MATEC Web of Conferences 173, 02002 (2018) https://doi.org/10.1051/matecconf/201817302002
SMIMA 2018

Research on Multi-UAV Collaborative Search in Dynamic Environment

ZHAN Jia[1,*], *XIE Wenjun*[1], and *GUO Qing*[1]

[1]Equiment Management and UAV Engineering College, AFEU, 710051 Xi'an, Shaanxi, China

Abstract. Combine the uncertainty of dynamic targets, a multi-UAV reconnaissance scheduling problem model was constructed under dynamic environment, take advantage of the characteristics of dual evolution, the insertion point operator and reverse sequence operator are improved, and the problem is solved by the artificial bee colony algorithm based on the semi-random search strategy. Finally, the simulation experiment was done in the background of South China Sea, and the experimental result shows the effectiveness and feasibility of the proposed algorithm for solving the multi-UAV reconnaissance scheduling problem.

1 Introduction

The unmanned aerial vehicle (UAV) reconnaissance scheduling problem is the core problem of multiple UAV cooperative reconnaissance, due to the uncertainty and dynamics of some targets, the multiple UAV reconnaissance scheduling problem become very complicated.

Literature [1] took the cost and benefit of task allocation as an overall objective function and assigns tasks based on the bidding process. Literature [2] built a single objective optimization model based on the maximum value of attack task, and utilized the sub-populations of ant colony algorithm solved the problem. Literature [3] completed the task assignment process based on the binary particle swarm algorithm. The Artificial Bee Colony (ABC) algorithm is based on the rationale of imitating the intelligent behavior of the swarm foraging behavior[5]. The solution quality of ABC is relatively good, and it has the characteristic of less control parameters, simple operation, strong robustness and higher search precision[6-7]. However, the basic ABC algorithm has a defect of " convergence precocity", which has shortcomings such as insufficient of development capability and slow convergence speed[8-9]. The literature [10] enhanced the convergence speed and global searching ability of the algorithm by improving the traditional artificial swarm algorithm. Literature [11] combined the ABC algorithm with genetic operator, and the search capability of algorithm was improved. In literature [12], an ABC algorithm based on particle swarm was designed to find optimal solution by combining the global search and local search. Literature [14] combined various of search strategies, and the local search capability of algorithm was enhanced. Literature [15] combined the global search capability of ABC algorithm with the local search capability of ACO algorithm to obtain an ACO-ABC hybrid algorithm to find optimal solution. Literature [16] set the optimal neighborhood solution to replace the current solution only after many times of not updated, so that the potential feasible solution can be preserved.

Contrapose the uncertainty about the emergence time of dynamic targets, this paper designed an improved double evolution artificial swarm algorithm. The algorithm was guided by the objective function of model, and the local optimal solution was processed in global search. The algorithm utilized the advantages of different local search operator, accelerated the search speed of algorithm, and enriched the diversity of feasible solution. Finally, through simulation experiment showed that the algorithm can effectively solve the UAV reconnaissance scheduling problem.

2 Mathematical model

2.1 Problem description

In battlefield environment, there is n targets for reconnaissance, corresponding number represents the corresponding reconnaissance target, 0 means the base, and $N=\{0,1,\dots,n\}$ constitute node set, d_{ij} means the distance between any two nodes of (i,j). A homogenous UAV reconnaissance unit locates in the base K and each UAV has the same effective reconnaissance payload Q. q_i represents the amount of reconnaissance payload consumed by each reconnaissance target. In addition, the UAV has a duration of flight. For each reconnaissance target i, there is a reconnaissance time window expressed as $[E_i, L_i]$. At each time point t of the mission, the reconnaissance objectives are divided into the following two categories:

* Zhan Jia: Mr_ZhanJia@163.com

(1) $N_t^{'}$ for static targets, the location of these targets and the moment of emergence are known.

(2) $N^{'}/N_t^{'}$ for dynamic targets, the location is known, but the moment of emergence is unknown.

For any moment τ, use $M_{i\tau}^{t}$ represent the reliability of the dynamic target i appears at the moment τ. So, for $i \in N_t^{'}$, if $\tau \in [E_i, L_i]$, then $M_{i\tau}^{t} = 1$; Otherwise $M_{i\tau}^{t} = 0$. For the $i \in N^{'}/N_t^{'}$, assume that the reliability distribution $M_{i\tau}^{t}$ is known.

2.2 Profit calculation

For each moment $t \in T$, and for each goal $i \in N_t^{'}$, make pf_i^{t} represent the profit of the moment t associated with the target i. Defined as equation (1):

$$pf_i^{t} = \begin{cases} \dfrac{1}{L_i - t}\left(1 + \dfrac{1}{\left|N_\rho^{'}(i)/N^{'t}\right|}\sum_{j \in N_\rho^{'}(i)}\left(1 - M_{ij}^{t}\right)\right), & L_i > t \text{且} N_\rho^{'}(i)/N^{'t} \neq \varnothing \\ \dfrac{C}{L_i - t^{'}}, & L_i > t \text{且} N_\rho^{'}(i)/N^{'t} = \varnothing \\ C, & L_i = t \end{cases} \quad (1)$$

M_{ij}^{t} is the estimate of the reliability of dynamic target j appears in the time window $[t+1, L_i]$. C as the normal number of large enough, in this paper, the reliability estimation of dynamic target j appears in the previous of L_i is estimated as equation (2):

$$M_{ij}^{t} = \sum_{\tau = t+1}^{L_i} M_{j\tau}^{t} \quad (2)$$

That is, the sum value of the reliability estimation of dynamic target j appears at the time $\tau \in [t+1, L_i]$.

2.3 Objective function

The objective function as equation (3):

$$\max \quad C_p \sum_{i=1}^{n}\sum_{k=1}^{m} pf_i^{t} x_{i0k} - \sum_{i=0}^{n}\sum_{j=0}^{n}\sum_{k=1}^{m} d_{ij} x_{ijk} - C_0 \sum_{j=1}^{n}\sum_{k=1}^{m} x_{0jk} \quad (3)$$

C_p and C_0 is the constant, x_{ijk} is the variable of $\{0,1\}$, if the UAV k goes to the node j from node i, $x_{ijk} = 1$, otherwise $x_{ijk} = 0$; the first part of objective function is the total reconnaissance profit, the second is the UAV's total flight distance, and the third is the inherent flight cost of UAV. If all the targets can be detected by UAV, the total reconnaissance profit is maximum; if complete the reconnaissance mission calls fewest UAV and the flight distance is minimum, inherent cost and the total distance of flight is minimum, so the overall goal is to complete the reconnaissance mission with a minimum flight mileage and a minimum quantity of UAV.

2.4The constraint

In the process of reconnaissance, UAV carries out a reconnaissance of a single target at most, it can reach target area before the start of the first reconnaissance moments, but must begin before the end of the reconnaissance time window, in addition to ensure the continuity of time. To sum up, the reconnaissance scheduling model of each decision stage is as follows:

$$\max \quad C_p \sum_{i=1}^{n}\sum_{k=1}^{m} pf_i^{t} x_{i0k} - \sum_{i=0}^{n}\sum_{j=0}^{n}\sum_{k=1}^{m} d_{ij} x_{ijk} - C_0 \sum_{j=1}^{n}\sum_{k=1}^{m} x_{0jk}$$

$$\begin{aligned} s.t. & \sum_{i=0}^{n}\sum_{j=0}^{n}\sum_{k=1}^{m} x_{ijk} \leq 1 \\ & \sum_{i=0}^{n}\sum_{h=1}^{n}\sum_{k=1}^{m} x_{ihk} - \sum_{j=0}^{n}\sum_{h=1}^{n}\sum_{k=1}^{m} x_{hjk} = 0 \\ & \sum_{i=1}^{n}\sum_{k=1}^{m} x_{0ik} = 1 \\ & \sum_{j=1}^{n}\sum_{k=1}^{m} x_{j0k} = 1 \\ & \sum_{i=1}^{n} q_i \sum_{j=0}^{n}\sum_{k=1}^{m} x_{ijk} \leq Q_k \\ & E_i \leq a_{ik}, \forall i \in N; k \in K \\ & a_{ik} \leq L_i, \forall i \in N; k \in K \\ & e_0 + t_{0j} - C\left(1 - x_{ijk}\right) \leq a_{jk}, \forall j \in N; k \in K \\ & a_{ik} + s_i + t_{i0} - C\left(1 - x_{i0k}\right) \leq a_{0k}, \forall i \in N; k \in K \end{aligned}$$

3 Scheduling solution

3.1 Initialize

Given the current scheme X and unallocated target set $N_t^{'}$, the initial population construction process is as follows (assuming the current scenario is empty):

1) The base is set as $v_1(1)$, the minimum cost LC set to infinity, and the maximum quantity of UAV is set to $\#veh$, initialize the best sequence of programs as $X = \{v_1(1)\}$.

2) As for each group of $\Delta \in \mathbf{\Delta}$, if the unallocated target set $N_t^{'}$ is not empty:

a) for each $j \in N_t^{'}$, test the feasibility of it as the next target.

b) If it is not possible to constitute a feasible scheme for any $j \in N_t^{'}$, and when $k < \#veh$, the base is assigned to $v_k(i+1)$, then $k = k+1$, and step d), otherwise the step c) will be taken.

c) If $g(\Delta, v_k(i), j) < LC$, then the value of $g(\Delta, v_k(i), j)$ will be assigned to LC, assigned the target j to $v_k(i+1)$.

d) Update the target set to be assigned and update the current plan.

3) Output the parameter set and it's corresponding best solution set.

3.2 Dual evolutionary process

The algorithm performs local search and adopts dual evolutionary method in the search process, and the specific operation process is as follows:

(1) Semi-random optimal insertion point operator, as shown in figure 1:

a) The insertion point r_1 is randomly selected, and the insertion location is denoted as r_2;

b) r_2 iterate through all feasible insertion locations, generate new feasible schemes, and calculate the adaptive value of each feasible scheme;

c) Find a feasible solution that minimizes the adaptive value and insert the target r_1 into the position.

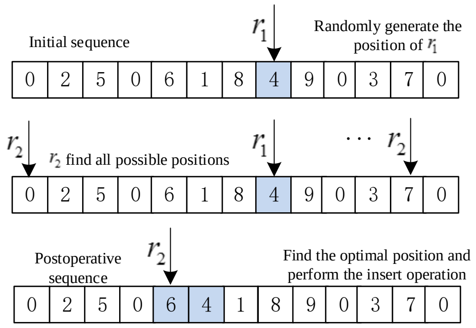

Fig.1. Semi-random optimal insertion point operator

(2) Semi-random optimal reversal sequence operator, as shown in figure 2.

a) One end of the random selection of the subsequence is denoted as r_1, the other end of the subsequence denoted as r_2;

b) r_2 traverses the other end of the feasible subsequence, and the subsequence determined by r_1 and r_2 is reversed to generate a new feasible scheme, and calculated the adaptive value of each feasible scheme.

c) Find the feasible solution to minimize the adaptive value and reverse the subsequence.

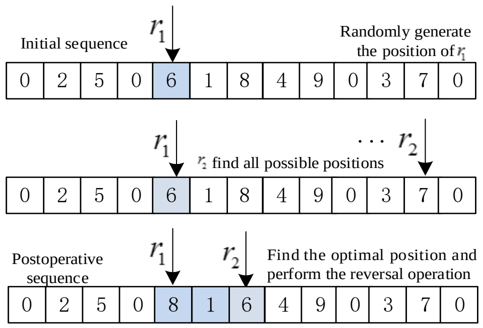

Fig.2. Semi-random optimal reversal sequence operator

This search process is relatively fast and efficient, with a small amount of computation. In this paper, it is named as a local search method based on the reconstruction plan.

3.3 Termination conditions

In general, if the set iteration number has completed in algorithm, the termination can be determined. In addition, it is also can be determined whether the solution generated by the algorithm in the global search process is rapidly convergent as the condition of the termination.

4 Experimental and results analysis

4.1 Apply scenarios

This article will set the task background as UAV spy on the south China sea reef monitoring, assuming the base is located in the midpoint of reef cluster (longitude 114.60 °; latitude 9.47 °). The reef position as shown in figure 3, the distance between each target (base) is determined by Euclidean space distance. Assume that there will be illegal vessels appearing near 5 islands, as dynamic uncertainty targets, the basic setting is shown in table 1.

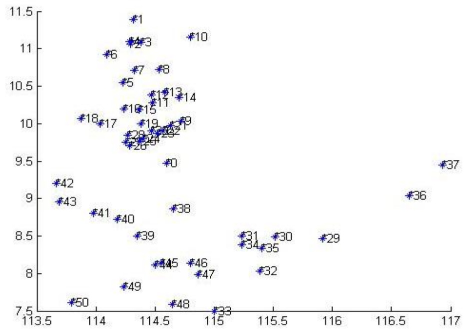

Fig.3. The position of the islands and reefs in the south China sea

Table1. The information of dynamic uncertainty targets

Dynamic target number	Adjacent islands number	The uncertain distribution of t_d	Time window (min)
1	5	$\mathcal{L}(298,358)$	$[t_{d1}, t_{d1}+30]$
2	9	$\mathcal{L}(117,187)$	$[t_{d1}, t_{d1}+30]$
3	23	$\mathcal{L}(384,444)$	$[t_{d1}, t_{d1}+30]$
4	33	$\mathcal{L}(480,540)$	$[t_{d1}, t_{d1}+30]$
5	43	$\mathcal{L}(268,328)$	$[t_{d1}, t_{d1}+30]$

The uncertainty distribution in table 1 is based on the known information and battlefield experience, and the specific content is the undetermined distribution of its occurrence time, duration is the length of time when other's ships stay in disputed waters. Set the speed of UAV is 144 km/h.

4.2 The simulation test

In the process of UAV's mission, combine the local search strategy of HB-ABC and RC-ABC, a dynamic multi-objective reconnaissance scheduling solution was performed. In the experiment, the maximum number of cycles is set to 1000, the value of β is 3, and the value of $Limit$ is set to 20. The experiment result gained by STK software shown in figure 4. As can be seen from the figure, the UAVs have conducted reconnaissance on all targets, and its total reconnaissance revenue reaches the maximum.

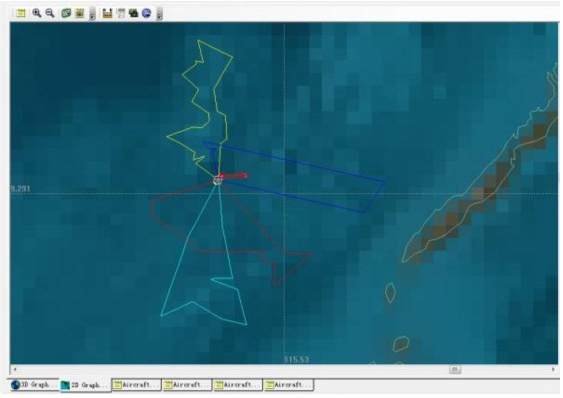

Fig.4. Reconnaissance scheduling project

To test the effectiveness of combining the local search strategy of RC-ABC algorithm and HB-ABC algorithm, with these two kinds of ABC algorithm to track separately, and compared with the eventually tracking results from RC-HB-ABC algorithm. In RC-HB-ABC algorithm, the parameters β related to the termination conditions is taken as 3, and the weight of dynamic target is greater than the known targets. The experiment design 2 different dynamic attitudes to test, 10% and 30% respectively. That is, 10 percent and 30 percent of the targets only have the experts' uncertain knowledge before the UAV begins reconnaissance. The test sets of C101, C106, R101, R106, RC101 and RC106 were randomly selected for modification and experiment. In the experiment, the points in the original test data set were randomly selected as the dynamic target points, and the appear moment was from the time window $[0, L_i]$. For each group of dynamic test data, the best results were selected through 30 operations, as shown in table 2 and table 3.

Table 2. The results of different algorithms in 10% dynamic degree

The test set	RC-ABC		HB-ABC		RC-HB-ABC	
	Dist-ance	Qua-ntity	Dist-ance	Qua-ntity	Dist-ance	Qua-ntity
C-101	994.3	10.5	1019.8	10.6	889.1	10.5
C-106	1015.7	10.7	1002.5	10.6	894.9	10.6
R-101	1950.3	20.2	1990.9	19.6	1740.2	19.2
R-106	1835.1	13.7	1831.4	13.7	1612.9	13.4

Table 3. The results of different algorithms in 30% dynamic degree

The test set	RC-ABC		HB-ABC		RC-HB-ABC	
	Dist-ance	Qua-ntity	Dist-ance	Qua-ntity	Dist-ance	Qua-ntity
C-101	1096.3	10.9	1083.2	10.7	1066.3	10.6
C-106	1165.3	10.9	1065.5	10.7	1165.3	10.5
R-101	2178.5	20.4	2114.5	20.1	2108.5	19.2
R-106	2144.0	14.6	1948.6	14.2	1944.0	13.6

It can be seen from table 2 and 3 that, from the perspective of optimal distance, the combination of two strategies is the best. The optimization results of RC-ABC algorithm and HB-ABC algorithm are different according to the test set dynamic attitude. On the whole, RC-HB-ABC algorithm has the best results in dynamic attitude test.

In order to evaluate the results, in 10% dynamic attitude, the convergence curve of the three tracking strategies to solve the R103 test set is shown in figure5.

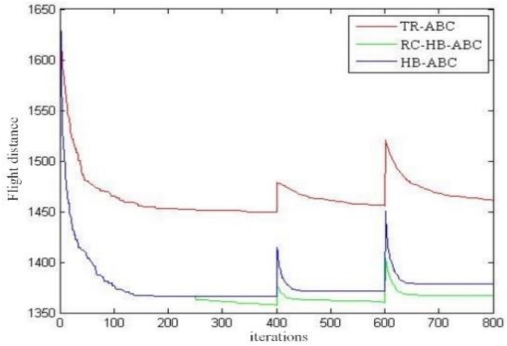

Fig.5. Convergence curves

Figure 5 shows that the search strategy of RC-HB-ABC algorithm combines the advantages of RC-ABC and HB-ABC, so in the case of time is higher pressing degree, the convergence speed is almost the same as the local search strategy of HB-ABC, in the case of long search time, it is possible to find a better solution than RC-ABC. The experimental results verify the validity of proposed algorithm and the feasibility of solving the multi-UAV scheduling problem.

5 Conclusion

This paper based on the model of multi-UAV scheduling in dynamic environment, an improved double evolutionary artificial bee colony is designed to solve this model. Through the simulation experiment, proves that the algorithm can completely detect all targets in the dynamic conditions to gain the maximum reconnaissance profit, and the UAV’s quantity and flight distance are the minimum, minimize the flight cost. Finally, the algorithm was compared with RC-ABC and HB-ABC algorithm, and the experimental results showed that the proposed algorithm can improve the convergence speed and global search performance observably.

References

1. Liu Y F, Zhang A. A collaborative task allocation method for man-machine/UAV formation[J]. Systems Engineering and Electronic Technology, 2010,32(3):484-588.
2. Chen Y. The application of ant colony optimization theory in UAV tactical control[D]. Chang Sha: University of National Defense Science and Technology, 2007.
3. Luo Q. A study on the integrated flight path planning and assignment method of ground attack under multiple threat conditions[D]. Chang Sha: University of National Defense Science and Technology, 2010.
4. Karaboga D. An idea based on honey bee swarm for numerical optimization, Technical Report-tr06 [R]. Engineering Faculty, Erciyes University,2005.
5. Karaboga D.A comparative study of Artificial Bee Colony Algorithm[J]. Applied Mathematics and Computation, 2009,214(1):108-132.
6. Karaboga, D. On the performance of Artificial Bee

Colony(ABC) algorithm[J]. Applied Soft Computing, 2008,8(1):687-697.

7. Li G Q, Niu P F, Xiao X J. Development and investigation of efficient Artificial Bee Colony algorithm for numerical optimization[J]. Applied Soft Computing, 2012, 12(3): 320-332.
8. Banharnsakun A, Achalakul T, Sirinaovakul B. The Best so-far selection in Artificial Bee Colony algorithm[J]. Applied Soft Computing, 2011, 11(2): 2888-2901.
9. Mao S, Xie W J, Zhang J Y, et al. Double evolutional artificial bee colony algorithm for solving vehicle routing problem[J]. Computer Engineering and Applications, 2016, 52(7):35-42.
10. Ozturk C, Hancer E, Karaboga D.A novel binary Artificial Bee Colony algorithm based On genetic operators[J].Information Sciences,2015,297:154-170.
11. Li Z Y, Wang W Y, Yan Y Y. PS-ABC: A hybrid algorithm based on particle swarm and Artificial Bee Colony for high-dimensional optimization problems[J].Expert Systems With Applications,2015,42(3): 8881-8895.
12. Wang H, Wu Z J, Rahnamayan S, et al. Multi-strategy ensemble Artificial Bee Colony alg-orithm[J]. Information Sciences, 2014, 279(6): 587-603.
13. Kefayat M, Lashkar Ara A, Nabavi Niaki S A.A hybrid of ant colony optimization And Artificial Bee Colony algorithm for probabilistic optimal placement and sizing of distributed energy[J].Energy Conversion and Management, 2015(4), 92: 149-161.
14. Szeto W, Wu Y, Ho S C. An Artificial Bee Colony algorithm for the capacitated vehicle routing problem[J]. European Journal of Operational Research, 2011,215(1):126-135