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Optimizing the Flight Route of UAV Using Biology Migration Algorithm

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Optimizing the Flight Route of UAV Using Biology Migration Algorithm

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Abstract. Optimizing the flight trajectory unmanned aerial vehicles (UAVs) is always a popular optimization problem in computation intelligence field, which aims to search optimal flight path for avoiding detection and complementing some highly difficult missions in complex military environments. This paper mainly utilizes a recent proposed biology migration algorithm (BMA) inspired by the species migration mechanism for dealing with the UAV trajectory optimization problem. The main goal of the UAV model is to search feasible parameters including the flight angle, coordinates and distance for minimizing the flight price computed based on the threat and fuel costs. As one of swarm intelligence techniques, BMA has the characteristics of self-organization, fast convergence and self-adaption in the optimization process, So, it is able to find a safe flight route between the start point and target point while avoiding the dangerous regions and minimum cost. Simulation experiments show that BMA can generate promising and better results with respective to other compared algorithms.
Keywords. Biology migration algorithm; unmanned aerial vehicle; trajectory optimization.

1. Introduction

With the development of science and artificial intelligence (AI) technology, the research on path planning of UAV have gained growing attention in recent years, since it has been widely appeared in various domains, such as mission planning system [1], aerial photography [2], surveillance [3], and search-and-rescue tasks [4]. The main task of trajectory planning is to obtain an optimal route from start location to desired locations considering some constraint conditions modelled by length, time-consuming, energy consumption, flight environment.

Over the last two decades, much effort has been devoted to designing efficient and effective optimization algorithms for solving this popular problem. Using swarm intelligence (SI) optimization techniques, UAV can automatically find, identify targets, dynamic plan path and efficient complete combat missions. Various optimization techniques have been designed in dealing with this problem, genetic algorithm [5], evolutionary computation [6], ACO-DE algorithm [7], collective decision optimization algorithm [8].

To solve the problem effectively, this paper employs a recent and proposed algorithm called BMA [9]. The main feature of BMA is that there are two important migration phase and updating phase, which simulate different rules in biology migration behavior. The former operator is designed based on the best agent for improving the convergence ability of algorithm, which aims to leads the search individuals to approximate the optimal member quickly. The migration phase is designed on two random search agents for improving the exploration ability of algorithm, which aims to move the search individuals toward different feasible regions randomly for generating promising solutions. These strategies are able to guarantee the search ability of algorithm effectively over the course of generations.

The following gives the rest of this manuscript. Section 2 presents the relevant mathematic model of the UAV route planning. The basic description of BMA can be found in Section 3. Then, the simulation experiment can be found in Section 4. Section 5 concludes this manuscript.

2. Mathematic Model

In order to ensure that the UAV can avoid all obstacles and reach the destination smoothly, the main task of this problem is to find a safe path with the minimum flight time and resources. The following provides the relevant descriptions of the mathematical model [10].

2.1. Task Region Model

In reference [10], it is necessary to model the task area and threat circumstances firstly before optimizing the flight trajectory of UAV. Figure1 provides the basic structure diagrams from the view of three-dimensional scenario.

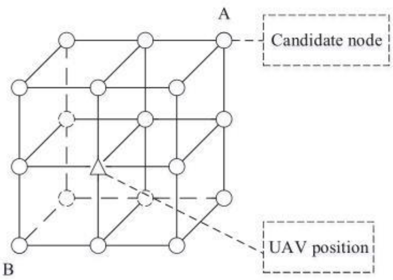

Figure 1. The basic structure diagrams in three-dimensional scenario.

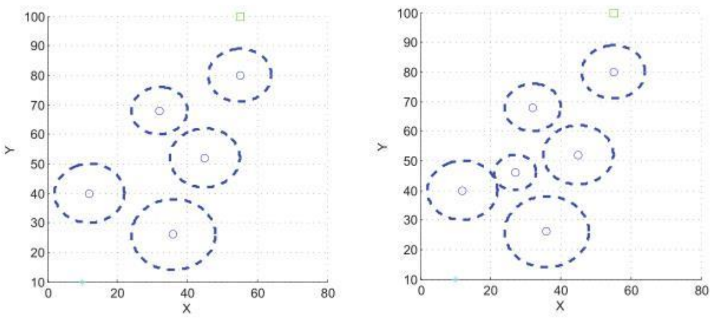

Figure 2. The basic structure model in two-dimensional scenario.

To simplify the trajectory planning problem, figure 2 provides the task area in two-dimensional space. In which, the starting location is set as A marked by “*” and the target location is set as B labelled by “□”. The dots are used for representing the threats. The center of the dangerous is marked by a circle. Once the UAV enter enters the area, which means UAV may fall in danger of being detected. The objective of route planning aims to optimize the flight trajectory between A and B while staying away from the treat circles. Here, it is supposed that the distance AB can be classified into *m* equal parts, then the following mathematic equation can be used to depict the flight path from the beginning position to destination location.

$$Path = \{A, L_1(x_1, y_1), L_2(x_2, y_2), ..., L_m(x_m, y_m), B\} \tag{1}$$

where $L_i(x_i, y_i)$ is the vertical direction of the i_{th} node.

2.2. Threat Price Model

As shown in figure 3, in this study, five different positions in each edge (e.g. k_{th} edge) are employed to compute the threat cost using the following formula.

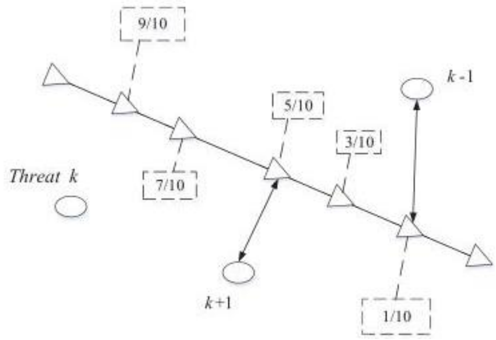

Figure 3. The structure model of threat cost.

$$W = \frac{Li}{5} \sum_{k=1}^{N_t} t_k \left(\frac{1}{d_{0.1,i,k}^4} + \frac{1}{d_{0.3,i,k}^4} + \frac{1}{d_{0.5,i,k}^4} + \frac{1}{d_{0.7,i,k}^4} + \frac{1}{d_{0.9,i,k}^4} \right) \tag{2}$$

where N_t denote the total number of threaten areas, Li shows the i_{th} sub-path distance, $d_{0.1,i,k}$ represents the length from the 1/10 position on the i_{th} edge to the k_{th} threat, and t_k is the threaten degree of the k_{th} area.

2.3. Evaluation Model

As mentioned before, the evaluation model of the UAV can be confirmed for minimizing the total price, which is the combination of the threat cost and fuel cost calculated by the equation below.

$$MinJ = q \times J_t + (1-q) \times J_f \tag{3}$$

where q denote a random weight generated from [0,1], J_t and J_f are the threaten cost and the fuel prices during the flight process, respectively.

3. Biology Migration Algorithm (BMA)

3.1. Inspiration and Mathematical Model

BMA algorithm model mainly includes two important operators: migration operator and updating operator. The former progress mimics the mechanism that the migration species search a new or better habitat from the current location. The latter process imitates the phenomenon that whether a species can move to better place during the whole migration process.

The aforementioned contents will be converted into proper operations. In the migration process of nature, a species should follow two regulations: on the one hand, BMA requires that each search agent searches a new position by referencing the best solution in the population. On the other hand, during the moving course, the search individual also considers the locations of its neighbour agents, so each population member modifies its position using its neighbour individuals. That is, there are two computation operators in this phase. The former regulation can be modelled mathematically as follows,

$$X_i(t+1) = X_i(t) + \gamma \times \sec(t) \times L(t) \times \left| X^* - X_i(t) \right| \tag{4}$$

where γ denote a random vector generated between 0 and 1, X^* is obtained best solution in the current search population, $L(t)$ is the moving step size at the iteration *t*.

According to the latter regulation, the relevant computation equation is shown as follows.

$$X_i(t+1) = X_i(t) + \varsigma \times (X_j(t) - X_k(t)), i \neq j \neq k \tag{5}$$

where ς represents a random vector generated between 0 and 1, $X_j(t)$ and $X_k(t)$ are neighbourhood individuals chosen from the population randomly.

Noting that another significant parameter is the step size, which generate great effect on the optimization performance. Therefore, this paper sets an adaptive step shown below over the course of generations, which aims to achieve the reasonable transformation from exploration to exploitation.

$$L(t) = 2 - 1.7 \times \frac{t-1}{T-1} \tag{6}$$

where *T* is the maximum number of iterations.

Besides that, if some species fails to find better habits during the migration process, which means that they are may be abandoned by nature. Therefore, BMA also defines a parameter, named $Cycle_{up}$, for simulating the mechanism, and requires that if the current solution fails to update themselves within the number of $Cycle_{up}$, it will be replaced by a new individual generated in the search space.

4. Simulation Results

4.1. Parameter Settings

The mean value (f_{mean}) and standard deviation (std) are selected as the evaluation indicators. Thirty independently runs are conducted to reduce the computation error, and the stop condition is set to 20,000 function evaluations. Besides that, eight existing optimizations are also employed as comparison algorithms, and the control parameters keep same as that of the corresponding reference as follows, CLPSO [11], ORCS [12], QPSO [13], AGGSA [14], PSOFIPS [15], CEP [16], PSOcfLocal [17] and UPSO [18]. According to reference [19], the settings of UAV flight environment and simulation results are summarized in tables 1-2 and 3-4, respectively.

Table 1. The parameters of flight environment considering five threaten positions.

Start Point	Goal Point	q	Threat center	Radius	Grade
[10,10]	[55,100]	0.5	[45, 50]	10	2
			[12, 40]	10	10
			[32, 68]	8	1
			[36, 26]	12	2
			[55, 80]	9	3

Table 2. The parameters of flight environment considering six threaten positions

Start Point	Goal Point	q	Threat center	Radius	Grade
[10,10]	[55,100]	0.5	[45, 50]	10	2
			[12, 40]	10	10
			[32, 68]	8	1
			[36, 26]	12	2
			[55, 80]	9	3
			[27, 46]	6	4

4.2. Simulation Results

In this section, tables 3-4 record the experimental results computed by each algorithm. In addition, figures 4-5 list the convergence curves and the optimal flight route, respectively.

Table 3. Simulation results obtained by all algorithms in environment with five threaten positions.

Index	CLPSO	ORCS	QPSO	AGGSA	PSOFIPS	CEP	PSOcflocal	UPSO	BMA
fmean	57.2726	54.2939	56.9463	51.1493	71.8416	65.9376	68.1173	69.8062	50.8168
std	3.63515	1.02756	9.33831	0.99566	4.70794	3.22001	4.65381	4.87420	1.01537

As observed from table 3 that BMA obtains the best results (50.8168) with respective to other compared algorithms considering the same termination conditions. Figure 4 gives the convergence curves of all algorithms in five different threat resources environment, in which, it is clear that AGGSA is superior to the other advanced version techniques at the beginning of the generation. However, BMA provides and approximates satisfactory results significantly better than other algorithms at the end of the iteration. Figure 5 displays the optimal flight trajectory of BMA in two-dimensional space, which is able to avoid all threats safely.

Table 4. Simulation results obtained by all algorithms in environment with six threaten positions.

Index	CLPSO	ORCS	QPSO	AGGSA	PSOFIPS	CEP	PSOcflocal	UPSO	BMA
fmean	69.1199	57.3281	62.2741	55.2964	79.7654	73.6836	78.5079	81.2567	53.5809
std	5.78334	1.13481	12.6408	6.17991	7.08512	5.61289	8.24321	9.63042	1.94701

From the comparison results considering the optimal length and standard deviation recorded in table 4, it is obvious that the best result (53.5809) belongs to BMA. The convergence graph of all algorithms in figure 4 shows that BMA show slightly weaker than AGGSA before the half of generations, but it performs faster than AGGSA at the end of iteration, and clearly better than other algorithms over the course of generation. Figure 5 give the flight route of BMA, which can keep away from all threat regions successfully. These results also illustrate that BMA is an effective tool for solving path planning problem in actual tasks.

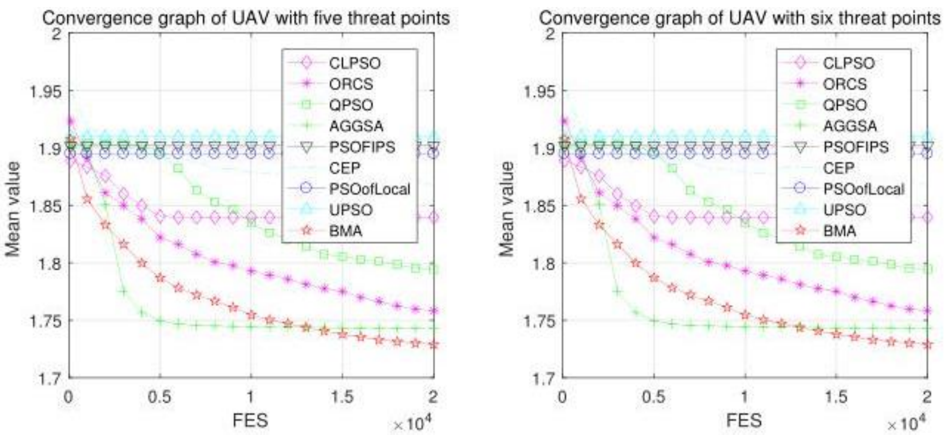

Figure 4. Convergence curves comparison between BMA and its peers.

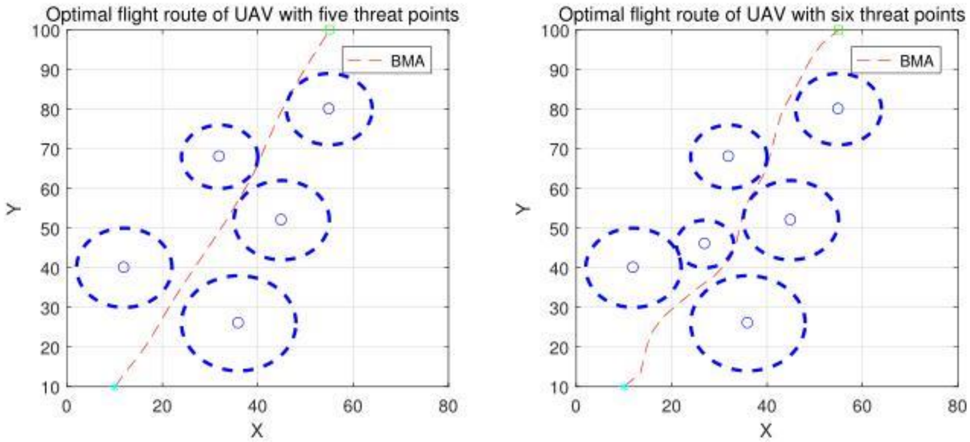

Figure 5. Trajectory planning result by BMA.

5. Conclusion

In this paper, a recent and efficient heuristic algorithm named BMA is utilized to solve the path-planning of UAV problem. BMA has two stochastic different computation operators for exploring and exploiting the search feasible space. Simulation experimental considering two flight environments with five and six threats show that BMA is able to generate better results than other version algorithms and provide a set feasible flight route while avoiding all threats safely. Therefore, in future work, BMA can be employed as potential algorithm for solving various difficult optimization tasks involved in different real-world fields.

Acknowledgments

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