IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received September 22, 2019, accepted October 19, 2019, date of publication October 24, 2019,
date of current version November 14, 2019.

Digital Object Identifier 10.1109/ACCESS.2019.2949249

A New Searching Approach Using Improved Multi-Ant Colony Scheme for Multi-UAVs in Unknown Environments

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This work was supported in part by the Natural Science Foundation of China under Grant 61703072, in part by the Dalian Science and Technology Innovation Fund under Grant 2019J12GX040, in part by the Key Laboratory of Intelligent Perception and Advanced Control of State Ethnic Affairs Commission under Grant MD-IPAC-201901, in part by the Fundamental Research Funds for the Central Universities under Grant 3132019355, and in part by the Liaoning Natural Science Foundation Project under Grant 20180540064.

ABSTRACT In this research, an important topic of cooperative search for multi-dynamic targets in unknown sea area by unmanned aerial vehicle (UAV) is studied based on improved multi-ant colony theory (IMAC). A specialized multi-UAV sea area search map is established, in which a novel target probability map (TPM) was designed to reduce the impact of uncertainties caused by dynamics targets. Then, the transfer rules of the cell were determined for multi-UAV by improving the behavior criterion of the ant colony algorithm and the updating principle of the pheromone map. Finally, the performance of the proposed method is tested in several search scenarios with different features, and the statistical comparison with the traditional algorithm shows the superiority of the new method.

INDEX TERMS Multi-UAV, ant colony optimization, cooperative search, TPM updating, pheromone.

I. INTRODUCTION

In recent years, due to the rapid development of sensors, microprocessors and information processing technologies, the functions of unmanned cluster system are increasing rapidly, and its application scope is also expanding. Because of its flexibility, expansibility and strong cooperative operation ability, the research on collaborative theory and application of unmanned cluster has attracted more and more attention from academia, industry and national defense [1]–[3]. The multi-UAV cooperative search system can effectively improve the search efficiency, especially in complex sea conditions such as uncertainties and strong interference. Therefore, the multi-UAV cooperative search in sea area is one of the important directions of the research of UAV cluster system [4]–[6].

The cooperative search mission can be formulated as a probabilistic exploration mission [7], [8]. The uncertain probability map is updated every time when a UAV makes an observation, which probabilistically described the target location and helps the multi-UAV to make more precise decisions for finding the targets [9]. Up to now, cooperative search for multi-UAVs has been investigated in different aspects and from different viewpoints [10], [11]. To name just a few, Zhen *et al.* [12] proposed an intelligent self-organized algorithm (ISOA) to solve a cooperative search-attack mission planning problem for multi-UAV. In [13], conducting cooperative area search based on Ant Colony (AC) Theory is proposed, which is not considered the environment information. For multi-UAV search problem, environment information is stored in the form of target probability map, and the online trajectory of UAV is calculated by adaptive model predictive control algorithm give in [14]. In [15], a statistical framework is proposed for predicting the amount of time an agent should spend in a cell to increase the target detection confidence in that cell. The probability associated with each cell is updated based on the detection result, which is 0 (no target detected) or 1 (target detected). In [16] based on the target probability map, the probability map is adopted to search the target, and a discrete time stochastic decision model for cooperative search of multi-UAV is established to maximize the number of targets found. In [17] proposed a method of opportunities

The associate editor coordinating the review of this manuscript and approving it for publication was Lin Wang.

to learn solve cooperative search, based on prior knowledge of the target location establish the TPM, and collaborative search goal is to reduce the uncertainty of the environment. In [18] in order to reduce the uncertainty of target motion, a target transition probability density function based on Gaussian distribution is proposed, and the maximum discovery probability and maximum coverage are adopted as search strategies to improve the search efficiency, but continuous integral operation is needed to increase the computational burden.

In this research, we proposed a novel cooperative search algorithm for multi-UAV in an unknown environment. The main contributions are listed as follows. Firstly, a new TPM model according to the initial target position is established, where the target initial position is known before search. Then, TPM updating mechanism is proposed, especially, for the unknown direction of the target motion, and known direction of the target motion update process is shown. Secondly, in order to know the target search performance of the strategies comprehensively, we established the objective function include target search revenue, information entropy to measure the search efficiency of the algorithm, Finally, a novel IMAC algorithm is designed for autonomous target search by a group of UAVs, which includes initialization of pheromone, waypoint select strategy pheromone updating, and its performance is analyzed for both search static target and dynamic target, which further highlights the completeness of the result. As will be shown in numerical simulations, the proposed algorithm can serve as an effective method for practical application.

The rest of this paper is organized as follows. Section 2 is devoted to problem description of cooperative search, which including the TPM model, updating mechanism and objective. The detailed presentation of initial path obtained by the IMAC algorithm and the coordination strategy are illustrated in Section 3. Simulation results are presented in Section 4. The last section offers conclusions and future work.

II. PROBLEM FORMULATION

In this paper, for a sea area E, there are N_v homogenous UAVs enter the sea area where the mission needs to be carried out. After that, each UAV uses its own detection sensors to search the unknown targets independently. It is expected that multiple UAVs can find as many targets as possible through cooperative search in the shortest time at the least cost. In this research, we assumed that all UAVs could communicate through pheromone to ensure that the communication between the UAVs was normal. In what follows, we provide detailed descriptions of our environmental model, target probability map and our objective one by one.

A. ENVIRONMENTAL MODEL

The environment E is represented as an $L_x \times L_y$ sea area, as shown in Fig1, $P_i(k) \in [0, 1]$ represents the target existence probability in a cell i at time k, and the index of the cell i is defined as $i = n_x + (n_y - 1) \times N_y$ where $n_x = 1 \ldots N_x$,

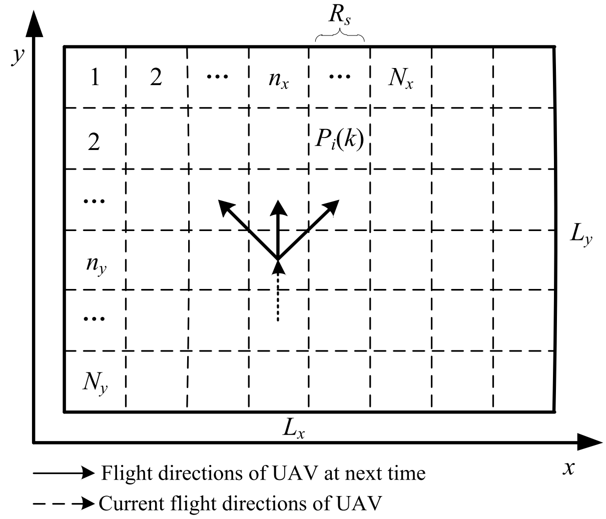


FIGURE 1. Search area division.

$n_y = 1 \ldots N_y$ with $N_x = L_x/R_s$, $N_y = L_y/R_s$, respectively, and the number of the cell is $N = N_x \times N_y$. The speed of each UAV is v, and the path of each UAV depends on the heading angle. Path planning is performed every ΔT to select the heading deflection angle of the next interval. Constraints by the dynamic characteristics of the UAV, cannot turn in any direction. As shown in Fig 1, the UAV can only choose one direction from $(-\alpha, 0, \alpha)$ at time k.

B. TARGET PROBABILITY MAP

TPM model: When Multi-UAV cooperative search targets in an unknown environment, the uncertainty of the target status makes the search process to be reduced as a probabilistic problem. Therefore, the probability function was adopted to describe the targets model. By using the initial target position is (x_m^0, y_m^0), the joint probability density function of the target can be expressed as:

$$f(x_m^0, y_m^0) = \frac{1}{2\pi\sigma_{0x}\sigma_{0y}} e^{-\left(\frac{(x_m^0)^2}{2\pi\sigma_{0x}^2}+\frac{(y_m^0)^2}{2\pi\sigma_{0y}^2}\right)} \tag{1}$$

where $P_i, (i = 1, 2 \ldots N)$ denotes the possibility that a target exists in cell i, and $P_i = \iint_S f(\cdot)dxdy$ with S as the region where cell i is located. Assume that the position of target is independent in the x and y directions, then $\sigma_{0x} = \sigma_{0y} = \sigma_0$.

TPM updating based on detection information: As the search task proceeds, the TPM are updating based on the information detected by the onboard sensor of UAVs. In order to avoid repeated detection of multiple UAVs during the subsequent search process, the updating method of the TPM is classified three types as follows.

(1) UAV not search the cell i

$$P_i(k) = P_i(k-1) \tag{2}$$

(2) UAV search the cell i without find any target

$$P_i(k) = \frac{P_f P_i(k-1)}{(1-P_d)P_i(k-1) + (1-P_f)} \tag{3}$$

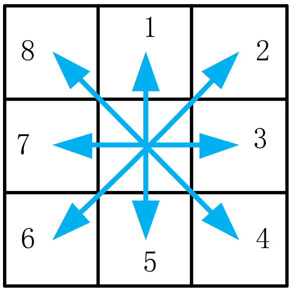


FIGURE 2. TPM diffusion direction.

(3) UAV search the cell i and find a target

$$P_i(k) = \frac{P_d P_i(k-1)}{P_d P_i(k-1) + P_f(1 - P_i(k-1))} \tag{4}$$

where $P_d \in [0, 1]$ is the detection probability indicating the probability of UAV finding a target when the target is within the current cell. $P_f \in [0, 1]$ Is the false alarm probability indicating the probability of UAV finding a target but no target is actually in the current cell.

TPM updating based on target motion prediction: By using the cellular automat model in [20], and combined with the initial distribution characteristics of the target, a new mechanism for TPM updating based on target motion prediction is proposed as follows,

$$\begin{aligned} P_i(k+1) &= P_i(k) + \delta_d \sum_{n \in N_m} d(j)(P_j(k) - P_i(k)) \\ &= P_i(k)(1 - \sum_{j \in N_i} \delta_d d(j)) + \delta_d \sum_{j \in N_i} d(j) P_j(k) \end{aligned} \tag{5}$$

where N_i is the number of cells around i, δ_d and $d(j) = (d_1(j), d_2(j), d_3(j), d_4(j), d_5(j), d_6(j), d_7(j), d_8(j))$ are constant which denotes the speed and direction of the TPM diffusion in cell i, and the TPM diffusion direction as show in Fig 2, respectively. Noting that by using the above TPM diffusion mechanism and the initial target distribution characteristics, we can predict the probability distribution of the target after a period of time, which guides UAV cooperative search.

C. OBJECTIVE FUNCTION

The main goal was to find as many targets as possible in an unknown sea area. Therefore, the optimization function $J(k)$ is composed by two terms, and designed as follows.

$$J(k) = \omega_1 J_T(k) + \omega_2 J_E(k) \tag{6}$$

where ω_1 and ω_2 are weighting coefficient, $J_T(k)$ is target search revenue, $J_E(k)$ is environment search revenue.

The target search revenue: As the search proceeds, the sum of the target discovery probability in the sea area is defined as target search revenue, and written in the following form,

$$J_T(k) = \sum_{(i \in E)} (1 - b_i(k)) p_i(k) \tag{7}$$

where $p_i(k)$ is the probability of the target in the cell i, when the UAV passes through the cell i, which is only related to the position of UAV; $b_i(k)$ denotes the possible of found the target, and given by

$$b_i(k) = \begin{cases} 1 & if\ p_i(k) \geq \delta_p \\ 0 & otherwise \end{cases} \tag{8}$$

where δ_p represents the threshold, which means that the target can be found only when the target probability at the search cell i is greater than the threshold δ_p.

Environmental search revenue: Using airborne sensors to search an area, the UAV will gradually understand the search area over time, and the change of the environment entropy represents the revenue of the environment search, as follows,

$$J_E(k) = \sum_{i=1}^{N} [e_i(k+1) - e_i(k)] \tag{9}$$

where $e_i(k)$ is the information entropy, which represents the uncertainty degree in the cell at time k, and described as,

$$e_i(k) = -\sum_{i=1}^{N} (1 - p_i(k)) \ln(p_i(k)) \tag{10}$$

TABLE 1. Relationship between multi-UAV search and ant colony foraging behavior.

	UAV cooperative search	Ant foraging behavior
Behavior	UAV	Ant
Behavior space	Search area	Foraging area
Behavior	Search	Foraging

III. DESIGEN OF IMPROVED MULTI-ANT COLONY SEARCH ALGORITHM

The problems of searching targets of multi-UAV have the same characteristics as the foraging behavior of ant colony, as shown in Table 1, an improved multi-ant colony algorithm for collaborative path optimization for multi-UAV was proposed in this section Ants can be divided into N_v population, $AC = \{AC_v, v = 1, 2 \ldots N_v\}$, each ant subgroup correspond a UAV and construct a search path for UAV meet the requirements, $AC_v = \{ant_{vm}, m = 1, 2 \ldots M\}$, where ant_{vm} is the member of population AC_v, M is the size of the ant subgroup. Multi-ant colony algorithm structure is shown in Fig3, each subgroup of every ant has an independent computing unit, according to the design state transition rules of search, interact with other ants in the same subgroup and different subgroup communicates through pheromones information. In what follows, the initialization pheromone, the state transition and pheromone update for multi-UAV cooperative path optimization is obtained one by one

A. INITIALIZATION OF PHEROMONE

In order to make full use of the existing target probability information and improve the search efficient of ants in each ant colony, the following pheromone initialization function is

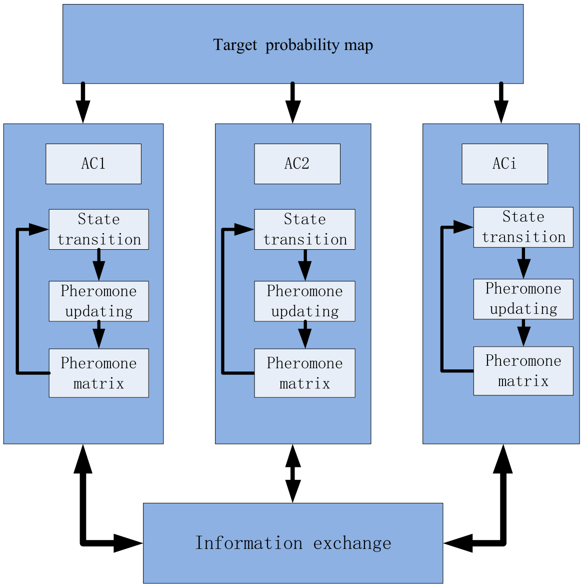


FIGURE 3. Structure of the IMAC algorithm.

proposed:

$$\tau_{i0} = P_i \tau_0 (i = 1, \ldots, N) \tag{11}$$

where τ_0 is the pheromone concentration in the cell i, p_i is the target probability value in cell i, τ_0 is a constant, and this initial function effectively associates the initial value of pheromone with the target probability map in the search area.

B. CELL SELECT STRATEGY

Each ant selects the next cell from the current cell according to the state transition rule. At tth iteration, the state transition rule of the ant m from cell i to cell j can be designed as follows:

$$p_{ij}^{vm}(t) = \begin{cases} \dfrac{[\tau_j^{vm}(t)]^{\alpha}[\eta_j^{vm}(t)]^{\beta}[\varphi_j^{\bar{v}\,m}(t)]^{-\gamma}}{\sum\limits_{j \in U_K}[\tau_j^{vm}(t)]^{\alpha}[\eta_j^{vm}(t)]^{\beta}[\varphi_j^{\bar{v}\,m}(t)]^{-\gamma}} & j \in U_K \\ 0 & otherwise. \end{cases} \tag{12}$$

where α is the relative importance factor of the pheromone, β is the relative importance factor of the heuristic function, γ is the relative importance factor of other ant colony pheromone, and indicating the influence of pheromones of other populations on route point selection, which can avoid repeated route point selection between different UAV. U_K is the set of cell, where $U_K = N - Tabuk$ with Tabuk represents the cell that ant m have visited, $\tau_j^{vm}(k)$ is the pheromone of ant m of colony v concentration in cell j at time k, and $\eta_j^{vm}(k)$ is a heuristic function of the target occupy probability in cell j, where $\eta_j^{vm}(k) = \begin{cases} k_1 * p_j \text{ heading angle change} \\ k_2 * p_j \text{ go straight} \end{cases}$, $\varphi_j^{\bar{v}\,m}$ is concentration pheromones expect ant colony v of other ant colony pheromones in cell j.

C. PHEROMONE UPDATING

After selecting cell j, the ant deposits pheromones in this cell and the pheromone concentration in this cell is increased. On the other hand, pheromones are volatile and evaporate over time. In this way, the quantity of pheromone in other cells will be much lower than that in most selected cells. After each round, the pheromone concentration is updated as follows,

$$\tau_j^{vm}(t+1) = (1-\rho)\tau_j^{vm}(t) + \rho\Delta\tau_j^{vm}(t+1) \tag{13}$$

where ρ is evaporation rate; $\tau_j^{vm}(t)$ denote the pheromone of the population v in the cell j; $\Delta\tau_j^{vm}(t+1)$ is the increase value of the pheromone, then the pheromone is updated by following formula,

$$\Delta\tau_j^{vm}(t+1) = \sum_{m=1}^{M} \Delta\tau_j^{vm}(t, t+1) \tag{14}$$

where $\Delta\tau_j^{vm}(t, t+1)$ is the pheromone left by the ant m of colony v in the cell j after the tth iteration, which can be written as,

$$\Delta\tau_j^{vm}(t, t+1) = \begin{cases} k_1\omega_{vm}J_{vm}Q & if\ m \in [1, u] \\ -k_2\omega_{vm}J_{vm}Q & if\ m \in [u+1, M] \end{cases} \tag{15}$$

where $\omega_{vm} = u_{vm}/v_{\bar{v}\,m}$ is the overlap degree between the path of population v and the path of other ant populations, u_{vm} denotes the total amount of pheromone of ant m in population v after searching for the iteration t; $v_{\bar{v}\,m}$ represents the total amount of other population pheromones (the larger $v_{\bar{v}\,m}$, the less overlap with other population in cell j); J_{vm} is the search cost of the ant m in the population v after completing a search, and rank the objective value of all ants in the this ant colony; Q represents enhancement coefficient of pheromone; k_1 and k_2 are the profit weight coefficients of search, respectively. When $m \in [1, u]$ the pheromone concentration of ant m was increased. When $m \in [u+1, M]$, the pheromone concentration of ant m was decreased.

Furthermore, in order to avoid the algorithm falling into local optimum, the pheromone concentration of each population in the cell is limited to $[\tau_{\min}, \tau_{\max}]$, which ensures the fast convergence speed of the algorithm while increasing the search space, and integrates local and global pheromone updating rules as follows,

$$\tau_j^{vm}(t+1) = \begin{cases} \tau_{\min} & \tau_j^{vm}(t+1) < \tau_{\min} \\ \tau(t) & \tau_{\min} \le \tau_j^{vm}(t+1) \le \tau_{\max} \\ \tau_{\max} & \tau_j^{vm}(t+1) > \tau_{\max} \end{cases} \tag{16}$$

IV. SIMULATION

In order to verify the effectiveness of the proposed method, a multi-UAV cooperative search simulation environment was established in MATLAB. The information in the search area was completely unknown and the purpose of the search was to find all targets in the sea area. Firstly, we compare with random, parallel and ant colony algorithm [19] in static target

TABLE 2. Procedures of multiple UAV cooperative search using IMAC.

Name: Cooperative searching using multiple UAV.	
Goal: Find targets as much as possible.	
1. The search region is uniformly portioned into N cells and initialized an TPM P;	
2. While $k<k_{max}$	▷k_{max} is the execution time
/* cell select based on IMAC*/	
3. Initialized the pheromone according to Eq.(11)	
4. For t=1:T	▷T is the iterations of the algorithm
5. For v=1:Nv	▷Nv is the number of the ant subgroup
6. For m=1:M	▷M is the number of the ant in each subgroup
7. For s=1:S	▷S is the number of cells that each ant visited
8. Each ant choose the cell according to Eq.(12)	
9. Save the cells that each ant have visited	
10.End for	▷each ant selected cells meet the requirements
11.End for	▷all ant in the same subgroup have visited
12.Calculated the objective according to Eq.(6)-(10)	
13.Pheromone updating according to Eq.(13)-(15)	
14.End for	▷ all subgroup accomplished
15.Pheromone concentration is limited $\left[\tau_{\min}, \tau_{\max}\right]$	
16.End for	▷iterated over
/* TPM updating*/	
17.TPM updating based on detection information (2)-(4)	
18.TPM updating based on motion prediction Eq.(5)	
19.k=k+1	
End while	▷time is over

scenario to verify the effectiveness of the proposed algorithm. Finally, we test that the probability of find target in dynamic target scenario can be improved by the TPM prediction mechanism. The relevant parameters in simulation are set as: the environment parameters: the size of search area is $50km \times 50km$ and divided into 50×50 cells with the same width and length $R_s = 1km$; the weighting parameters: $Nv = 3$, $M = 100$, $\alpha = 1$, $Q = 100$, $\beta = 4$, $\gamma = 2$, $\rho = 0.25$.

A. SCENE1: STATIC TARGETS

In order to demonstrate the performance of different search strategies, several Monte-Carlo simulation experiments were carried out. 3 UAVs are cooperative search 10 targets that randomly distributed in the sea area. Fig. 4 shows UAVs search trajectories at the simulation steps $k = 300$ by using different search strategies, respectively.

As can be seen in Fig. 4, these 4 search strategies have different characteristics: the Parallel search strategy has fixed search path, and can cover the whole region if time is enough; and the search trajectories in random strategy can be seen that trajectories are many duplicate search paths and highly random, because the method is a blind search. Although the method of ant colony decrease the path overlap, heading angle change frequently. Trajectories that UAVs have visited have less overlap and less heading change by the guidance of the improved ant colony algorithm proposed in this paper.

Fig. 5 shows the target search revenue in different strategies. We can see that, at the end of simulation, the target search revenue in random search strategy is 0.6, and the target search revenue in parallel search strategy is 0.68, ant colony and our method are 0.75 and 0.86 respectively.

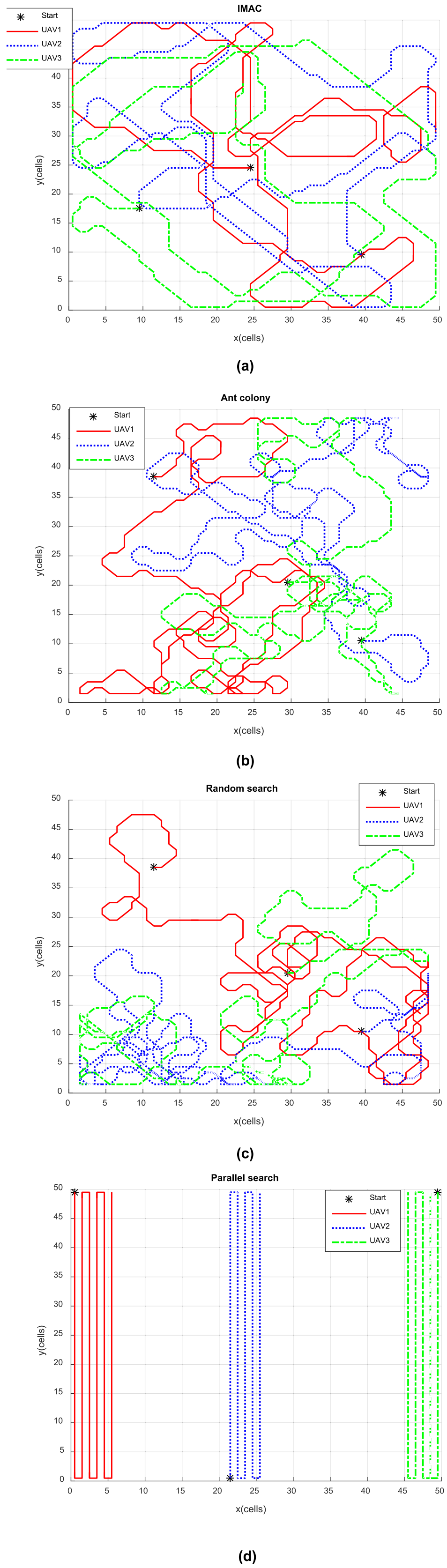


FIGURE 4. Snapshots of 3 UAVs search simulation in different strategies at step $k = 300$. (a) Shows the UAVs search trajectories under IMAC, and (b) (c) (d) are ant colony, and random search, Parallel strategy.

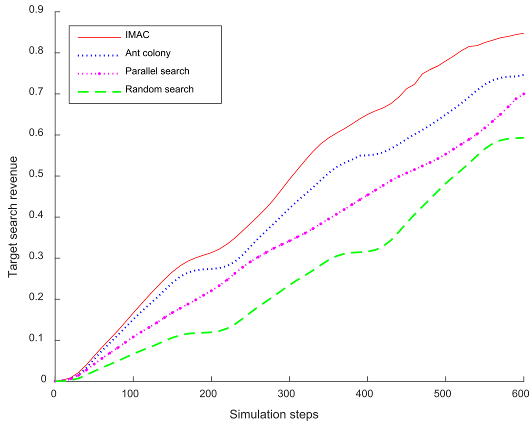


FIGURE 5. Comparison of the target search revenue in different strategies.

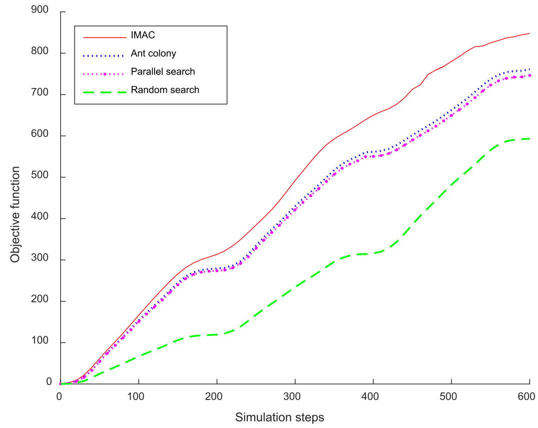


FIGURE 7. Comparison of the objective function in different strategies.

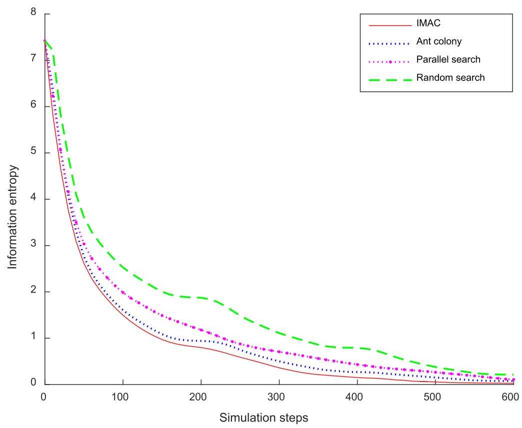


FIGURE 6. Comparison of the information entropy in different strategies.

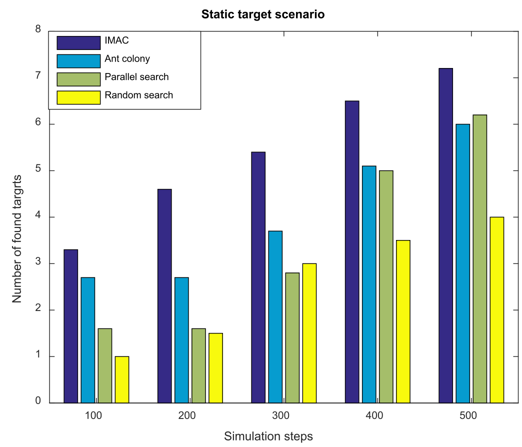


FIGURE 8. Number of found in static target scenario.

Therefore, the parallel search is indeed a complete area coverage search method, and our method is better than the random search and ant colony search in the search efficiency.

Fig. 6 shows the target search revenue with increasing time in different search strategies. As can be seen, the initial information entropy started at 7.4201, at 400 simulation steps, the information entropy in the random search strategy dropped to 0.8934, declined by 87.96%; and in parallel search strategy, information entropy dropped to 0.4313, declined by 94.19%; in ant colony search strategy information entropy was 0.2695, declined by 96.37%. While in IMAC strategy, the information entropy was 0.1614, declined by 97.82%. From the entropy descending process can be seen: before 600 simulation steps of simulation, the information entropy fall at fastest rate in our method, which shows that the proposed search strategy can result in the faster detection of the unknown regions, so as to obtain the more effective information.

Fig. 7 describes the objective function in different strategies. We can find that the objective function of the parallel search and ant colony search are almost the same of the search, and random search is lower than the two methods and the objective function based on the improved multi-ant colony algorithm is slightly higher than other three methods. With the increase of the time, when the algorithm runs to 600 steps, the objective function of the improved ant colony algorithm proposed in this paper is 847.8; the advantage of the improved multi-ant colony algorithm is more obvious in this stage.

Furthermore, in order to measure the ability of target found in different search strategies, 100 times of simulations are respectively carried out in different search strategies, in which are the static conditions for the 10 fixed randomly distributed targets. The results are shown in Figure.8. It can be seen that at the end of simulation, the number of target found in parallel search is 6.2, which is high on ant colony found of the number 6. However, the random search is actually a blindness search method, it has the minimum number of target found with only 4; Our method shows better ability than parallel search random search and ant colony method, the number is 7.2. It can be seen that the improved ant colony algorithm proposed in this paper is the highest all the time, Whereas the efficiency of the parallel search method linearly increases with time, As for the random search method, the search efficiency is the lowest in the whole process, and there is increasing trend is lower in the later period.

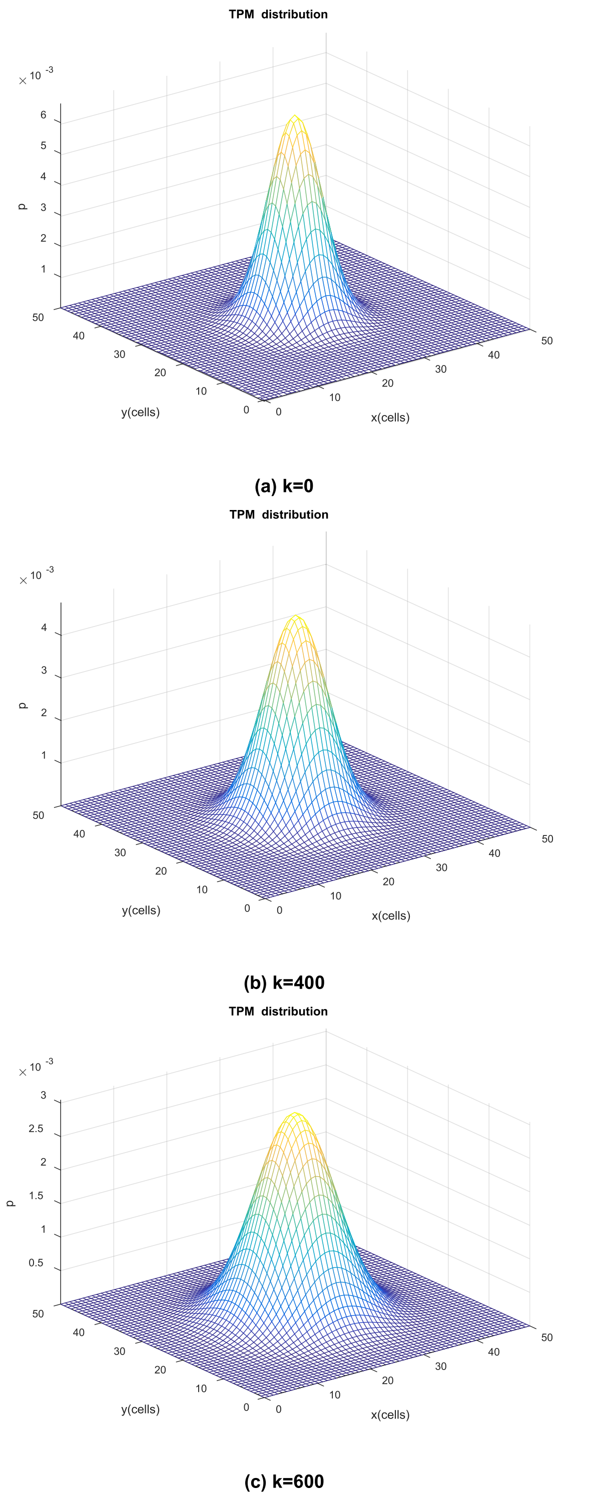


FIGURE 9. **TPM updating process with unknown direction of the target.**

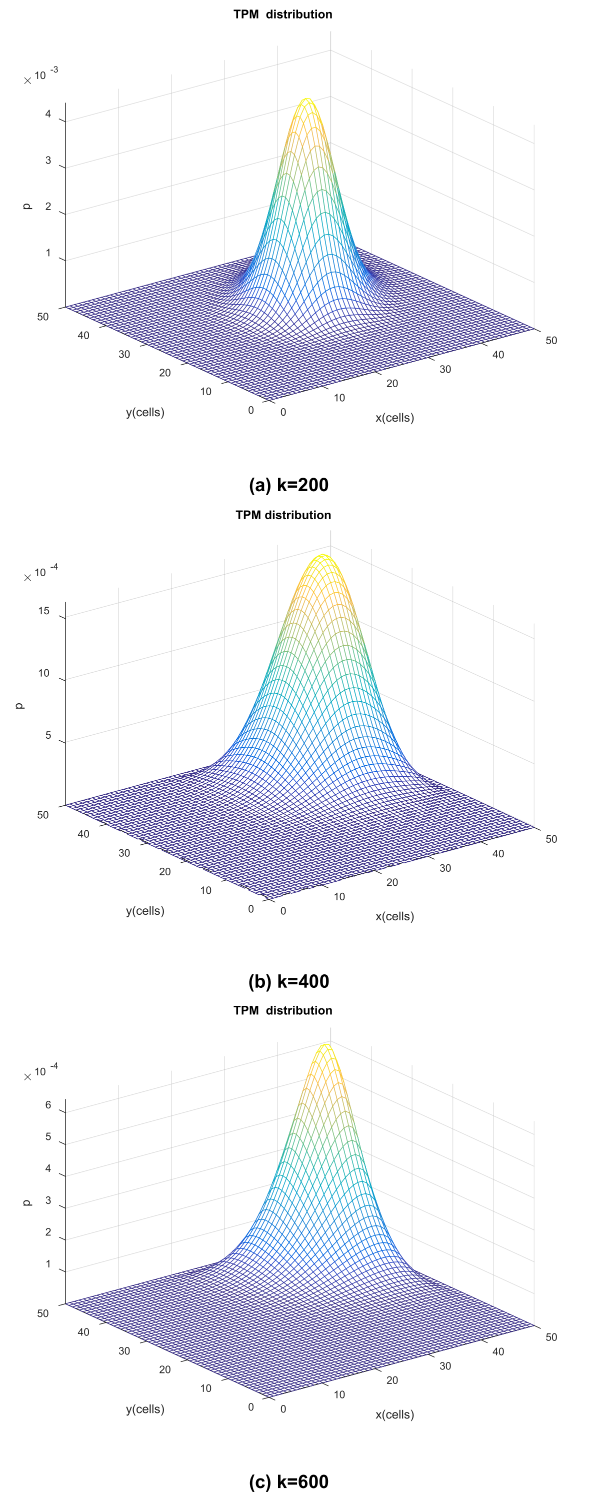


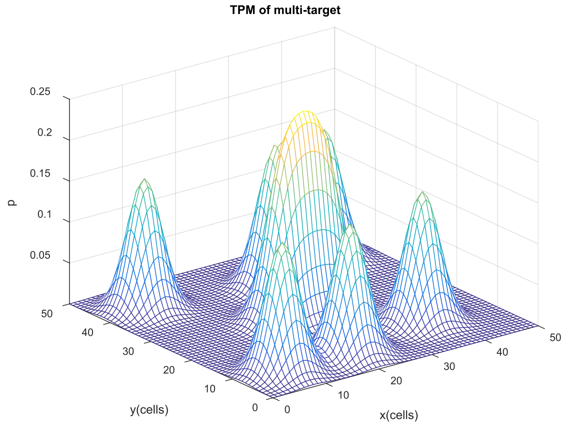
FIGURE 10. **TPM updating process with known direction of the target.**

B. SCENE 2: DYNAMICS TARGETS

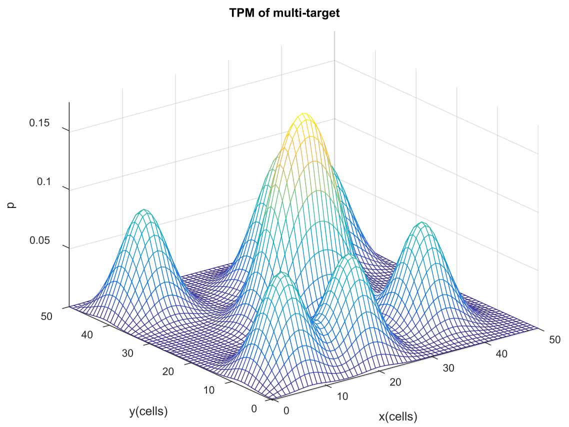
According to the probability diffusion equation (3) and the initial target probability map is known before the search. It can predict the probability distribution of the target after a period of time, the unknown direction of the target is shown in Fig. 9, and known direction of the target update process is shown in Fig. 10.

TPM initial distribution is show in Fig. 9(a), and the initial target position is (25, 25). Fig 9 (b) (c) show TPM updating process with unknown direction of the target at simulation steps $k = 400$, $k = 600$, respectively, and $\delta_d = 0.1$, d_n=(0.2,0.2,0.2,0.2,0.2,0.2,0.2,0.2)

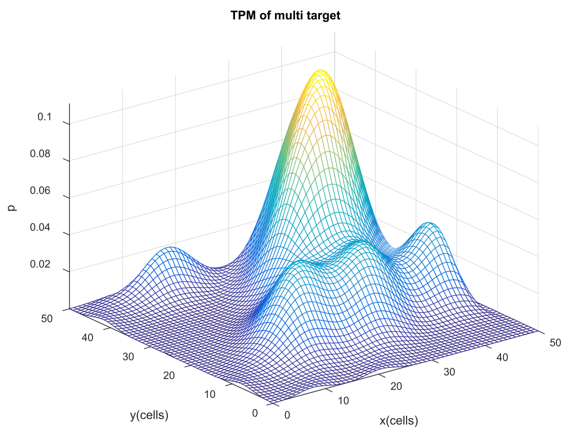
Fig. 10 (a) (b) and (c) show the predicted diffusion process of the TPM with known direction of the target



(a) Case1

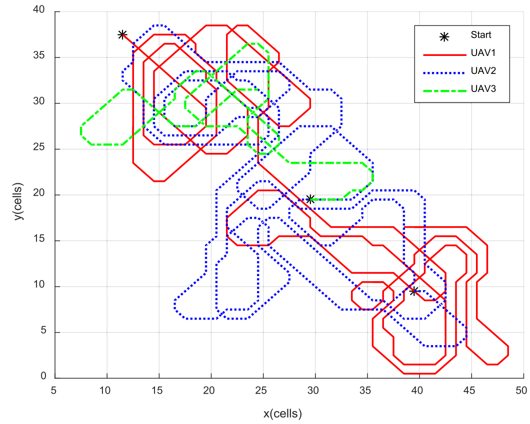


(b) Case2

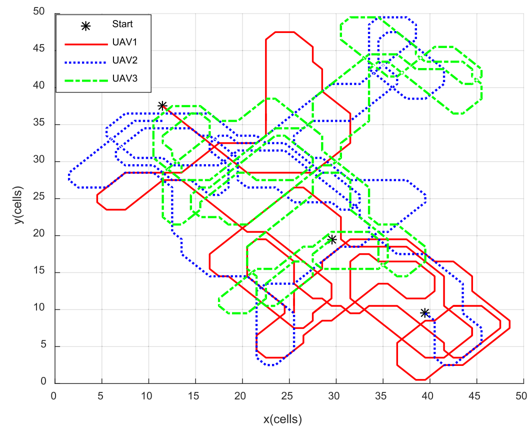


(c) Case3

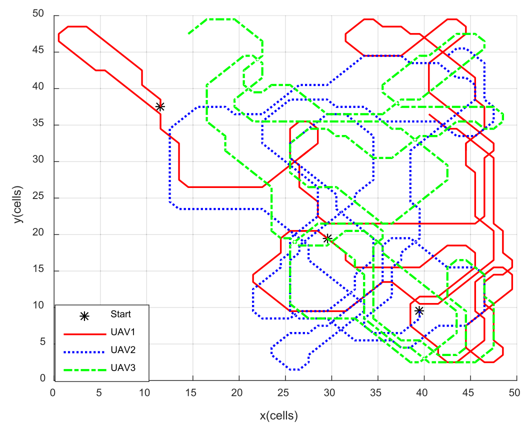
FIGURE 11. **TPM updating process with known direction of the multi-target.**



(a) Case1



(b) Case2



(c) Case3

FIGURE 12. **Search trajectories of 3 UAVs under IMAC corresponding to case1, case2 case3 and at step $k = 300$.**

at the simulation steps $k = 200$, $k = 400$, $k = 600$, $\delta_d = 0.1$ d_n=(0.2,3,0.2,0.2,0.2,0.2,0.2,0.2), and the movement direction of the target is 45°.

Furthermore, in order to test the diffusion mechanism of dynamic target scenario. Now there are several dynamic targets using different diffusion mechanisms according to different priori information. As shown in Fig. 11, (a) Case 1: the velocity and direction of the moving target is unknown; (b) Case 2: according prior information the speed of the target is known but don't know the direction. (c) Case 3: according prior information velocity and the direction of the target is known. The IMAC algorithm is applied to search path planning for the above three case.

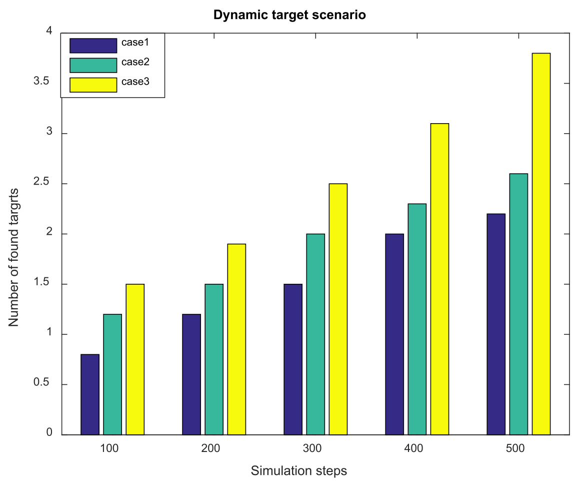


FIGURE 13. Number of found in dynamic target scenario.

As show in Fig. 12 (a) (b) and (c), according to the different diffusion mechanism, the IMAC is used to realize the search path planning and ensure the maximum discovery of the targets. And the number of the found targets shown in Fig. 13.

In order to measure the performance of the diffusion mechanism of dynamic target scenario, 100 times of simulations are respectively carried out in different prior information corresponding to Fig11 (a)–(c), in which are the dynamic conditions for the 10 move targets,The results are shown in Figure 13.It can be seen that the at the end of simulation, the number of target found in case3 is most, the number is 3.8; the number of target found in case 2 is most, the number is 2.6; the number of target found in case 1 is most, the number is 2.2; and further explanation IMAC could applied to dynamic target scenario and diffusion mechanism proposed in this paper is the highest improve the number of found in dynamic scenario.

V. CONCLUSION AND FUTURE WORK

This paper focuses on an improved multi-ant colony method for the multi-UAVs cooperative search in static target scenario and dynamic target scenario. Through the several comparison simulations with random search, parallel search and Ant Colony search method, the simulation results show that: the proposed search strategy is an effective one; it can guide the multi UAV to realize better target searching in static scenario. Then, a TPM diffusion mechanism based on the prior information was further proposed for dynamic target. The simulation results showed that the improved Multi-Ant colony could apply in dynamic target search and adopted the diffusion mechanism improved search efficiency obviously.

Future work will focus on combining reinforcement learning method with multi-ant colony algorithm and improving search strategies through online learning of human-computer game, more effective and practical search methods are expected to be obtained.

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