Game Decision of Multi-UAV Based on Improved Shark Smell Optimization Algorithm

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Abstract. Decision-making is one of the key technologies in the air combat field. In this work, a game decision method based on an improved shark smell optimization (SSO) algorithm is developed for unmanned aerial vehicles (UAVs). The air combat situation assessment result of multi-UAV is described as an uncertain set, and a game model of game decision is established. Then, to upgrade the efficiency of game decision, an improved θ-SSO algorithm is proposed. Finally, the simulation results turn out the effectiveness of the algorithm.

Keywords: Game decision · multi-UAV air combat · Shark smell optimization

1 Introduction

In future air combats, UAVs will play a more important role with the advancement of UAV technology [1]. Game decision-making has attracted much attention because it can reflect the confrontational characteristics. [2].

In recent years, many valuable algorithms have been proposed on game decision field. In [3], the UAV swarm decision problem was solved by a mixed integer linear programming method. In [4], a multi-UAV combat decision method based on particle swarm optimization was studied, which verified the feasibility of particle swarm optimization in multi-UAV combat decision.

However, due to the complexity and variability of the battlefield environment, the uncertainties in game decision are always inevitable [5]. Furthermore, these uncertain parameters will directly affect the effectiveness of air combat decisions [6]. Therefore, in order to make the decisions obtained more consistent with the battlefield environment, it is necessary to study the problem of game decision under uncertain information [7]. In fact, the uncertain game decision problem can be solved by the wolf swarm algorithm [8] and the shark algorithm [9] as uncertain optimization problem. However, due to the unpredictability of the battlefield environment and the slow convergence speed of swarm optimization algorithms, there are not many related research results at present.

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Furthermore, most studies on air combat decision cannot reflect the confrontation characteristics of the two sides. In actual air combat, attack-defense confrontation is actually a game process between two sides. The optimal benefit of air combat decision-making can be obtained by introducing game theory [10]. In [11], a new weighted adaptive objective function is proposed to find the optimal strategy by using the Nash equilibrium of the game, but the influence of uncertain information on the decision results is not considered.

As discussed above, for the UAV uncertain decision-making problem, a new game decision method is proposed based on an improved θ-SSO algorithm in this paper. Firstly, a game model of decision-making with uncertain information is established. Then, the solution of the Nash equilibrium is transformed into a linear programming problem. To promote the efficiency of game decision, an improved θ-SSO algorithm is proposed to solve the uncertain game decision problem, and a simulation examples is provided to turn out the effectiveness of the algorithm.

2 Problem Description

2.1 Uncertain Game Model

In actual air combat, the game of attack and defense is a zero-sum game. The game model of decision-making can be established as

$$G = \left\{N, S^M, U\right\} \tag{1}$$

where $N = \{R, B\}$ are the participants in the game, R is our UAVs, and B is the enemy's UAVs, $S^M = \left\{s_{Ri}^k, s_{Bj}^k\right\}$ is the action space, s_{Ri}^k is the i-th action strategy for the k-th stage of our UAVs, s_{Bj}^k is the j-th action strategy for the enemy's UAVs in the k-th stage, $U = \left\{u_R\left(s^{k.i}\right), u_B\left(s^{k.j}\right)\right\}$ is the utility of each sides corresponding to the participating UAVs after selecting each possible action combination, $u_R\left(s^{k.i}\right)$ is the utility of our UAVs choosing the i-th action strategy in the k-stage.

The payout function of multi-UAV air combat game under uncertain information can be described as

$$\tilde{f}_{aij} = \sum_{i=1}^{m} b_{ab}\left(u_B + \varDelta u_B\right) - \sum_{j=1}^{n} r_{ba}\left(u_R + \varDelta u_R\right) \tag{2}$$

where b_{ab} and r_{ba} are the decision variables, b_{ab}=1 means that our a-th UAV attacks the enemy's b-th UAV, r_{ba} =0 means that the b-th UAV of enemy is not assigned to attack our a-th UAV, $u_B = S_z^B$, $u_R = S_z^R$, S_z^B is the overall superiority of our UAVs, S_z^R is the overall superiority of the enemy's UAVs, and $\varDelta u_B$, $\varDelta u_R$ are the uncertain parameters.

Generally, reasonable air combat decision-making is carried out by reasonable situation assessment. The air combat situation assessment is determined by an overall superiority function, which includes angle superiority, distance superiority and energy superiority. The superiority of our a-th UAV to the enemy's b-th UAV can be determined as

$$S_{Zab} = k_1 \times S_{Aab} + k_2 \times S_{Dab} + k_3 \times S_{Eab} \tag{3}$$

where k_1, k_2, k_3 are the superiority weights, and $S_{Aab}, S_{Dab}, S_{Eab}$ are the angle superiority, distance superiority and energy superiority of our a-th UAV to the enemy's b-th UAV, S_{Eab} can be calculated from the UAV's altitude and velocity, and the detailed calculation can be referenced in [12].

To reflect the uncertain information of actual air combat, the uncertainty can be described as an uncertain set. According to [13], the polyhedral uncertain set for generating air combat situation assessment can be expressed as

$$D = \left\{ u_a + \Delta u_a \,\middle|\, \left\| \Omega^{-\frac{1}{2}} \Delta u \right\| \le \eta_\beta \right\} \tag{4}$$

where Ω is covariance of Δu_a, η_β is given confidence probability.

According to Eq. (2), the payoff matrix can be determined as

$$\tilde{A}_{ij} = \begin{array}{c} \\ x_1 \\ x_2 \\ \vdots \\ x_m \end{array} \begin{array}{c} \begin{array}{cccc} y_1 & y_2 & \cdots & y_n \end{array} \\ \begin{bmatrix} \tilde{f}_{a11} & \tilde{f}_{a12} & \cdots & \tilde{f}_{a1n} \\ \tilde{f}_{a21} & \tilde{f}_{a22} & \cdots & \tilde{f}_{a2n} \\ \vdots & \vdots & \cdots & \vdots \\ \tilde{f}_{am1} & \tilde{f}_{am1} & \cdots & \tilde{f}_{amn} \end{bmatrix} \end{array} \tag{5}$$

where $x = (x_1, x_2, \cdots, x_m)$ is the mixed strategy of player R, and $y = (y_1, y_2, \cdots, y_n)$ is the mixed strategy of player B.

2.2 Linear Programming Model

According to the payoff matrix (5), the Nash equilibrium value is described as

$$\tilde{v}_1 = \max_{x \in X_n} \min_{1 < j \le n} \sum_{i=1}^{n} \tilde{A}_{ij} x_i \tag{6}$$

Equation (6) can be transformed into the following linear programming problem as follows.

$$\begin{gathered} \tilde{v}_1 = \max \tilde{u}(x) \\ s.t. \begin{cases} \sum\limits_{i=1}^{n} \tilde{A}_{ij} x_i > \tilde{u}(x) \\ x_1 + x_2 + \cdots + x_m = 1 & \begin{array}{l} i = 1, 2, \cdots, n \\ j = 1, 2, \cdots, m \end{array} \\ x_i > 0 \\ \Delta u_1 \in U_1, \Delta u_2 \in U_2 \end{cases} \end{gathered} \tag{7}$$

where $\varDelta u_1 \in U_1$, $\varDelta u_2 \in U_2$, U_1, U_2 are the closed interval uncertain sets, and $\tilde{u}(x) = \min\limits_{1<j\leq n} \sum\limits_{i=1}^{n} \tilde{A}_{ij} x_i$.

However, due to the influence of uncertain parameters, the linear programming problem (7) cannot be solved directly. Thus, the θ-SSO algorithm is considered in this paper.

3 Improved θ-SSO Algorithm

As a swarm optimization algorithm, the SSO algorithm was proposed according to the ability of sharks for finding a prey [14]. The movement of sharks for finding a prey depended on the odorant particle concentration is shown in Fig. 1. The θ-SSO algorithm is developed based on the SSO algorithm, and the selection of the direction is added during the search. But for the application requirements of air combat decision-making, it is always required a faster decision-making speed. Therefore, on the basis of θ-SSO, we consider the selection of the position during the search, and propose an improved θ-SSO, which further improves the optimization rate of the algorithm. Then, the linear programming problem (7) is solved by the improved θ-SSO algorithm, which satisfies the requirement of the rapidity of air combat. The improved θ-SSO algorithm is described as follows.

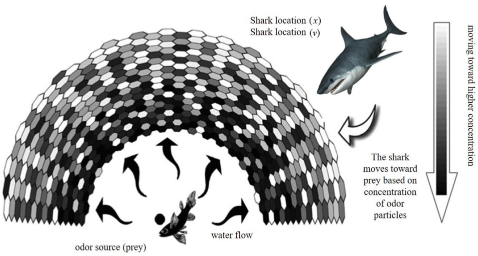

Fig. 1. The movement of sharks for finding a prey

(1) Initialization

The initial population of the possible locations is generated as $\left\{X_1^1, X_2^1, \cdots, X_{NP}^1\right\}$, where NP is the population size, and the l-th initial position vector X_l^1 can be expressed as follows

$$X_l^1 = \left[x_{l,1}^1, x_{l,2}^1, \cdots, x_{l,ND}^1\right] \tag{8}$$

where $x_{l,p}^1$ is the p-th dimension of the initial position of the l-th shark. The superscript '1' in Eq. (8) is the first iteration of the improved θ-SSO algorithm.

According to [12], $x_{l,p}^1$ can be obtained by the following equations

$$\theta_l^h = \left[\theta_{l,1}^h, \theta_{l,2}^h, \cdots, \theta_{l,ND}^h\right] \tag{9}$$

$$x_{l,p}^{h} = \frac{x_{l,p}^{\max} - x_{l,p}^{\min}}{2} \sin\theta_{l,p}^{k} + \frac{x_{l,p}^{\max} + x_{l,p}^{\min}}{2} \tag{10}$$

where $p = 1, \ldots, ND$, $x_{l,p}^{h} \in \left[x_{l,p}^{\min}, x_{l,p}^{\max}\right]$ and $\theta_{l,p}^{h} \in [-\pi/2, \pi/2]$.

(2) Evolutionary process

During this process, the shark's position and speed evolve according to its movement towards its prey. The improved θ-SSO algorithm consists of NP velocity vectors, $\left[V_1^1, V_2^1, \cdots, V_{NP}^1\right]$.

According to the observation of sharks in nature, the motion of sharks can be divided into "forward motion" and "rotational motion" in the improved θ-SSO algorithm. Early in the iteration, the sharks move forward. This motion can be mathematically established as follows.

$$V_l^1 = \left[v_{l,1}^1, v_{l,2}^1, \cdots, v_{l,ND}^1\right] \tag{11}$$

$$V_l^h = \eta_h R_1 \nabla\left(OF\right)\Big|_{X_l^h} \tag{12}$$

where V_l^1 is the l-th velocity vector, $l = 1, \ldots, NP$, $h = 1, \ldots, h_{\max}$, h and $h_{\max}$ represent the h-th iteration and the maximum number of the iteration respectively, R_1 randomly distributed within [0,1], and according to Eq. (7), the objective function is $OF = \sum_{l=1}^{n} \tilde{A}_{lp} x_l - \tilde{u}\left(x\right)$, and $\nabla\left(OF\right)$ defines its gradient.

Considering the speed in the $(h-1)$-th iteration $v_{l,p}^{h-1}$, the h-th speed can be obtained as

$$\left|v_{l,p}^{h}\right| = min\left\{\left|\eta_h R_1 \frac{\nabla\left(OF\right)}{\partial x_p}\right|_{x_{l,p}^{h}} + \alpha_h R_2 v_{l,p}^{h-1}\right|, \left|\beta_h . v_{l,p}^{h-1}\right|\right\} \tag{13}$$

where $\eta_h \in [0,1]$ and $\alpha_h \in [0,1]$ can be designed by the designer, R_2 randomly distributed within [0,1], and β_h is the velocity limit for the h-th iteration.

The $(h+1)$-th position of the shark in forward motion can be defined as

$$Y_l^{h+1} = X_l^h + V_l^h . \Delta t_h \tag{14}$$

where $\Delta t_h = t_{h+1} - t_h$.

The rotational motion of the shark is modeled as

$$Z_l^{h+1,m} = Y_l^{h+1} + R_3^m\left(Y_l^{best} - R_4^m Y_l^{h+1}\right) + R_5^m\left(Y_{l,1}^{h+1} - Y_{l,2}^{h+1}\right) \tag{15}$$

where R_3^m , R_4^m , R_5^m are three random numbers uniformly distributed in the range of [−1,+1], Y_l^{best} is the fastest position in $Y_l^1, Y_l^2, \ldots, Y_l^{k+1}$, and $Y_{l,1}^{h+1}$, $Y_{l,2}^{h+1}$ are two random selected positions in $Y_l^1, Y_l^2, \ldots, Y_l^{h+1}$.

Y_l^{best} in Eq. (15) can provide the positive guidance for the directional selection in rotational motion. The improved θ-SSO algorithm selects the quickest point instead of randomly picking the rotational direction. This learning mechanism allows the direction of the rotational motion to be closer to the best solution.

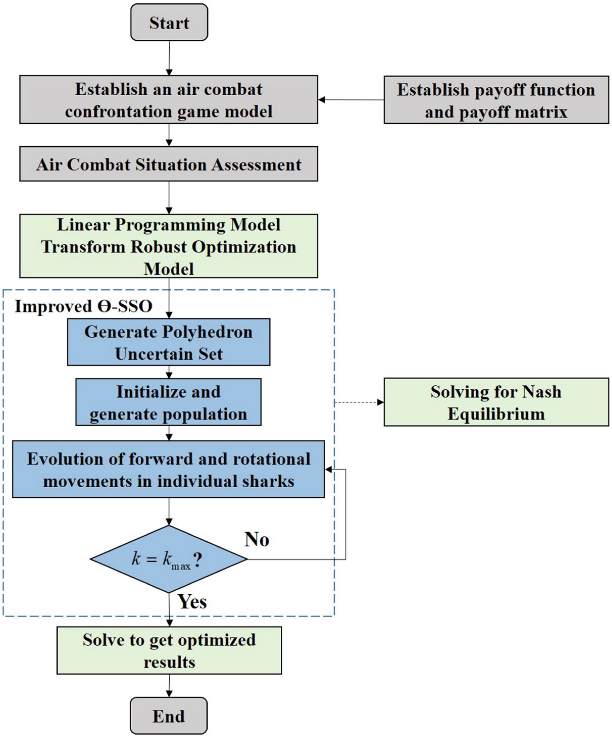

Fig. 2. Multi-UAV air combat game decision process

The position of the shark is chosen as the best of these points, which is the optimization problem of OF.

$$X_l^{h+1} = \arg\max \left\{ OF\left(Y_l^{h+1}\right), OF\left(Z_l^{h+1,1}\right), \ldots, OF\left(Z_l^{h+1,M}\right) \right\} \tag{16}$$

where $\arg\max\{\cdot\}$ returns the parameter with the maximum value of $OF(\cdot)$.

The multi-UAV air combat game decision process is shown in Fig. 2.

4 Simulation Examples

Assume that the capability of UAVs in a certain air combat is identical. The red side includes $R1$ and $R2$, and the blue side includes $B1$, $B2$, $B3$, and $B4$. The position information of both UAVs is obtained based on sensor data, as shown in Table 1.

Assuming that the detection distance of UAV is 80, the maximum attack distance is 150. The set of game decision strategies for both side is shown in Table 2.

Table 1. The location information of the UAVs at a certain moment in the air battle

UAV number	Abscissa $x\,(km)$	Altitude $z\,(km)$	Velocity $v\,(km/h)$	Angle $(^\circ)$
$R1$	0	90	60	0
$R2$	30	30	70	30
$B1$	100	10	80	100
$B2$	50	80	60	50
$B3$	90	10	40	90
$B4$	120	0	60	120

Table 2. Game decision strategy set

Strategy	Implication	Strategy	Implication
x_1	Our drone $R1$ attacks $B3$	y_1	Enemy drone $B3$ attacks $R1$
x_2	Our drone $R1$ attacks $B4$	y_2	Enemy drone $B3$ attacks $R2$
x_3	Our drone $R1$ attacks $B5$	y_3	Enemy drone $B4$ attacks $R1$
x_4	Our drone $R1$ attacks $B6$	y_4	Enemy drone $B4$ attacks $R2$
x_5	Our drone $R2$ attacks $B3$	y_5	Enemy drone $B5$ attacks $R1$
x_6	Our drone $R2$ attacks $B4$	y_6	Enemy drone $B5$ attacks $R2$
x_7	Our drone $R2$ attacks $B5$	y_7	Enemy drone $B6$ attacks $R1$
x_8	Our drone $R2$ attacks $B6$	y_8	Enemy drone $B6$ attacks $R2$

The polyhedral uncertain set is constructed based on Eq. (5). The Nash equilibrium is solved by the improved θ-SSO algorithm. Set the population number $NP = 10$, the maximum number of iterations $h_{\max} = 1000$, $\eta_h = 0.6$, $\alpha_h = 0.6$ and the speed limit rate $\beta_h = 0.8$. After initializing the shark population, each shark executes forward and rotating motions, with the following results:

$$x_1 = 0.0136, x_2 = 0.0477, x_3 = 0.9245, x_4 = 0.0142, \tilde{u}\,(x) = 0.0519$$
$$x_5 = 0.0241, x_6 = 0.0186, x_7 = 0.0684, x_8 = 0.8889, \tilde{u}\,(x) = 1.0147$$

The result of game decision is the UAV $R1$ of red side attacks the UAV $B5$ of blue side, and the UAV $R2$ of red side attacks the UAV $B6$ of blue side.

The fitness function value of the improved θ-SSO algorithm and PSO algorithm proposed in [4] as shown in Fig. 3. The improved θ-SSO algorithm converges substantially faster than PSO. At the same time, the optimal solution found by PSO is not as large as the solution found by the improved θ-SSO algorithm, so it is more suitable to apply the improved θ-SSO algorithm to solve this target game allocation problem.

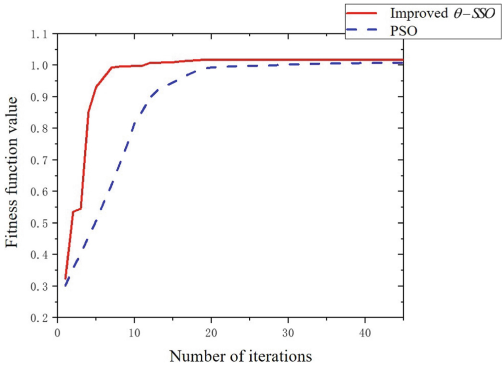

Fig. 3. Comparison curve between particle swarm algorithm and the improved θ-SSO algorithm

5 Conclusion

A new game decision method is proposed based on an improved θ-SSO algorithm in this paper. Firstly, a game model of decision-making with uncertain information is established. Then, the solution of the Nash equilibrium is transformed into a linear programming problem. To promote the efficiency of game decision, an improved θ-SSO algorithm is proposed to solve the uncertain game decision problem, and a simulation examples is provided to turn out the effectiveness of the algorithm.

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