Cooperative Area Search Algorithm for Multi-UAVs in Uncertain Battlefield Environment

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Abstract. Aiming at the problem of multiple unmanned aerial vehicles (UAVs) cooperative area search in uncertain battlefield environment, a multi-UAVs cooperative area search algorithm based on co-evolutionary genetic algorithm (CEGA) is proposed. Firstly, the raster Map and extended Search Probability Map (SPM) model of the task area are constructed, the UAV state model and sensor detection model are established, and the search environment updating method based on the Bayesian criterion is presented. Then, considering the cooperative elements of multi-UAVs, the cooperative area search planning model is established, and based on the rolling optimization idea, the co-evolutionary genetic algorithm with elite retention strategy is used to optimize the solution, and the multi-UAVs cooperative search paths are generated. Through simulation experiments and comparative analysis, the effectiveness of the proposed algorithm is verified.

Keywords: Uncertain Battlefield Environment, Multiple Unmanned Aerial Vehicles, Cooperative Area Search, Co-evolutionary Genetic Algorithm.

1. Introduction

With the development of artificial intelligence technology and the deepening of information war, UAVs have been widely used in military and civil fields, and multi-UAVs cooperative area search has gradually become a hot issue in the field of intelligent unmanned system research [1-3]. When performing reconnaissance and search tasks in an uncertain battlefield environment, a single UAV is difficult to adapt to the complex and changing harsh battlefield environment due to the limitations of search scope, sensor accuracy, energy consumption, etc. Therefore, multiple UAVs are used to search the area cooperatively to give full play to the cooperative advantages of multiple UAVs, thus improving the perception of search area information and target search efficiency [4].

For the problem of multi-UAVs cooperative search under uncertain environment, Wu et al. proposed a multi- UAVs autonomous cooperative search control method based on the model predictive control idea [5]. Fu studied the cooperative area search problem of multiple UAVs under communication constraints, and proposed a multi-step optimization path search decision algorithm based on predictive control [6]. Wu and Guo established a UAV area search model based on a two-dimensional discrete grid, and proposed a rolling optimization method of search path based on particle swarm optimization algorithm [7]. In order to enhance the search and capture capability of UAVs for targets and the revisit capability for areas with high uncertainty, Liu proposed a multi-UAVs cooperative target search method with revisit mechanism based on digital pheromone [8].

The above researches have actively explored the cooperative search methods of multiple UAVs in uncertain environments, but the cooperative search information of UAVs when performing tasks has not been fully and effectively utilized, and the search efficiency is low. Therefore, based on the grid map of the task area, this paper constructs an extended SPM model with a three-dimensional information structure to enhance the information interaction during multi-UAVs cooperative search and reduce the blindness of search; The UAV state model and sensor detection model are established, and the search environment is dynamically updated based on Bayesian criteria; Considering the cooperative factors of multi-UAVs, a cooperative area search planning model is established, and based on the rolling optimization idea, a cooperative evolutionary genetic algorithm with elite retention strategy is used to plan the multi-UAVs search paths; The effectiveness of the algorithm is verified by simulation and comparative analysis.

2. Overall research framework

The overall research framework of multi-UAVs cooperative area search planning in uncertain battlefield environment is shown in Figure 1. Firstly, the targets information, task area information, UAVs information and other input elements are obtained, and then the task area model, search probability map model, UAV state model, sensor detection model are constructed according to the relevant inputs. Then, the intelligent optimization algorithm is used to optimize the established cooperative area search planning model. Finally, the simulation verification and comparative analysis of the algorithm are carried out.

3. Cooperative area search planning model

3.1. Problem description

During the operation of both sides, multiple enemy targets are distributed in the battlefield task area. In the early stage, we have obtained some information about the battlefield environment through other intelligence and reconnaissance means. However, due to the complex battlefield environment, there may be errors in the early information. The initial prior information obtained is only a preliminary description of the current task area information, and cannot completely determine the location and type of targets in the battlefield area.

At present, N UAVs with the same reconnaissance capability are dispatched to search and reconnaissance M static targets with partial prior information in the task area. It is required to obtain as much target information and battlefield information as possible within the specified time, reduce the uncertainty of the environment, and determine the location and type of targets on the basis of making full use of the previous intelligence, to provide support for subsequent operational situation assessment, task allocation, target attack and other operations.

3.2. Task area model

To describe the area search process of UAVs, the grid map is used to represent the task area E. Set the search task area as a rectangular area with the length and width of L and W respectively. Divide the task area into equal parts and discrete it into a $m \times n$ grid model. Then, $E = \{(x, y) | x = 1, 2, \cdots m, y = 1, 2, \cdots n\}$. Use the center of the grid to represent the location of the grid.

To facilitate the research, the following assumptions are made [9]:

(1) The target in the task area can be regarded as an ideal particle, and each cell can have at most one target;

(2) All UAVs have good communication capability, regardless of the possible impact of communication delay or interruption;

(3) UAVs fly in the air and can search at different altitudes. Generally, there is no collision problem. Therefore, possible collision problems of UAVs are not considered here.

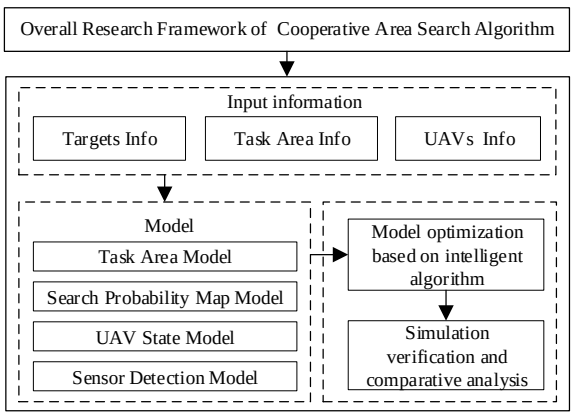


Figure 1. Overall research framework

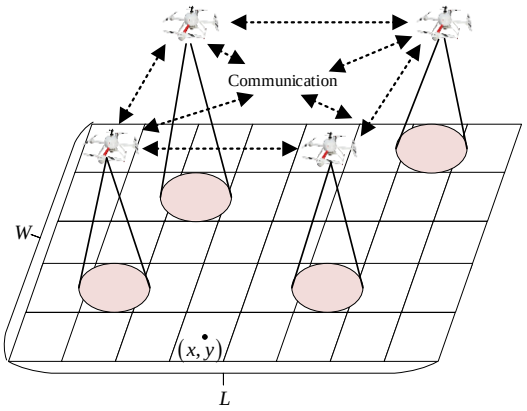


Figure 2. Cooperative area search scenario

3.3. Extended SPM model

According to the characteristics of the search environment and tasks, the search probability map model is used to describe the environmental information of the entire task area. The basic SPM model only considers the probability of target existence and environmental uncertainty, and has no status information about other UAV platforms performing tasks. Therefore, in order to improve the information interaction between UAVs, enhance the understanding of other UAV status information in the battlefield, and make the UAV platform more accurate in the perception of the battlefield situation, it is necessary to add platform information about other UAVs in the basic SPM model, so that it can coordinate multiple UAV platforms to search targets efficiently.

This paper refers to the idea of occupancy chart [10], adds the description of UAV occupancy probability in the basic SPM, expands the two-dimensional information structure in the basic SPM to a three-dimensional information structure, and forms an extended SPM model. To sum up, vector information $D_{xy}(t)$ is assigned to each grid in the task area to comprehensively describe the battlefield environment information in the grid at time t.

$$D_{xy}(t)=\left\{p_{xy}(t),\chi_{xy}(t),o_{xy}(t)\right\} \tag{1}$$

Where $p_{xy}(t)\in[0,1]$ is the probability of target existence of the grid (x,y) at time t; $\chi_{xy}(t)\in[0,1]$ is the environmental uncertainty of the grid (x,y) at time t, which is used to measure the degree to which the UAV has mastered the grid information at time t; $o_{xy}(t)\in\{0,1\}$ indicates the occupancy status of the grid at the current time.

3.4. UAV state model

The UAV motion state model is combined with the environment model, and the discrete particle kinematics model is adopted [11]. Assuming that each UAV moves at a certain speed and direction, the UAV is abstracted as a particle. Each time the UAV searches for a discrete grid cell, $(x_i(t),y_i(t))$ represents that UAV i is conducting reconnaissance and search on the grid at time t. In the process of target search based on the grid map, the navigation direction of the UAV at the adjacent time is specified as an eight-chain code direction, that is, $U=\{0,1,2,3,4,5,6,7\}$. At the same time, due to the track boundary constraints in the task area, the feasible course corresponding to UAVs at different positions at the next discrete time is shown in Figure 3.

3.5. Sensor detection model

In the process of searching, the UAV uses sensors to detect the grid passing by, and uses the information obtained to dynamically update the probability of the existence of the target in the grid.

Due to the sensor error, the sensor has a detection probability p_d and false alarm probability p_f in the detection process, and $p_d + p_f = 1$.

If the UAV accesses (x, y) at time t, the sensor obtains detection information $b_{xy}(t) \in \{0,1\}$. $b_{xy}(t) = 1$ means that the UAV has detected the target in cell (x, y). Then, at time t, formulas (2) and (3) are used to dynamically update the probability of target existence. This method is updated based on Bayesian criteria [12].

When $b_{xy}(t) = 1$, the update strategy of cell (x, y) target existence probability is

$$p_{xy}(t) = \frac{p_d p_{xy}(t-1)}{(p_d - p_f) p_{xy}(t-1) + p_f} \tag{2}$$

When $b_{xy}(t) = 0$, the update strategy of cell (x, y) target existence probability is

$$p_{xy}(t) = \frac{(1 - p_d) p_{xy}(t-1)}{(1 - p_f) + (p_f - p_d) p_{xy}(t-1)} \tag{3}$$

The environment uncertainty update policy is

$$\chi_{xy}(t) = \alpha \cdot \chi_{xy}(t-1) \tag{4}$$

Where $\alpha \in [0,1]$ is the attenuation factor of the environmental uncertainty, which is generally taken as 0.5.

In the static target scenario, the binary decision variable $\zeta_{xy}(t) \in \{0,1\}$ is used to indicate whether the target at the grid (x, y) is determined to exist. The update policy is as follows:

$$\zeta_{xy}(t) = \begin{cases} 1 & if\ p_{xy}(t) \geq \delta_p \\ 0 & else \end{cases} \tag{5}$$

Where δ_p represents the target discovery threshold.

4. Cooperative area search algorithm

4.1. Co-evolutionary genetic algorithm

Coevolution refers to the interaction, mutual influence, and final coevolution among multiple populations. Coevolution not only considers the evolution within a single population, but also considers the interaction between multiple populations. Co-evolutionary algorithms can be roughly divided into cooperative co-evolutionary and competitive co-evolutionary [13]. For the multi-UAVs cooperative area search problem in this paper, the cooperative coevolution mechanism is introduced based on the general genetic algorithm. Through the cooperation and constraint relationship between UAVs, multiple populations are promoted to evolve forward at the same time. In the population evolution, the elite retention strategy is used to retain the elite chromosomes, and finally the optimization solution of the established search planning model is achieved.

4.2. Cooperative area search algorithm based on CEGA

Drawing on the basic idea of rolling time domain optimization in Model Predictive Control (MPC), the rolling optimization strategy [14] is adopted. At time t, each UAV forecasts and plans the q-step flight path forward. The UAV only executes the first step of the planned path. At time $t+1$, the path is re-planned based on the new system status and environmental information.

This paper sets the path population number of UAVs to N, and makes evolutionary operations on the search path of N UAVs. If UAV i is located in grid (x, y) at time t, the result of path planning at time t is a path with length q starting from (x, y). When $q=3$, the expansion of the UAV route search status is shown in Figure 4.

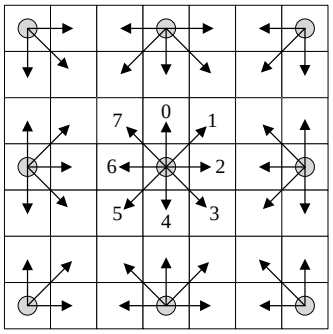


Figure 3. UAV search direction

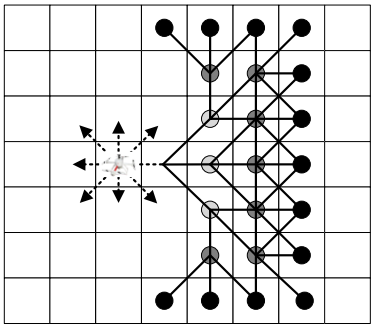


Figure 4. Route search status expansion

4.2.1 Coding strategy

The UAV heading action $u \in U$ is encoded as a gene, indicating that the UAV moves from its current position to the grid pointed by u, and the chromosome length is the number of path-planning steps q.At the time t, if the UAV i is located in the grid (x, y), the path represented by chromosome $\{2,1,2,1,2,1\}$ is shown in Figure 5.

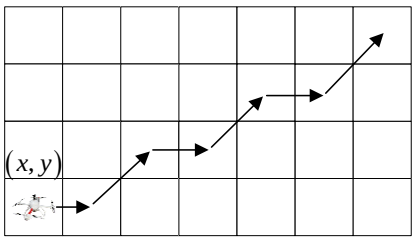


Figure 5. Predicted path

4.2.2 Fitness function

When UAVs perform cooperative search tasks, they should make full use of the cooperative advantages between UAVs, and select the path with the greatest benefits from cooperative search. The fitness function of the cooperative search is defined from the following four aspects and set as the fitness function of the individual to be evaluated.

(1) Find as many goals as possible and define target discovery revenue J_T.

$$J_T = \sum_{t=k}^{k+q} \left(1-\zeta_{xy}(t)\right) p_{xy}(t) \tag{6}$$

(2) Reduce environmental uncertainty as much as possible and define environment search revenue J_E.

$$J_E = \sum_{t=k}^{k+q} \left(\chi_{xy}(t) - \chi_{xy}(t+1) \right) \tag{7}$$

(3) Detect uncertain areas as much as possible and define expected detection revenue J_F.

$$J_F = \sum_{t=k}^{k+q} \chi_{xy}(t)\, p_{xy}(t) \tag{8}$$

(4) Avoid repeated detection between UAVs as much as possible, coordinate actions between UAVs, improve search efficiency of UAVs, and define cooperative revenue J_C.

$$J_C = \sum_{t=k}^{k+q} \left(1 - o_{xy}(t) \right) \tag{9}$$

Therefore, for chromosomes in various populations, the fitness function is

$$f = \omega_1 J_T + \omega_2 J_E + \omega_3 J_F + \omega_4 J_C \tag{10}$$

Where $\omega_i \in [0,1], i = 1,2,3,4$ is the weight coefficient, reflecting the degree of preference for various indicators, $\sum_{i=1}^{4} \omega_i = 1$.

4.2.3 Genetic operators

N UAVs correspond to subpopulations, and the evolutionary operations of subpopulations are selected as follows: 1) Selection operator: use the roulette method to perform selection operations; 2) Crossover operator: randomly select crossover points, and perform single-point crossover operation with crossover probability P_c; 3) Mutation operator: randomly select mutation points, and perform single-point mutation operation with mutation probability P_m.

4.2.4 Algorithm steps

The steps of the multi-UAVs cooperative area search algorithm proposed in this paper are as follows.

Step 1: Initialize the task area and UAVs parameters, including the size of the task area, the number of UAVs N, and the corresponding search starting point.

Step 2: Determine the control parameters of the algorithm, including the population size NP of the subpopulation, the crossover probability P_c, the mutation probability P_m, the evolutionary algebra T, and the algorithm cut-off condition T_{stop}.

Step 3: Solve the cooperative search model. For UAV i, the q-step optimal path at a time k is generated.

1) Initialize the population. Randomly generate N chromosomes with length q.

2) Calculate the fitness value. Select representative individuals from other subpopulations, and calculate the fitness value of each chromosome in the subpopulation to be evaluated according to the defined fitness function.

3) Evolutionary operations. Genetic operations such as selection, crossover, and mutation are performed on chromosomes in the subpopulation to generate a new generation of population, and elite chromosomes in the sub- population are retained by an elite retention strategy.

4) The best individual in the population is selected as the representative individual.

5) Judgment of evolution termination conditions. If $it = T$, the evolution will stop and the optimized q-step path will be output. Otherwise, let $it = it + 1$ and go to step 2) in Step 3 to continue.

Step 4: Action execution and information update. The UAV executes the first step of the optimal chromosome (i.e. the optimal path), moves UAV i , and updates the UAV i status and the corresponding grid information.

Step 5: Judge the termination condition of the algorithm. If $k = T_{stop}$, the algorithm termination condition is met and the algorithm terminates. Otherwise, let $k = k + 1$ and go to step 1) in Step 3 to continue.

5. Simulation analysis

Set the battlefield task area as a 30 * 30 rectangular area, and 60 static targets are distributed in the environment. The initial prior information of the battlefield environment can be known through early intelligence analysis. The initial battlefield environment is shown in Figure 6. The black circle represents the real target position, which is unknown to UAVs, and the hexagonal star represents the initial position of the UAV. At present, four UAVs are used to conduct a cooperative search in the task area, and the initial positions of each UAV are (1,1), (1,30), (30,1), and (30,30) respectively.

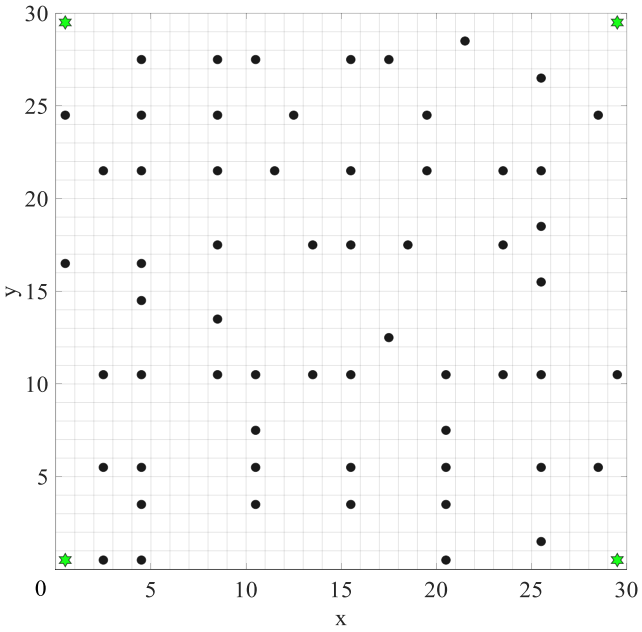
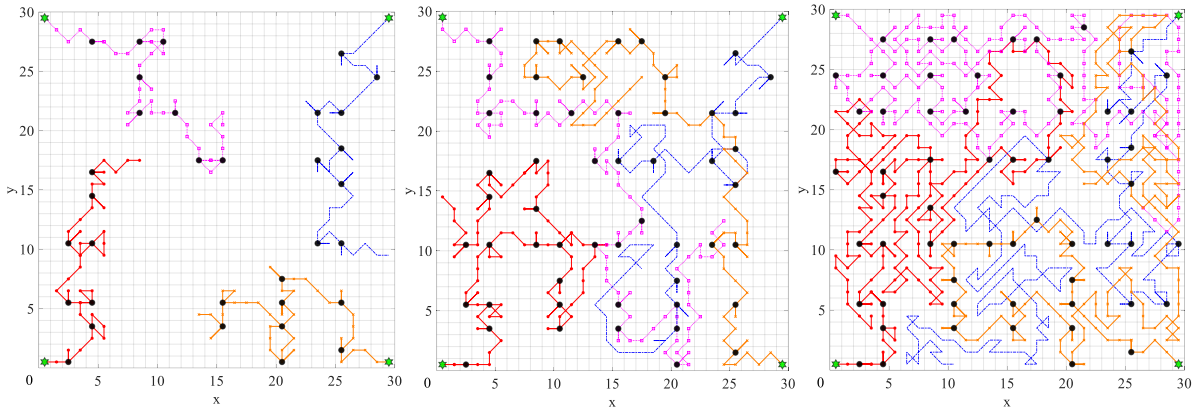


Figure 6. Cooperative area search simulation environment

We assume that the ground detection range of the sensors carried by each UAV is a 1 * 1 grid cell, and set the detection probability $p_d = 0.8$, the false alarm probability $p_f = 0.2$, the corresponding subpopulation size $NP = 50$, the predicted path length $q = 6$, the crossover probability $P_c = 0.7$, the mutation probability $P_m = 0.05$, the maximum evolutionary algebra $T = 100$, the target discovery threshold $\delta_p = 0.9$, and the simulation step size $T_{stop} = 200$.

Figure 7 shows the simulation operation results under three different search steps. When the target is found, it is represented by a small black circle, and four UAVs' search paths are displayed by four different colors and marked lines. In a simulation, the number of targets searched is 33 when $k = 50$, 53 when $k = 100$, and all 60 static targets are searched when $k = 200$. It can be seen that with the advance of simulation time, UAVs can make full use of the advantages of early intelligence and information sharing to achieve effective cooperative search of targets in the task area.



(a) $k=50$ (b) $k=100$ (c) $k=200$

Figure 7. Cooperative area search paths

To verify the effectiveness of the search algorithm proposed in this paper, this method is compared with the particle swarm optimization (PSO) search method, greedy search method (GS), and random search method (RS) through simulation. To reduce the impact of randomness on simulation, 10 comparative simulation experiments were conducted. The number of simulation steps was set to $k=200$, and the average environmental uncertainty (AEU), average area coverage (AAC), average target discovery quantity (ATDQ), and average search revenue (ASR) were selected as indicators to evaluate the effectiveness of the cooperative strategy. The simulation results are given in Figure 8~Figure 11 and Table.1.

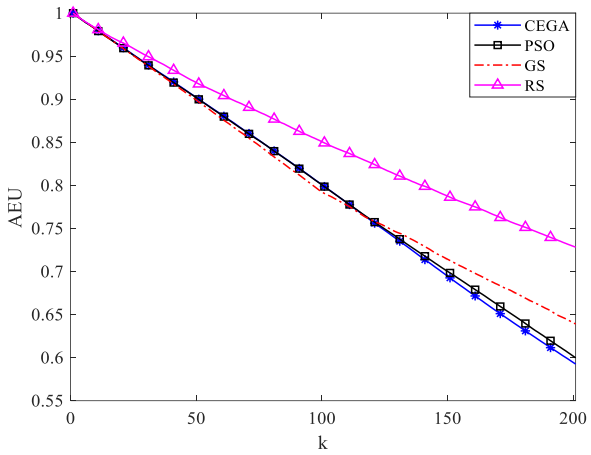


Figure 8. Comparison of AEU

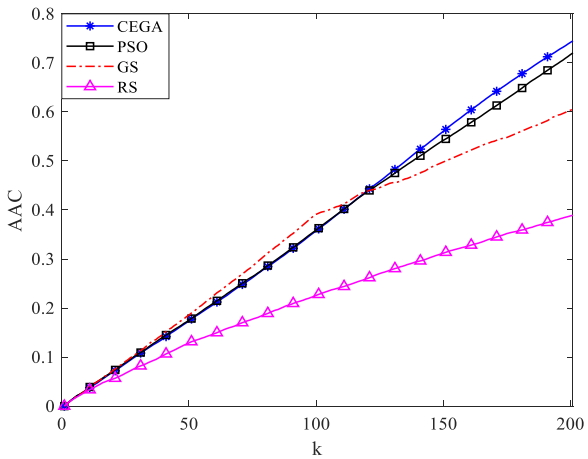


Figure 9. Comparison of AAC

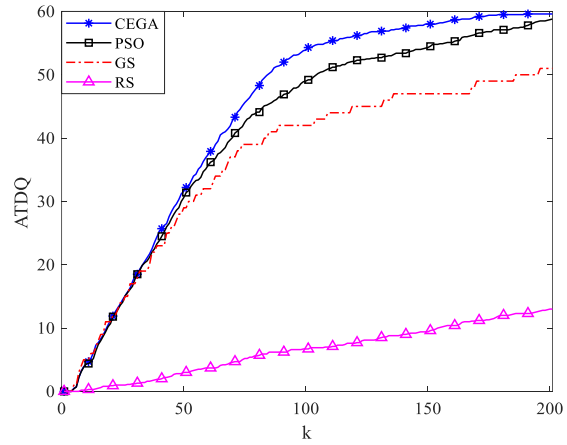


Figure 10. Comparison of ATDQ

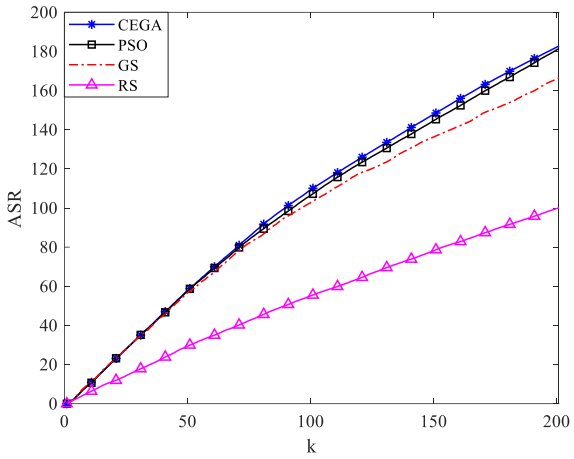


Figure 11. Comparison of ASR

Table.1 shows the search performance of four Algorithms in 10 simulation experiments ($k = 200$).

Table 1. Search performance results of four algorithms

Algorithms	ATDQ	AEU	AAC	ASR
CEGA	59.6	59.26%	74.49%	182.7958
PSO	58.8	59.98%	72.02%	181.4766
GS	51	63.91%	60.56%	166.3895
RS	13	72.83%	38.92%	100.0721

It can be seen from the results that, under a given step size, except for random search, the other three methods all have optimization processes, so their efficiency is obviously higher than that of random search methods. For the three search methods CEGA, PSO, and greedy search, the environmental uncertainty, area coverage, target discovery quantity, and search revenue of the three methods are almost the same within a period at the beginning of the search. However, with the increasing number of simulation steps, the advantages of the method proposed in this paper are gradually reflected. Compared with other algorithms, it has higher search efficiency and can search and find targets more quickly, the number of targets found in the final is more than that of other search methods, the environmental uncertainty decreases most, and the area coverage and search revenue are also higher than those of other search strategies.

It can be concluded that the multi-UAVs cooperative area search algorithm proposed in this paper can realize UAVs' effective cooperative search for the task area, better cover the area with a higher probability of the existence of the target, effectively reduce the uncertainty of the environment, and find more targets in the environment, which is better than the other three search methods.

6. Conclusions

This paper studies and analyzes the problem of multi-UAVs cooperative area search in uncertain battlefield environment, establishes task area environment model, extended SPM model, UAV state model and sensor detection model, and defines target discovery revenue, environment search revenue, expected detection revenue and cooperative revenue to build an optimization problem model. Then, based on the idea of rolling optimization, a co-evolutionary genetic algorithm with an elite retention strategy is used to optimize the solution. The simulation results show that the proposed method makes full use of the cooperative information among multiple UAVs, and can achieve multiple UAVs' effective cooperative search on the task area. It has higher search performance than the particle swarm optimization search method, greedy search method, and random search method for the problem studied in this paper.

Acknowledgements

The authors gratefully acknowledge the ground target and damage assessment system project (LJYX2019-05-001) and the Open Fund of the Key Laboratory of Information System Requirements (LHZZ2021-M05) for their enthusiastic support of the paper.

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