Research on target assignment method based on ant colony-fish group algorithm

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Abstract. Target assignment problem has always been the focus of scholars. The solution of target problem belongs to classical mathematical problem. This paper combines ant colony algorithm with artificial fish swarm algorithm by understanding intelligent algorithm. The concept of crowding degree is introduced into fish swarm algorithm. In the early stage of the algorithm, the dispersion is large, avoiding premature maturity. In the later stage, the convergence speed of the algorithm is faster and the time is saved. Compared with other algorithms, the hybrid algorithm has the characteristics of strong optimization ability and fast speed.

1. Introduction

Target assignment problem is essentially the problem of resource allocation. When multiple targets require multiple resources, and each target and resource have a many-to-many relationship, the whole problem will become complicated. How to allocate resources rationally to maximize benefits is a problem we have been trying to solve.

The method of target assignment has been studied by many scholars. Wang [1] improved the genetic algorithm to solve the problem of multi-UAV cooperative combat target assignment in complex environment, improved the population fitness by using heuristic information and random generation, and added penalty mechanism to investigate the scheme that did not meet the conditions. And then inherit the genetics, inserting excellent individuals into the original population and enriching the population. Finally, the feasibility was confirmed by experimental comparison. Yang [2] proposed a new genetic algorithm by introducing the theory of visual fuzzy set to solve the problem of air defense combat target assignment which has slow convergence and easily premature. Wu [3] inserted simulated annealing algorithm into the crossover operator of genetic algorithm, which can not only maintain the breadth of the algorithm, but also enhance the depth of the search. Gao [4] generated random population and artificial population, carried out cross mutation evolution, used new immigration operator to exchange information among populations. Finally, by comparing with artificial immune algorithm, it is found that the algorithm can improve the search efficiency and get the optimal scheme. Sun [5] proposed an improved Cuckoo search algorithm. The simulation results show that the algorithm can effectively balance the relationship between convergence speed and global exploration ability.

All of the above methods are centralized allocation methods, which have the following advantages.

Since the command center has basically fully understood the information of the whole problem, a centralized understanding can be used to obtain a global understanding.

Because superiors and subordinates belong to the relationship between commanded and subordinate, decision-making by superiors can avoid conflicts very well.

However, these algorithms generally have a slow convergence rate, the algorithm is easy to fall into the local optimum, and there are also phenomena such as premature aging and early lag, which greatly affects the speed and quality of decision making.

2. Description of the problem

This paper expounds this kind of problem based on the air defense combat scenario. In the air defense combat, the superior command center acts as the center of command and decision, and collects the incoming target information uploaded from the sensor to the command and control center, It is responsible for collecting the information of attacking targets uploaded from sensors to command and control center, and solves them through the target allocation mechanism, and transmits the results of target allocation to each of subordinate command centers, and they will send the command to the air defense weapon equipment. Its battle process is shown in Figure 1.

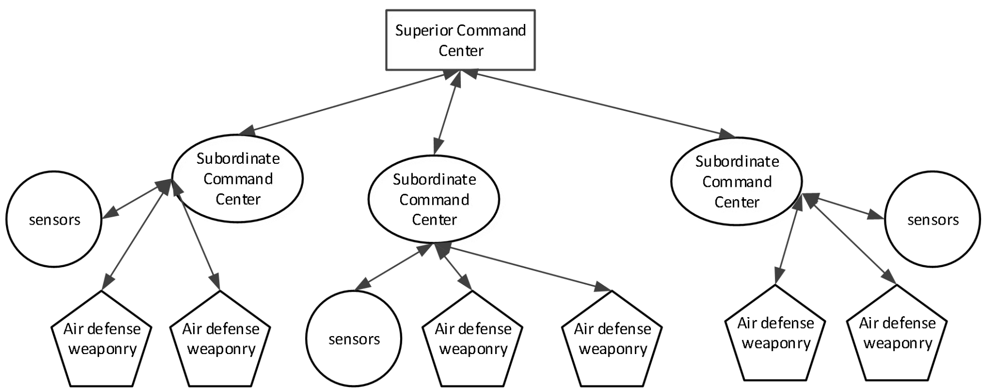

Figure 1. Centralized air defense decision-making process.

Such a decision-making process will bring great communication pressure to the superior command center, and the communication speed will be very slow, which will reduce the

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decision-making time of the superior command center. The speed and quality of target allocation will directly affect the whole operation, so we need a more reasonable problem solving method in the allocation speed and the quality of the allocation results.

3. Model establishment

3.1. Objective function

In air defense operations, air defense weapons must strike against air strike targets. The significance of target allocation is to exchange a small amount of cost for the maximum benefit. Therefore, we construct its objective function.

$$Y = \mathrm{E} - \mathrm{C} \tag{1}$$

Among them, E is the total return value, which refers to the income from the distribution and attack of the target, and C is the total cost, which refers to the cost of the implementation of the distribution plan, including the cost of the missile, etc. Y is the total absolute return value, which refers to the absolute return of the entire target allocation. Our goal is to have the largest absolute return value. This is also an important criterion for us to measure the effect of target allocation.

The return value can be solved using equation (2).

$$E = f_E(W, P_s) = \sum_{i=1}^{n} W_i \times \left\{ 1 - \prod_{j=1}^{m} \left[d_{ij} \times (1 - P_{sij}) \right] \right\} \tag{2}$$

d_{ij} is the result of the allocation of the air defense weapon j against the target i. The result can only be represented by 0 or 1. 0 is not assigned, 1 is assigned; the W_i is the threat of attacking target i; P_{sij} is the probability of destruction of target i.

It total cost is the sum of the costs of each part. It can be expressed by the formula (3).

$$C = \sum_{i=1}^{m} \sum_{j=1}^{n} (d_{ij} \times \mathrm{c}_j) \tag{3}$$

3.2. Constraints

3.2.1. Space constraintsSpatial

Constraints refer to the fact that certain targets of the target relative to the air defense weaponry are within a certain range to be hit by a certain probability. Formula (4) is a constraint.

$$\begin{aligned} & l_i \le l_{\max} \\ & h_{\min} \le h_i \le h_{\max} \\ & v_i \le v_{\max} \\ & RCS_i \ge RCS_{\min} \end{aligned} \tag{4}$$

Where l_i is the route shortcut of target i, l_{max} is the maximum route shortcut that the target can intercept for air defense weapon equipment; h_i is the height of target i, h_{min} and h_{max} is the minimum height and maximum height that can be intercepted by air defense weapon equipment respectively; v_i is the speed of target , v_{max} is the maximum speed that can be intercepted for air defense weapons. RCS_i is the target radar cross-sectional area , RCS_{min} is the minimum radar cross-sectional area at which the target can be struck.

3.2.2. Target assignment constraint

Target Assignment constraint refers to the target allocation should be carried out according to certain constraint, which are mainly divided into air defense weapon constraint, allocation of target constraint.

Air defense weapon constraint refer to the limitation of the number of air defense and anti-missile missiles and fire passages. We simplified the problem.We assume that each target will be attacked by two missiles with same air defense weapon, which can be expressed by formula (5) (6).

$$\sum_{i=1}^{m} d_{ij} \times 2 \le n_{\text{missile j}} \tag{5}$$

$$\sum_{i=1}^{m} d_{ij} \times 2 \le n_{\text{channel j}} \tag{6}$$

$n_{\text{weapon j}}$ is the number of missiles carried by air defense weapon j, and $n_{\text{channel j}}$ is the number of fire channels currently available by air defense weapon j.

We assume that our missiles are sufficient. Target assignment constraint means that each of our targets is allocated at least one air defense weapon to attack, which can be expressed by formula (7).

$$\sum_{j=1}^{n} d_{ij} \ge 1 \tag{7}$$

3.2.3 Time constraint

Time constraint refers to the fact that the command center needs to make decisions on the target within the time from the detection to the launch area. distribute the target reasonably, and pass the distribution result to each weapon. It can be expressed by the formula (8).

$$t_{\text{decision}} \le t_{\max} \tag{8}$$

t_{decision} represents the decision-making time and $t_{\max}$ represents the upper limit of the decision-making time.

4. Ant-fish swarm hybrid algorithm

4.1 Overview of Artificial Fish Swarm and Ant Colony Algorithms

Hybrid algorithms have been studied by many scholars, and many achievements have been made in other fields[6][7]. This paper proposes a hybrid algorithm based on ant colony algorithm and fish colony algorithm, which is introduced below.

4.1.1 Artificial Fish Swarm Algorithm

Artificial fish swarm algorithm was proposed by Li [8] in 2002. Through observation, it was found that the most dense area of fish activity is the place where nutrients are the most abundant in the water area, and then the optimization algorithm of artificial fish swarm algorithm is made.

We assume that the number of fish is A, The current state of the fish is $X = (\mathrm{x}_1, \mathrm{x}_2, \ldots \mathrm{x}_\mathrm{n})$, Each parameter in the state is a optimization variable, We set the nutrient concentration of the fish at its current location as $Y = f_{food}(\mathrm{X})$, The distance between the fish is $j_{ij} = \left\| X_i - X_j \right\|$, We assume that the fish's perception range is a spherical area with a radius of $Perceive$, The step size of the fish is $Step$, The algorithm mainly considers three behaviors of fish: foraging, clustering and rear-end. These three behaviors are briefly described below [9].

(1) foraging behavior

Let's assume that our current fish state is X_i, we choose a state of X_j within its range of perception. Expressed by the formula (9).

$$X_j = X_i + Perceive \times Rand \tag{9}$$

Where $Rand$ denotes 0 to 1 random value, Comparing the objective function values Y_i and Y_j of the two, if we are solving the maximum value, when $Y_i < Y_j$, then we move one step to the current range, which can be expressed by formula (10).

$$X_i^{t+1} = X_i^t + \frac{X_j - X_i^t}{\| X_j - X_i^t \|} \times Perceive \tag{10}$$

If $Y_i \geq Y_j$, Then the state is randomly re-selected, and if the appropriate region is not found after repeated repetitions, then the state is randomly moved one step.

(2) Clustering Behavior

Fish will choose the way of group foraging and avoiding attack, which is the survival mode formed by the long-term survival of the fittest. Fish will randomly explore the number of fish in the perceptual range n_k, and find a new location center X_k, expressed by the formula (11).

$$X_k = X_i + Perceive \times Rand \tag{11}$$

The new location center objective function Y_k is compared with the current regional objective function Y_i.If the new objective function is better than the current objective function and is not crowded ($Y_k / n_k > CY_i$), it moves one step to the current location, expressed by the formula (12).

$$X_i^{t+1} = X_i^t + \frac{X_k - X_i^t}{\| X_k - X_i^t \|} \times Perceive \tag{12}$$

Otherwise foraging.

(3)Rear-end behavior

When a few fish find food, the fish in the vicinity and even further will follow. The fish explores the position of the best fish around X_l, and the number of fish around is n_l, when the function value Y_l of the surrounding optimal position is greater than the current position function value Y_i and not crowded($Y_l / n_l > CY_i$).the fish will move one step to it, expressed by the formula (13).

$$X_i^{t+1} = X_i^t + \frac{X_l - X_i^t}{\| X_l - X_i^t \|} \times Perceive \tag{13}$$

Otherwise foraging.

4.1.2 Overview of Ant Colony Algorithm

Ant colony algorithm was proposed by M. Dorigo [10] in 1991 based on the foraging behavior of ants. The main principle of this method is that in order to find a suitable route quickly, the ants search the routes randomly. When the ants encounter the intersection, they will choose the path through the pheromone left by the previous ants. The more pheromones there are, the more likely they will choose the route. The ants will also leave pheromone when they pass through this path, No. Passing pheromones will evaporate over time, and the shortest path pheromones will become more and more, which will form positive feedback, which is the key [11].

Next, we analyze the model.

Suppose that at a certain moment, there is an ant o on the position i, and the probability of selecting the next position as j is as shown in the formula (14).

$$p_{ij}^{o}(t_1)=\begin{cases}\dfrac{\left[\tau_{ij}(t_1)\right]^{\alpha}\left[\eta_{ij}(t_1)\right]^{\beta}}{\sum\limits_{k\in \text{allow}_o}\left[\tau_{ik}(t_1)\right]^{\alpha}\left[\eta_{ik}(t_1)\right]^{\beta}}, \text{j}\in \text{allow}_o \\ 0, \text{j}\notin \text{allow}_o\end{cases} \quad (14)$$

$\tau_{ij}(t_1)$ denotes the current pheromone value from position i to position j at time t_1, and $\eta_{ij}(t_1)$ is a heuristic function, which denotes the expected value from position i to position j at time t_1. $\eta_{ij}(t_1)$ is inversely proportional to the distance between two points, and can be solved by formula (15).

$$\eta_{ij}(t_1)=\frac{1}{j_{ij}} \quad (15)$$

α denotes the importance of pheromones, β denotes the importance of heuristic functions, and allow_o denotes the set of positions that ant o can choose. The pheromones of each location are updated every other unit of time.

$$\tau_{ij}(t_1+1)=(1-\rho)\tau_{ij}(t_1)+\Delta\tau_{ij}(t_1) \quad (16)$$

$$\Delta\tau_{ij}(t_1)=\sum_{o=1}^{q}\Delta\tau_{ij}{}^{o}(t_1) \quad (17)$$

Q is the total number of ants, $\Delta\tau_{ij}{}^{o}(t_1)$ refers to the pheromone left by ant o on the path i to j at that time, ρ is the pheromone volatilization coefficient.

4.2 Hybrid algorithm flow

The ant colony algorithm has the advantages of fast solution speed and high efficiency, but its shortcomings are also obvious, and it is easy to fall into local optimum. The artificial fish swarm algorithm has strong global search ability. The main feature of the hybrid algorithm is that it can combine the advantage of two algorithms,and avoiding the shortcomings of the two algorithms, and make full use of their strengths and avoid their weaknesses [12].

Here we embed the congestion directly into the iterative process of the ant colony algorithm, so that when the ant chooses a route with a high congestion degree, it will give up the route and select other routes. Congestion is expressed by formula (18).

$$C_{ij}=\frac{2\tau_{ij}(t_1)}{\sum\limits_{i\neq j}\tau_{ij}(t_1)} \quad (18)$$

In order to expand the search range of the algorithm at the initial time and focus on the search range at the later stage of the algorithm, we calculate the congestion threshold by formula (19).

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$$\sigma(t) = 1 - e \tag{19}$$

Where b is the congestion threshold coefficient.

The algorithm flow is as follows:

(1) Initialize the parameters, set the initial time, the number of ants, the pheromone, the congestion threshold, the importance of the pheromone, the importance of the heuristic function, and the maximum number of iterations. Put the ants in

(2) According to the pheromone selection path, the selection probability is as shown in formula 13.

(3) After the ant selects the path, the congestion degree detection is first performed. If the congestion degree is greater than the threshold, the ant will select other available paths, and if not crowded, transfer to the route.

(4) Repeat steps 2 and 3 until the ant's selection meets the requirements or the number of iterations reaches a maximum.

(5) The output ends.

The algorithm flow chart is shown in Figure 2.

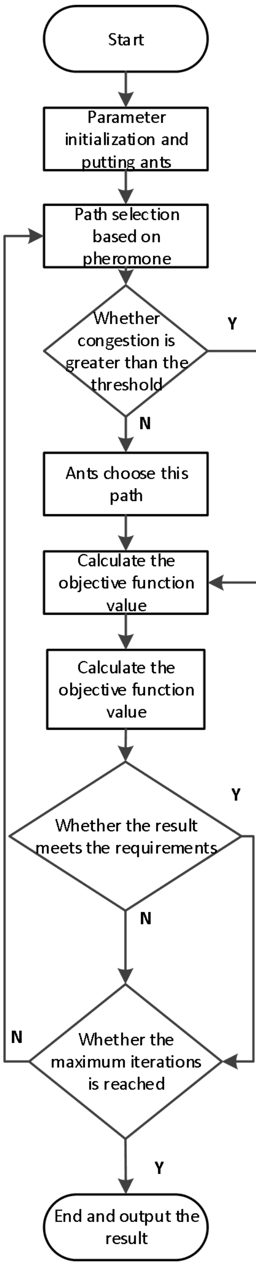

Figure 2. Hybrid algorithm flow chart.

5. Simulation

Assume that the superior command center commands four firepower units, each firepower unit has three launch vehicles, each of which has two available firepower passages, and two missiles. Each firepower unit has only one type of missile, at a certain moment. As for the 10 targets, the target parameters of the 10 incoming targets are shown in Table 1.

Table 1. Target parameter table.

	target1	target2	target3	target4	target5	target6	target7	target8	target9	target10
classification	aircraft	aircraft	UAV	UAV	UAV	UAV	UAV	UAV	UAV	Missile
velocity X (m/s)	116.3	251.8	146.8	146.7	146.8	146.8	146.7	146.8	146.6	1116.6
velocity Y (m/s)	232.6	97.4	104.2	104.2	104.3	104.1	104.2	104.1	104.1	1001.6
velocity Z (m/s)	-0.3	-0.3	-0.2	-0.3	-0.2	-0.2	-0.2	-0.2	-0.2	-0.2
velocity X (km)	42.0	62.8	62.6	63.0	62.7	62.9	62.7	62.9	62.6	107.2
velocity Y (km)	60.0	38.1	55.3	55.4	55.6	55.4	55.6	55.4	55.3	100.8
velocity Z (km)	12.4	13.7	10.2	10.3	10.3	10.5	10.4	10.4	10.6	16.2

The threat degree of the target relative to the combat unit is shown in Table 2.

Table 2. Threat Scale.

	aircraft 1	aircraft 2	UAV 3	UAV 4	UAV 5	UAV 6	UAV 7	UAV 8	UAV 9	Missile 10
CU A	0.670	0.513	0.475	0.449	0.447	0.444	0.455	0.460	0.445	0.974
CU B	0.751	0.574	0.501	0.481	0.475	0.473	0.491	0.497	0.469	0.810
CU C	0.722	0.629	0.671	0.601	0.592	0.571	0.612	0.623	0.584	0.916
CU D	0.604	0.742	0.574	0.523	0.514	0.501	0.539	0.547	0.510	0.717

Each missile launch has its own cost and interception probability, as shown in Table 3.

Table 3. Cost and interception probability of each missile.

	antiaircraft missile A	antiaircraft missile B	antiaircraft missile C	antiaircraft missile D
Cost per missile	0.2	0.16	0.12	0.17
Interception probability	0.7	0.5	0.4	0.6

The location of our combat units is shown in table 4

Table 4. Location of our combat unit.

	Combat unit A	Combat unit B	Combat unit C	Combat unit D
Postion X (km)	0	23	20	40
Position Y (km)	0	14	30	25

We assume that the combat capability parameters of each combat unit are the same, and the same combat unit has different capability parameters for different targets, as shown in table 5.

Table 5. Combat unit operational capability parameter table.

	UAV	aircraft	missile
Height limit (km)	15	15	20
Low limit (km)	1	1	1
Far limit (km)	30	30	40
Close limit (km)	6	6	8
Maximum height and low angle (degrees)	60	60	60
Maximum shortcut (km)	15	20	25

We simplify the problem, and each incoming target is only attacked by two missiles of the same firepower unit. Solving it according to the method described above yields the following results.

We set the various parameters as follows.

α=1, β=1, ρ =0.5, m=20, Q=200, c=1

We use hybrid algorithm, ant colony algorithm and artificial fish swarm algorithm to compare and simulate with matlab. The simulation results are shown in Fig. 3.

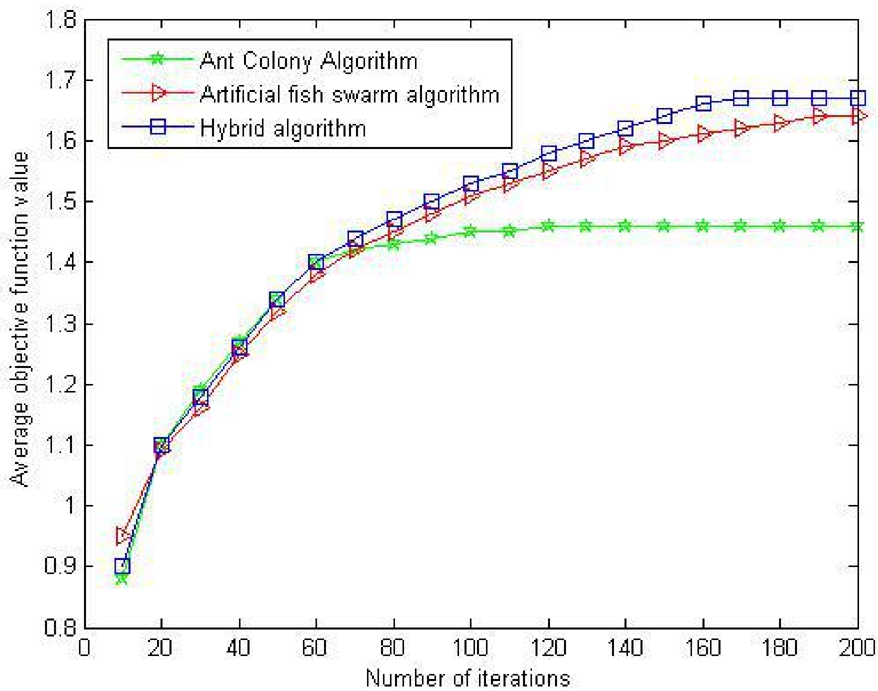

Figure 3. Comparison of the average results of the three algorithms.

By comparing the algorithms, we can draw the following conclusions. Among the three algorithms, ant colony algorithm converges fastest and artificial fish swarm algorithm converges slowest. The results of hybrid algorithm and artificial fish swarm algorithm are far greater than those of ant colony algorithm. Thus, the performance of the hybrid algorithm is better than that of the other two algorithms.

6. Summary

Based on the understanding of ant colony algorithm, this paper quotes the crowding rule of artificial fish swarm algorithm on the basis of ant colony algorithm. Through experiments, it can be found that the crowding rule can avoid the premature problem of ant colony algorithm, and also can converge quickly in the later period of the algorithm. The simulation results show that the algorithm has strong applicability. Although the hybrid algorithm has a good ability, its algorithm speed does not exceed the ant colony algorithm. In the future, it can continue to optimize the algorithm's optimization ability and speed, and propose a new algorithm to solve such problems.

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