UAV cooperative attack and route planning based on DPSO algorithm

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Abstract: For UAV cooperative attack and route planning problem, a cooperative attack allocation model is established in fully considering the attack cost and attack revenue. Considering the threat cost and path distance cost, a flight path planning model is also established. An improved particle swarm optimization algorithm called DPSO is proposed by discrete space mapping, which can reduce redundant search and speed up search. Based on the model and optimization algorithm, reasonable cooperative attack target assignment and route planning are worked out, and the optimal performance is achieved.

1. Introduction
With the launching of the US trade war and the intensification of international disputes, the threat of instability in the world is increasing year by year. In order to strengthen China’s voice and control power in international friction and disputes, the powerful air precision strike capability has become as important a conventional deterrent as nuclear deterrence. Among them, UAV has become a research hotspot in recent years because of its long-range reconnaissance and strike capability. Aiming at the target that UAV finds at a certain time, how to assign the UAV to the most suitable task state reasonably is the key to the cooperative work efficiency of multiple UAVs.

Many researchers combine ant colony algorithm [1], annealing algorithm [2], genetic algorithm [3] and other optimization methods to find the optimal solution. At present, it has become a new research hotspot to solve computational problems by simulating the behavior of biological groups. Particle swarm optimization (PSO) is widely used in research and practice as a simple, general and robust method with strong optimization ability. In this paper, an improved particle swarm optimization algorithm is used to solve UAV cooperative attack mission and flight path planning problem.

2. Cooperative Attack Task Model
The target function of UAV attacking target consists of two parts, one is attacking cost, the other is attacking profit [4]. The objective function can be set as a function value of attack cost and attack benefit. Generally speaking, we should grasp the following principles: the higher the attack cost is, the smaller the target function value is. The cost and benefit of an attack are as follows:

\[ C_{ij} = \alpha^c [1 - \prod_{i=1}^M (1 - p_i)] + (1 - \alpha^c) L_{ij}, \quad 0 < \alpha^c < 1 \]

In Formula (1), \( \alpha^c \) is the proportional relationship between distance cost and threat cost. \( p_i \) is the
probability that the UAV will be destroyed by the first threat. So according to probability theory, 

$$\prod_{i=1}^{M}(1 - p_i)$$

is the probability of UAV surviving after M threats. 1 - $$\prod_{i=1}^{M}(1 - p_i)$$ is the probability that the UAV will be destroyed after passing through M threats. It can represent the threat cost of enemy ground fire. $$L_{ij}$$ is the Euclidean distance between the location of UAV and target I, which can represent the distance cost of ground target i. So $$G_{ij}$$ is the attack cost of the j-th UAV attacking the i-th target.

$$V_{al} = \sum_{i=1}^{M} \left( \frac{c_{ij}}{V_{ij}} \right)$$

(3)

(2) Attack gains refer to the factors that promote the UAV to attack the target, i.e. the damage to the target value, which we call nominal gains. The greater the degree of damage become, the more likely it is to perform the task, as shown in Formula (2).

$$V_{ij} = G_{ij} \prod_{i=1}^{M}(1 - p_i) p_{ij}^d$$

(2)

$$G_{ij}$$ is the value of goal (when the number of targets is greater than 1, it needs to be normalized). $$p_{ij}^d$$ is the destruction probability of the first UAV to target J (determined by the number and performance of airborne weapons). $$\prod_{i=1}^{M}(1 - p_i)$$ is the survival probability of the UAV, that is, the probability that the UAV can reach and attack. Form (3) represents the attack revenue generated by the jth UAV attacking the I I target, i.e. the nominal gain. According to the cost $$G_{ij}$$ and the benefit $$V_{ij}$$, task goal is to minimize costs and maximize benefits. Particle fitness is calculated using the following formula: 

$$V_{al} = \sum_{i=1}^{M} \left( \frac{c_{ij}}{V_{ij}} \right)$$

(3)

In summary, there are two contradictory optimization indicators in task allocation: cost and benefit. In order to use some intelligent optimization algorithm to optimize the objective function, it is necessary to transform them into single-objective optimization problems to reduce the difficulty of judgment. Using the following discriminant factors:

$$\rho_c = \frac{V_{1} - V_{2}}{\max(V_{1}, V_{2})} - \frac{c_{1} - c_{2}}{\max(c_{1}, c_{2})}$$

(4)

C and V represent costs and benefits respectively, 1 and 2 represent the serial numbers of the two schemes.

3. Route Planning Model

There are two kinds of cost functions (or fitness) in route planning. One is the threat cost function, which includes the value of the cost function of each threat on the route of UAV. One is the cost of path length. Generally speaking, the length of path determines fuel consumption and time cost. So the path length cost function is also an important factor we should consider. The cost function of general route planning consists of the following two parts [6], as shown in Formula (5):

$$J_{opt} = k_1 \sum_{j=1}^{n}(\sum_{i=1}^{n} a_{ij} T_{ij}) + k_2 \sum_{j=1}^{n} W P_{l,j+1}$$

(5)

In formula, $$W P_l$$ represents any path point from the beginning to the end, the path point in this paper is the inflection point of UAV state change. $$k_2 \sum_{j=1}^{n} W P_{l,j+1}$$ is the cost of distance, the sum of the distances between the points. $$k_1$$, $$k_2$$ are the weight coefficients, which refer to the preferential choice made by people according to the task requirements. The distance cost is related to the fuel consumption of UAV, and the threat cost affects the survival probability of UAV.

This paper mainly discusses the problem of route planning modeling in two-dimensional environment. The method of model construction is as follows: For a given starting point and end point, we need to plan a path in two-dimensional environment. The basic method is to select several feasible nodes or points in the coordinate area (hereinafter referred to as "navigation points"), and connect each point according to a certain rule.

4. Discrete Particle Swarm Optimization

Particle swarm optimization arises from the study of bird predation behavior. When birds hunt, the easiest and most effective way for each bird to find food is to search the area around the bird closest to
the food. In the iteration process, each particle follows its historical best position and the historical best position of the whole population to search and fly in the problem space to obtain the optimal solution. But the traditional PSO is easy to fall into local optimum solution, so the discrete space mapping of the traditional PSO is carried out here. Define "addition and subtraction" between vectors as "exclusive or" operation of binary bits, denoted by $\oplus$. Multiplication between vectors is an AND operation for binary bits, denoted by $\&$. The DPSO algorithm in discrete space is obtained. The updating formula of particle state is as follows:

$$V_{i,k+1} = V_{i,k} \alpha \& \left( P_{best} - X_{i,k+1} \right) \oplus \beta \& \left( G_{best} - X_{i,k} \right)$$

$$X_{i,k+1} = X_{i,k} \oplus V_{i,k+1}$$

(a) Initialize a group of particles, including positions and velocities. The distribution of particles in each dimension follows a uniform distribution or a normal distribution centered around each threat point;

(b) Calculate the fitness of each particle;

(c) For each particle, compare its fitness with its best location $P_{best}$, and if it is better, consider it as the best current location $P_{best}$. Compare its fitness with the best position $G_{best}$ experienced by the whole world, and if it is better, regard it as the best position $G_{best}$ in the whole world;

(d) Change the velocity and position of particles according to the equation of particle velocity change;

(e) If the end condition is not met (usually a sufficiently good fit or a set number of iterations), step (b) is returned;

(f) When conditions are met, the iteration process ends.

5. Simulation verification

Under the software environment of MATLABR2013a, the cooperative attack planning of UAV is simulated first. The number of UAVs and targets is set at 6. Task allocation table is shown in Table 1.

| No | T1   | T2   | T3   | T4   | T5   | T6   |
|----|------|------|------|------|------|------|
|    | cost | benefit | cost | benefit | cost | benefit | cost | benefit | cost | benefit | cost | benefit | cost | benefit |
| 1  | 0.312 | 0.016 | 0.487 | 0.441 | 0.126 | 0.475 | 0.368 | 0.628 | 0.274 | 0.519 | 0.433 | 0.591 |
| 2  | 0.631 | 0.744 | 0.873 | 0.470 | 0.536 | 0.878 | 0.716 | 0.559 | 0.587 | 0.586 | 0.059 | 0.564 |
| 3  | 0.591 | 0.291 | 0.579 | 0.881 | 0.839 | 0.863 | 0.285 | 0.246 | 0.268 | 0.519 | 0.885 | 0.865 |
| 4  | 0.054 | 0.756 | 0.421 | 0.645 | 0.239 | 0.996 | 0.789 | 0.656 | 0.784 | 0.140 | 0.256 | 0.219 |
| 5  | 0.869 | 0.103 | 0.813 | 0.146 | 0.022 | 0.757 | 0.205 | 0.132 | 0.148 | 0.315 | 0.287 | 0.301 |
| 6  | 0.728 | 0.227 | 0.695 | 0.212 | 0.148 | 0.885 | 0.429 | 0.513 | 0.773 | 0.861 | 0.223 | 0.587 |

In DPSO algorithm, setting population size $popsize=40$, evolutionary algebra $maxgen=20$, $V_{max} = 1.2$, $V_{min} = 0.4$, $C_1 = C_2 = 2.05$. By calculating, the optimized sequencing sequence can be obtained as $G_{best} = (4,3,2,6,1,5)$. The wiring diagram is shown in Figure 1, fitness evolution is shown in Figure 2. The simulation results show that DPSO algorithm has successfully completed the task assignment of six UAVs to six targets, and the optimal value of 2.07 is converged to the 14th generation of particles.
Under the software environment of MATLAB R2013a, the route planning of UAV is simulated. The simulation uses 700km×700km two-dimensional map (unit 1 km). There are three peaks (red solid circle) and eight enemy radars (black hollow circle). In DPSO algorithm, setting population size \( \text{popsize}=20 \), evolutionary algebra \( \text{maxgen}=150 \), \( V_{\text{max}} = 1.2 \), \( V_{\text{min}} = 0.4 \), \( C_1 = C_2 = 2.05 \). The simulation results are shown in Fig. 3 and Fig. 4. It can be seen that the optimal path distance is 870.5 km after 50 iterations.
Figure 3. UAV route planning

Figure 4. Particle fitness curve

6. Conclusion
The simulation results show that the particle swarm optimization algorithm based on discrete space (DPSO) has good ability to solve the problem of multi-UAV cooperative attack task allocation and route planning. Because the particle has memory function, the particle swarm optimization algorithm can approach the optimal result as a whole, converge to the optimal value quickly, and finally get the optimal planning scheme effectively. Based on the traditional particle swarm optimization algorithm, this method maps the discrete space, solves the redundant search problem in the traditional PSO, speeds up the search speed, avoids the algorithm falling into the local optimal solution, and has a good effect in solving such engineering problems.

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