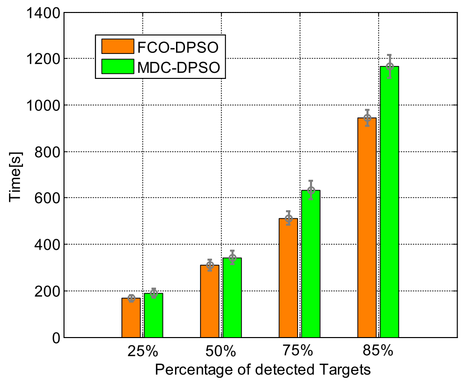


FIGURE 20. The comparison of average time consuming between FCO-DPSO and MDC-DPSO.

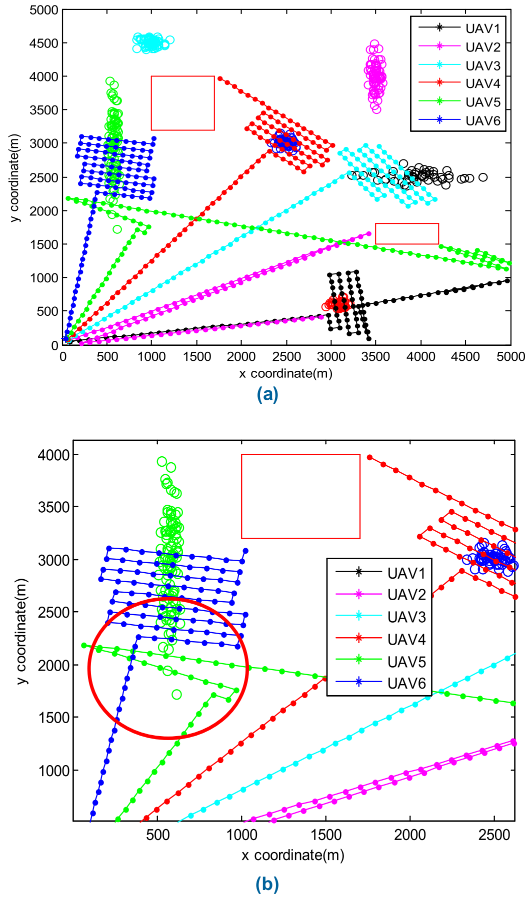


FIGURE 21. UAV paths combined with the online lawn mower. (a). The performance of ACE-DPSO. (b). Partial enlarged detail of path of UAV 6.

In order to test the characteristic of FCO-DPSO algorithm, the distribution of each target cluster is changed in each simulation. Fig. 20 shows the time consuming for detecting the 25%, 50%, 75% and 85% of targets with 100 Monte Carlo simulations. Compared with time consuming of the MDC-DPSO algorithm, it take less time to detect the 25%, 50%, 75% and 85% of the targets with lower standard deviation. It is obvious that FCO-DPSO algorithm possess more exploration ability to detect new target in the reconnaissance mission and it takes less than 1000s for FCO-DPSO algorithm to detect 85% of the target.

D. THE PERFORMANCE OF ACE-DPSO

Similar with the MDC-DPSO and FCO-DPSO, the simulation results of ACE-DPSO can be sorted into two types, the one is without UAV communication and the other is with UAV communication.

As Fig. 21(a) shows, the ACE-DPSO algorithm is realized by combining DPSO algorithm with the online lawn mower algorithm. This method combines the advantages of random search characteristic of DPSO algorithm and accurate coverage exploration of lawn mower algorithm. The threshold value of turning around is set as $\alpha = 4$ time steps, the threshold value of termination is set as $\beta = 10$ time steps.

As Fig. 21(b) shows, the UAV 5 and UAV 6 satisfy the communication constrain. They exchange and memorize the serial number and positions of discovered targets. Then, the number of discovered targets by each UAV is compared. Apparently, the moment they establish communication, UAV 6 has explored more targets than UAV 5. Thus, according to the proposed algorithm, UAV 6 stays in this cluster and keeps searching the whole cluster while UAV 5 leaves this cluster to find another cluster. Although for each cluster, only one would stay and search targets, the effectiveness of ergodic exploration can be improved.

VIII. CONCLUSION

In this paper, we have presented path planning algorithms for a reconnaissance mission conducted by UAV swarms based on DPSO algorithm, where targets appear in the form of clusters, and each particle corresponds to a real UAV without prior knowledge of clusters. Three algorithms with different tactic needs of a reconnaissance mission called MDC-DPSO, FCO-DPSO and ACE-DPSO are proposed corresponding to fast convergence, random cross-over search and accurate search, respectively. Specific fitness functions in three algorithms are designed to meet the different needs of tactic intentions and requirements of time and accuracy.

The velocity updating rules of UAV swarms are divided into three phases, in which the parameter setting of inertia weight, pbest weight and gbest weight are different to enhance the algorithm performance. Geofence is applied to deal with forbidden zones, boundary solutions and collision avoidance. Moreover, the jump-out mechanism and revisit mechanism are proposed to save invalid search efforts and avoid falling into local optimum. Simulations verify the validation and good performance of proposed algorithms.

In current model, the targets can be either static or maneuvering while the centric position of each cluster is static. For more realistic scenario, we will extend this work to maneuvering centric position circumstance. Besides, the parameter selection method for PSO based algorithm will be further studied. Moreover, the cooperation between a team of heterogenous UAVs (i.e., speed difference, sensor difference) is to be considered next.

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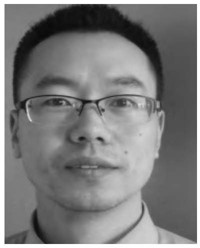

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