# Dynamic Target Search of UAV Swarm Based on Improved Pigeon-Inspired Optimization

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**Abstract.** In this paper, an improved pigeon-inspired optimization (IPIO) algorithm based on natural selection and Gauss-Cauchy mutation is proposed for unmanned aerial vehicle (UAV) swarm to rapidly realize cooperative dynamic target search and full coverage of target area under uncertain environment. Firstly, the environment awareness map is established, which includes coverage distribution map, target probability map (TPM), digital pheromone map and their updating mechanism. Meanwhile, in order to improve the possibility of discover targets, the target probability map is integrated into the attraction pheromone updating mechanism. Next, by the helps of the above environment awareness map, a reasonable collaborative search task optimization model is designed. Furthermore, based on the classical PIO algorithm, the integer encoding method, discrete compass operator and discrete landmark operator are designed in detail. Gaussian mutation and Cauchy mutation operators are introduced to guarantee the evolution escaping from local optimum, and natural selection is applied to accelerate the convergence. Finally, the simulation results show the effectiveness and superior of the proposed target search strategy.

**Keywords:** UAV swarm · Dynamic target · Target probability map · Digital pheromone · Pigeon-inspired optimization

## 1 Introduction

With increasingly complex battlefield environment, a single UAV is usually unable to complete a given task, but the overall combat effectiveness can be significantly improved in terms of mission performance, robustness and reliability through the capability complementarity and action coordination of multiple UAVs [1]. Therefore, UAV swarm operation is becoming a new combat style that military powers all over the world are striving to study [2]. UAV swarm cooperative search will be an important means to perform regional search in the future [3]. Hou et al. used coverage as real-time search index function, and used differential evolution solution to realize collaborative regional search of UAV swarm [4]. Information sharing of local particle swarm optimization algorithm was applied to achieves cooperative search of stationary targets of multiple UAVs in reference [5]. In order to realize collaborative search of UAV swarm, reference [6]


Z. Ren et al. (Eds.): *Proceedings of 2021 5th Chinese Conference on Swarm Intelligence and Cooperative Control*, LNEE 934, pp. 361–371, 2023.
https://doi.org/10.1007/978-981-19-3998-3_35

established a method based on digital pheromone. Probability model was established for a decision-making method of UAVs search in reference [7]. Although, many cooperative target search algorithms have been proposed for UAV swarm in the above literatures, there are still some challenges to be further studied. To the best of our knowledge, the results about the dynamic target research are very limited, and the area coverage of the existing strategies need to be improved. In addition, it should be pointed out that some of the above algorithms are easy to fall into local optimum.

Inspired by the above related studies, a novel IPIO-based cooperative target research scheme is designed. The main contributions of this paper can be summarized as follows.

(i) By combining the coverage distribution map, target probability map (TPM) and digital pheromone map, a new environment search map is firstly constructed, which can effectively improve the regional coverage.
(ii) The target existence probability is integrated into the attraction pheromone map to improve the ability of fast target detection and confirmation.
(iii) Different from the previous literatures, the IPIO is proposed based on natural selection and Gauss-Cauchy mutation for the mission optimization model. Meanwhile, avoiding local optimum and faster convergence can be guaranteed.

## 2 Preliminaries

### 2.1 Problem Description

There are $N_V$ UAVs connected by networks, $N_T$ dynamic targets randomly distributed in mission area $\Omega$. Suppose that the part of targets is known. For the convenience, it is assumed that all the altitudes of UAVs are the same. The UAV swarm are instructed to carry out target search and identification assignment in the mission area. As is shown in Fig. 1, mission area $\Omega$ is discretized into $L \times W$ grids with fixed length and width. The search radius of each UAV is $R_s$, and only the targets within $R_s$ could be detected. If the velocity of UAV is $v$ and the decision-making step size is $\Delta$t, then the displacement of UAV is $\Delta d = v \times \Delta t$. Assume the maximum turning angle is $\varphi_{\max}$.

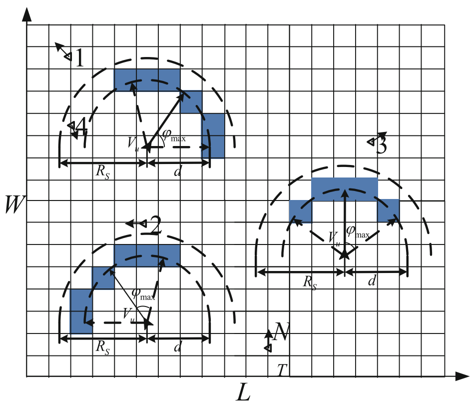



**Fig. 1.** Area rasterization and UAV state space

The main objective of this study is to design an efficient online cooperative search method for UAV swarm, which can cover more mission areas and discover more targets in the shortest possible time.

### 2.2 Coverage Distribution Map

To find more targets without any prior knowledge and improve the coverage area of mission area, the coverage distribution map is introduced into the search map model. Each grid $gd_{m,n}$ of search area has a certain value indicating its state at time $k$, and the state $grid_{(m,n)}(k)$ of $gd_{m,n}$ is expressed as

$$grid_{(m,n)}(k)=\begin{cases} 1 & gd_{m,n} \in CDM_c(k) \\ 0 & gd_{m,n} \in CDM_{nc}(k) \end{cases} \tag{1}$$

where $CDM_c(k)$ and $CDM_{nc}(k)$ represent the covered grid set and uncovered grid set of the distribution map, respectively. At the initial stage of search, the coverage map of the whole region is completely unknown to the UAV swarm, and the value of each grid is $grid_{(m,n)}(0) = 0$. Therefore, it is necessary to carry out coverage search for the whole region. $grid_{(m,n)}(k)$ will change as the search progresses in real time, and coverage distribution map can be updated and shared among UAV swarm through the communication network. At the later stage, the coverage rate becomes the main indicator bacause the most targets have been discovered.

### 2.3 Target Probability Map

Suppose the target existence probability of grid $gd_{m,n}$ at time $k$ is $p_{(m,n)}(k)$, and $p_{(m,n)}(k) \in [0, 1]$. The target existence probabilities of all grids constitute a probability distribution map, which can be determined by the following steps.

**TPM Initialization.** The targets are dynamic, and there is a time-delay between receiving instructions and arriving the mission area, which lead to the time-varying of TPM.

Due to the uncertainties of targets, four types of targets should be considered [8]:

a. The targets without any information: Targets may be distributed in any position in mission area, so it can be assumed that target distribution obeys uniform distribution;
b. The targets with known position and unknown velocity: Assuming that the movement of target is an independent incremental process, wiener stochastic process can be used to describe the randomness of the target;
c. The targets with known position and velocity, unknown direction: Due to the fixed velocity of the target, probability density of targets will diffuse from the target point to the circular arc;
d. The targets with known initial position, velocity and direction: the probability density can be easily obtained by calculation.

**Detection and Prediction Update of TPM.** In the search process, the target probability map will be updated according to the detection information from the neighborhood UAV and the local information. The update law can be described by

$$p_{mn}(k+1) = \begin{cases} \tau p_{mn}(k) & undetected \\ \frac{P_D \cdot p_{mn}(k)}{P_F + (P_D - P_F) \cdot p_{mn}(k)} & detected\ and\ b_k = 1 \\ \frac{(1-P_D) \cdot p_{mn}(k)}{1 - P_F + (P_F - P_D) \cdot p_{mn}(k)} & undetected\ \ and\ \ b_k = 0 \end{cases} \tag{2}$$

where $P_D$ is the detection probability of the sensor, $P_F$ is the false alarm probability, $b_k \in \{0, 1\}$ is the observation result, $b_k = 0$ means there is no target, $b_k = 1$ means there is a target.

Due to the time-sensitive characteristics of the target, the TPM may be inaccurate. Thus, the TPM should be update based on the movement of target prediction [9].

For the above target types, the following prediction approaches can be adopted:

Type *a* and *b*: Because the target motion is an independent increment, it can be estimated by wiener stochastic process.

Type *c*: Targets will be evenly distributed on the arc centered on the target;

Type *d*: It is very convenient to predict the probability density function by the taget's linear moment, and then the target existence probability of the grid can be also obtained.

### 2.4 Digital Pheromone Map

Digital pheromone map is composed of the attraction pheromone and repulsion pheromone, which can improve the cooperative search efficiency and avoid searching the same grid repeatedly [6]. The attraction pheromone content of grid $gd_{m,n}$ is defined as $s_\alpha(gd_{m,n}, k)$, and the repulsive pheromone content is defined as $s_\gamma(gd_{m,n}, k)$ at time $k$. The update rules of $s_\alpha(gd_{m,n}, k)$ and $s_\gamma(gd_{m,n}, k)$ are designed as follows.

The accessed state of $gd_{m,n}$ in the previous period is $last_{m,n} \in \{0, 1\}$. $last_{m,n}$=0 represent $gd_{m,n}$ was not searched in the previous period. Otherwise, $gd_{m,n}$ has been searched. Only when $last_{m,n}$=0, the attraction pheromone will be released and guide the UAV to $gd_{m,n}$. When $last_{m,n} \neq 0$, the attraction pheromone $s_\alpha(gd_{m,n}, k) = 0$. Then, the repulsive pheromone needs to be calculated. Due to the dynamic change of the environment, new targets may still appear in the searched grid. In order to discover the new targets, the revisit time window $T_0$ is defined. If $k - gd_{m,n}(last) \leq T_0$ , then $c_{m,n} = 0$, where $gd_{m,n}(last)$ is the last research time of grid $gd_{m,n}$, $k$ is the current time, and $c_{m,n}$ is the switching coefficient of the attraction pheromone of the corresponding grid. If $k - gd_{m,n}(last) > T_0$ , then $c_{m,n} = 1$.

Prescribe pheromone to propagate first, then evaporate. Introducing TPM, the updating rule of attraction pheromone is designed as

$$s_\alpha(gd_{m,n}, k) = (1 - E_a)\{(1 - G_a)[s_\alpha(gd_{m,n}, k-1) \ + c_{m,n} d_a f(TPM)] + GP_a(gd_{m,n}, k)\} \tag{3}$$

where $E_a$ and $G_a$ respectively represent the volatilization coefficient and propagation coefficient of attraction pheromone. $d_a$ represents the attraction pheromone constant released by the grid, $f(TPM)$ is the function related to the probability of target existence and $f(TPM) = \lambda \times TPM$, $\lambda$ is a time-varying coefficient. By introducing the function, the UAV will move in the direction where the increasing rate of TPM is the fastest, so as to find and confirm the target faster. Moreover, the term $GP_a\left(gd_{m,n}, k\right)$ is the sum of attraction pheromones obtained from adjacent grids in time interval $(k-1, k]$, and it can be described by

$$GP_a(gd_{m,n}, k) = \sum_{gd' \in N(gd_{m,n})} \frac{G_a}{|N(gd')|}\left[s_\alpha(gd', k-1) + d_a\right] \tag{4}$$

where $N(gd_{m,n})$ is the adjacent grid set of grid $gd_{m,n}$, $gd'$ is the adjacent grid of grid $gd_{m,n}$, and $\left|N(gd')\right|$ represents the total amount of adjacent grids of grid $gd_{m,n}$.

The update rule of repulsion pheromone is similar to the attraction pheromone, which can be referred to [6].

### 2.5 UAV Search Mission Optimization Model

For the cooperative target search of UAV swarm, three aspects should be taken into consideration: to cover more unknown areas, to find more targets, and to improve the cooperative search efficiency between UAVs as much as possible. Thus, the mission optimization model is established as follows:

**Environment Search (Coverage) Benefits**

$$J_C(k) = COV_c(k+1) - COV_c(k) \tag{5}$$

$$COV_c(k) = \sum_{m=1}^{W}\sum_{n=1}^{L} grid_{(m,n)}(k)/L \times W \tag{6}$$

where $COV_c(k)$ is the coverage rate, which represents the ratio of the searched grids to the number of grids in the mission area during time $k$ to $k+1$.

**Target Discovery Benefits**

$$J_P(k) = \sum_{i=1}^{N_V}\sum_{gd_{m,n}\in C_i} p^i_{mn}(k) \tag{7}$$

where $J_P(k)$ represents the sum of probabilities of all detected grid during $k$ to $k+1$, and $C_i$ represents the grid set detected by the $i^{th}$ UAV during $k$ to $k+1$. $p^i_{mn}(k)$ is the target existence probability of $gd_{m,n}$ detected by the $i^{th}$ UAV at time $k$.

**Cooperative benefits between UAVs**

$$J_V(k) = \sum_{i=1}^{N_V}\sum_{gd_{m,n}\in C_i} \alpha \cdot s^i_\alpha(gd_{m,n}, k) - \beta \cdot s^i_\gamma(gd_{m,n}, k) \tag{8}$$

where $\alpha$ and $\beta$ represent the intensity coefficients of attraction and repulsion pheromones, respectively.

By linear integration of the above benefits, the optimization model of UAV swarm cooperative search mission is obtained:

$$J(X(k), U(k)) = \mu_1 J_C(k) + \mu_2 J_P(k) + \mu_3 J_V(k) \tag{9}$$

where $\mu_1, \mu_2$ and $\mu_3$ represent the weights of environmental search benefits, target discovery benefits and cooperative benefits between UAVs respectively.

## 3 Improved Pigeon-Inspired Optimization Algorithm

Inspired by the natural behavior of pigeons homing, Duan et al. [10] proposed Pigeon-inspired optimization algorithm, which mainly simulates the different navigation tools used at different stages of searching targets for pigeons.

In order to overcome the shortcomings of the above-mentioned classical pigeon optimization algorithm that it is easy to fall into local optimum, and to accelerate algorithm convergence, a discrete IPIO algorithm is proposed integrating with natural selection and Gauss-Cauchy mutation.

***Integer Encoding Method***

Due to the rasterization of UAV motion, it is necessary to select an integer grid as the next waypoint while meeting the maximum yaw angle. Thus, each grid is numbered and its encoding becomes an integer programming problem. For a swarm composed of $N_T$ UAVs, the amount of pigeons is set up as $s$ in the IPIO algorithm. Then the solution of each pigeon is $P_i$, which is $N_T + 1$ dimension and can be expressed as

$$P_i = (P_i \cdot c_1, P_i \cdot c_2, \cdots, P_i \cdot c_{N_T}, P_i \cdot v) \tag{10}$$

where $P_i \cdot c_j \in \{1, 2, \ldots, n_j\}$, $(i = 1, 2, \ldots, s; j = 1, 2, \ldots, N_T)$ represents the position of the pigeon, which means the $j^{th}$ UAV selects grid $P_i \cdot c_j$. And $n_j$ is the amount of grids available for the $j^{th}$ UAV, The velocity of the $i^{th}$ pigeon is denoted as $P_i \cdot v \in (0, N_T/2)$.

***Discrete Compass Operator***

Based on the above integer coding, a new discrete compass operator is proposed by modifying the continuous compass operator in the PIO algorithm. Its update rules are as follows:

$$P_i^t \cdot v \in \left\lceil P_i^{t-1} \cdot v \cdot e^{-R \cdot t} \right\rceil \tag{11}$$

$$P_i^t \cdot c = P_i^{t-1} \cdot c\big(P_i^t \cdot v\big) \cup P_b^{t-1} \cdot c\big(N_T - P_i^t \cdot v\big) \tag{12}$$

where $\lceil \cdot \rceil$ represents rounding up, $t$ and $R$ represent the number of iterations and the compass operator factor, respectively. Equation (12) indicates that $P_i^t \cdot v$ random numbers will be retained from the $t - 1^{th}$ iteration to the $t^{th}$ iteration, and at the same time, $N_T - P_i^t \cdot v$ elements will be selected from the current global optimal solution $P_b^{t-1}$.$P_b$ has the following form:

$$P_b = \arg \max_{1 \le i_1 \le P_s^t} J(X(k), U(k)) \tag{13}$$

***Discrete Landark Operator***

Similarly, according to the idea of the classical PIO algorithm, in the landmark operator, the total number of pigeons in each iteration is halved.

$$P_{\mathrm{s}}^{\mathrm{t}}=\left\lceil P_{\mathrm{s}}^{\mathrm{t-1}}/2\right\rceil \tag{14}$$

Because the selection of the center landmark position of the classical PIO algorithm is not applicable to the problem in this paper, a new method for selecting the center position of the pigeon swarm is proposed as

$$P_l^t \cdot c_j = \arg\max_{1\le h\le n_j} \sum_{1\le i\le P_s^t} J(P_i^t | P_i^t \cdot c_j = h) \tag{15}$$

where $P_l^t \cdot c_j$ is the grid corresponding to the maximum sum of fitness values among all candidate grids for the $j^{th}$ UAV. Then the position of the center landmark of the $t^{th}$ iteration is

$$P_l^t = (P_l^t \cdot c_1, P_l^t \cdot c_2, \cdots, P_l^t \cdot c_{N_T}) \tag{16}$$

In order to reduce the complexity of the algorithm, the influence of velocity can be ignored for the updating of the position solution. Based on the central landmark $P_l^t$, the update rules for the location of the pigeon swarm are as follows

$$P_i^t = P_i^{t-1} \cdot c(z) \cup P_l^{t-1} \cdot c(N_T - z) \tag{17}$$

where $z \in [0, 1, 2, \ldots N_T]$ is a random integer.

***Discrete Gaussian – Cauchy Mutation***

In the evolutionary algorithm, Cauchy mutation can avoid falling into the local optimal solution effectively, and Gaussian mutation can realize the local convergence faster [11]. Therefore, two mutation operators are introduced into the PIO algorithm.

In terms of Gaussian operator, $X$ is a random variable generated by Gaussian mutation, expressed as $X \sim N(\mu, \sigma^2)$, and the probability density distribution of $X$ is

$$f_N(x) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{(x-\mu)^2}{2\sigma^2}}, x \in (-\infty, +\infty) \tag{18}$$

For Cauchy operator, $Y$ is a random variable generated by Cauchy mutation, expressed as $Y \sim C(\gamma, x_0)$, and the probability density distribution of $Y$ is

$$f_C(y) = \frac{1}{\pi} \frac{\gamma}{(y - y_0)^2 + \gamma^2} \tag{19}$$

In the IPIO algorithm, discrete Gaussian mutation operator is adopted in compass operator stage, namely

$$P_i^t \cdot c = P_i^t \cdot c(N_T - \overline{X}_g) \cup \tilde{P}_l^t \cdot c(\overline{X}_g) \tag{20}$$

where $\tilde{P}_l^t \cdot c(\overline{X}_g) = [\tilde{c}_1, \tilde{c}_2, \ldots, \tilde{c}_{\overline{X}_g}]$, $\tilde{c}_i \in \{0, 1, \ldots, n_j\}$ is a random grid among the total number $n_j$ of optional grids for the $j^{th}$ UAV at each mutation position. $\overline{X}_g = \lceil X_g \rceil$, $X_g \sim N(\mu, \sigma^2)$ represents the number of mutation positions generated by Gaussian mutation.

Similarly, Cauchy mutation is introduced into the landmark operator, namely

$$P_i^t \cdot c = P_i^t \cdot c(N_T - \overline{Y}_g) \cup \tilde{P}_l^t \cdot c(\overline{Y}_g) \tag{21}$$

where $\tilde{P}_l^t \cdot c(\overline{Y}_g) = [\tilde{c}_1, \tilde{c}_2, \ldots, \tilde{c}_{\overline{Y}_g}]$, $\overline{Y}_g = \lceil Y_g \rceil$,$Y_g \sim C(\gamma, y_0)$.

***Natural Selection***

Since removing half of pigeons in landmark operator stage will rapidly reduce population diversity, which is not conducive to global search. Therefore, this paper resets the method of eliminating pigeons. The idea of natural selection is to sort the pigeons according to their fitness in each iteration, and replace the velocity and position of the $1/pf$ pigeons with the worst fitness value with the position of the $1/pf$ pigeons with the best fitness in the group. Meanwhile, the optimal solution memorized by each pigeon is retained to improve the convergence velocity.

$$pf = pf_{\max} \times CDF(iter2, \mu, \eta) \tag{22}$$

where $pf_{\max}$ is the maximum value of $pf$, $CDF$ is the cumulative distribution function, and $iter2$ is the evolution times of the landmark operator.

**Remark 1.** In the early stage of the algorithm, replacing more pigeons with poor positions will help the pigeons to approach the optimal value quickly, and increase the correct information exchange among the pigeons, and accelerate the convergence. In the later stage of the algorithm, most of the pigeons are gathered together. Therefore, fewer pigeons should be replaced to maintain the diversity of the pigeon swarm. At the same time, the search velocity and accuracy of the pigeons can be improved.

## 4 Simulation Results and Analysis

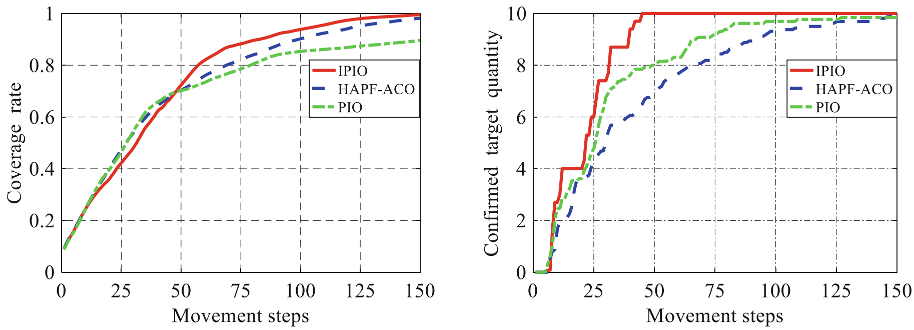
In this section, the simulation experiments are performed under two different cases and the simulation results are given to verify the effectiveness and superiority of the proposed algorithm in this paper.

***Case One***

In this case, suppose the mission area is set to 40 km × 40 km and divided into 40 × 40 grids. According to the prior knowledge of the environment, there are 10 static unknown targets in the mission area. The UAV swarm is composed of 4 UAVs and the number of UAV swarm is 4 and the movement length is 150 steps. The parameters of each UAV are set as $v = 100\,\mathrm{m/s}$, $R_s = 3\,\mathrm{km}$. For comparison, the classical PIO algorithm and the hybrid artificial potential field with ant colony optimization (HAPF-ACO) algorithm [12] are also simulated under the same experiment environment.

In order to eliminate the influence of the randomness of the algorithm, the simulations are performed 100 times by using the above algorithms. The average numbers of targets confirmed and the coverage rates by using IPIO, classic PIO and HAPF-ACO are depicted in Fig. 2.

It can be seen that the IPIO algorithm can discover and confirm more targets, although the coverage rate could be slightly lower than other algorithms in the early stage, which benefits from the TPM. From Fig. 2, all targets can be confirmed at the 45$^{th}$ step by the IPIO algorithm. Meanwhile, the coverage rate under IPIO algorithm can reach 100% more quickly. However, applying the classic PIO and HAPF-ACO algorithms, UAV swarm may take at least 125 steps to confirm all the targets. Based on the comparative simulation results and analysis, the performance of the IPIO algorithm is far better than the other two algorithms.



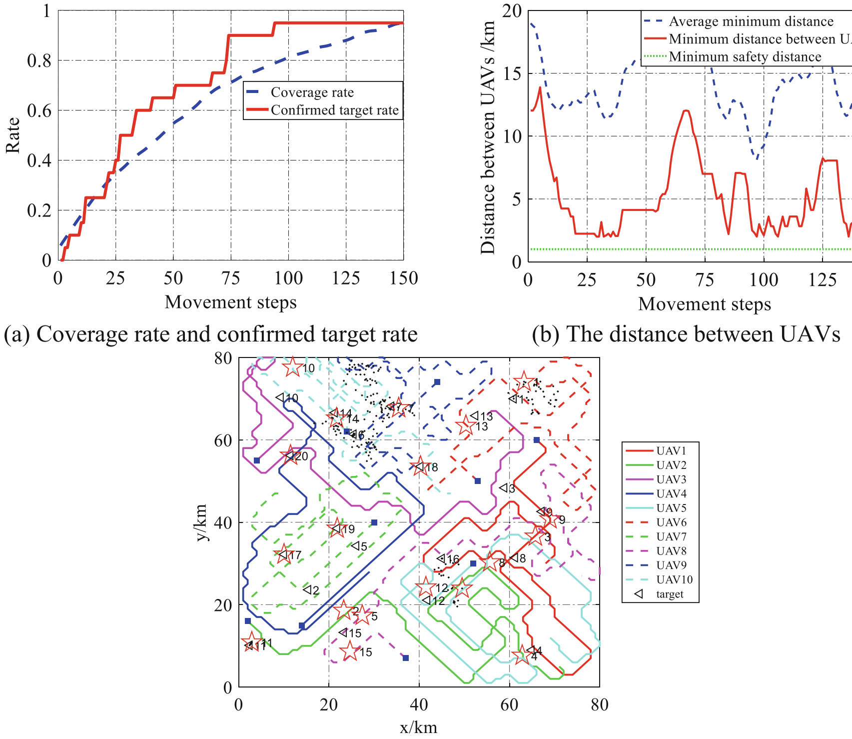

(a) Average mission area coverage rate (b) Average number of confirmed targets

**Fig. 2.** Simulation results under case one

***Case Two***

In order to verify the scalability and applicability of the algorithm, the number of UAV in swarm is increased to 10 and the mission area expands to 80 km × 80 km. The total number of targets is 20, and the number of each type of target is 5. The minimum safety distance between the UAV is specified as one grid. After receiving the mission instruction, the UAV swarm enter the mission area after 60 s. If the target probability of the grid is greater than the predefined threshold, there could be targets in this grid. For each target type, only one target movement path is shown. For the remaining targets, only their starting points and ending points are denoted by triangle and star, respectively.

It can be seen from Fig. 3 that the UAV swarm can quickly find the target, and continue to approach and confirm the target by the IPIO algorithm. Until to 150 steps, the UAV swarm has found and confirmed 19 targets, the area coverage reached 94.9%, and the confirmed target ratio was 95%. Therefore, the algorithm in this paper satisfies the mission requirements of higher coverage rate and higher search efficiency. At the same time, cooperative collision avoidance between UAVs can be achieved.




(a) Coverage rate and confirmed target rate

(b) The distance between UAVs

(c) Trajectories of the UAV swarm

**Fig. 3.** Simulation results under case two

## 5 Conclusions

This paper makes an attempt to solve the problem of cooperative search mission planning in UAV swarm using a discrete IPIO algorithm. In order to avoid trapping into local optimum and accelerate the convergence ability, natural selection and Gauss-Cauchy mutation are introduced. Three strategies are proposed for the TPM, which can accurately describe the dynamic target distribution. Cooperating with digital pheromone map, the target can be quickly discovered and confirmed. The simulation results have verified that the IPIO algorithm has satisfactory performance in the cooperative dynamic target search. In the future, the more complex mission environment with obstacles and UAV damages would be considered in the cooperative algorithm design.

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