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Path planning of unmanned aerial vehicle based on improved gravitational search algorithm

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Path planning of Uninhabited Aerial Vehicle (UAV) is a complicated global optimum problem. In the paper, an improved Gravitational Search Algorithm (GSA) was proposed to solve the path planning problem. Gravitational Search Algorithm (GSA) is a newly presented under the inspiration of the Newtonian gravity, and it is easy to fall local best. On the basis of introducing the idea of memory and social information of Particle Swarm Optimization (PSO), a novel moving strategy in the searching space was designed, which can improve the quality of the optimal solution. Subsequently, a weighted value was assigned to inertia mass of every agent in each iteration process to accelerate the convergence speed of the search. Particle position was updated according to the selection rules of survival of the fittest. In this way, the population is always moving in the direction of the optimal solution. The feasibility and effectiveness of our improved GSA approach was verified by comparative experimental results with PSO, basic GSA and two other GSA models.

uninhabited aerial vehicle, path planning, gravitational search algorithm, social information, weighted value, selection rules

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1 Introduction

Path planning of Uninhabited Aerial Vehicle (UAV) is a complicated global optimum problem, which is about seeking a superior flight route according to the mission objectives. Path planning is a key component of UAV mission planning system, which is to search out an optimal or near-optimal flight path between an initial location and the desired destination under specific constraint conditions [1–3]. Many factors are taken into consideration in modeling, such as terrain, data, threat information, fuel consumption and time constraint. Series of algorithms have been proposed to solve this complicated optimization problem, including feasible direction method, the A* algorithm and genetic algorithm (GA). The research on UAV path planning at home and abroad advances towards intelligence, real-time and realizability, but it is still in an original state.

Gravitational Search Algorithm (GSA) was originally presented as a new optimization algorithm by Esmat Rashedi in 2009, which is under the inspiration of the Newtonian gravity [4]. It is a heuristic algorithm similar to Particle swarm optimization (PSO) and the swarm intelligence instructed optimization research is produced by cooperation and competition among swarms in colony [5]. It has been proved to possess a better performance in a serial of optimization problems, compared with PSO algorithm and GA [6]. However, the algorithms have been proposed bring eas-

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ily premature convergence and are lack of effective acceleration mechanism.

To solve the problems above, an improved GSA is proposed to generate the feasible flight route. Firstly, we introduced the idea of memory and social information of PSO into GSA to get a superior performance. Secondly, a weighted value was assigned to inertia mass of every agent in each iteration process to accelerate the convergence speed of the search. Thirdly, the optimized solution saving strategy was used during the operation of selecting with reference to differential evolution (DE) algorithm [7]. The comparative experiments with PSO, basic GSA and two other GSA models are conducted, and the results show that our proposed method manifests better performance than the other models.

2 UAV path planning problem

We take the location that UAV flies into the enemy's defensive areas as a starting point and the tactical target's location of attack as the target point. Then we can obtain a network diagram connected the starting point and the target point by meshing the mission area. Thus the essence of the UAV path planning turns into a path-optimization problem. We assume that the UAV maintains constant flight altitude and speed when on a mission and the enemy's defensive areas are flat, in this way the path planning problem is simplified into a two-dimensional problem [8–10].

2.1 Environmental modeling for UCAV path planning

Modeling of the threat sources is a key part in UAV optimal path planning. In our model, define the starting point and the target point respectively as S and T, as is shown in Figure 1. There are some threatening areas in the mission region, such as radars, missiles, and anti-aircraft artillery, which all are presented in the form of a circle, inside of which will be vulnerable to the threat with a certain probability proportional to the distance away from the threat center, while out of which will not be attacked. The flight task is to generate an optimal path between S and T considering all these threatening areas.

Firstly, we connect point S and point T, and divide segment ST into D equal portions. At each segment point, draw the vertical line of ST, defined as $L_1, L_2, \cdots, L_k, \cdots, L_{D\text{-}1}$. Take a discrete point at each vertical segment L_k, engendering a collection of discrete points $\boldsymbol{C}=\{S, L_1(x(1), y(1)), L_2(x(2), y(2)), \cdots, L_k(x(k), y(k)), \cdots, L_D(x(D\text{-}1), y(D\text{-}1)), T\}$. By connecting the points in sequence we can get a flight path. In this way, the path planning problem is turning into optimizing the coordinates series to obtain a better fitness value of the objective function.

Coordinate conversion: We can let line ST be the x axis and take the coordinate conversion on each discrete point (x, y) according to eq. (2), where θ is the angle that the original x axis contrarotates to parallel segment ST and is presented by eq. (1), while (x', y') represents the coordinates in the original coordinate system and $\boldsymbol{AB}$ is the vector represents segment ST.

$$\theta = \arcsin \frac{y_2 - y_1}{\left|\overrightarrow{AB}\right|}, \tag{1}$$

$$\begin{pmatrix} x \\ y \end{pmatrix} = \begin{pmatrix} \cos\theta & \sin\theta \\ -\sin\theta & \cos\theta \end{pmatrix} \begin{pmatrix} x' \\ y' \end{pmatrix} + \begin{pmatrix} x_1 \\ y_1 \end{pmatrix}. \tag{2}$$

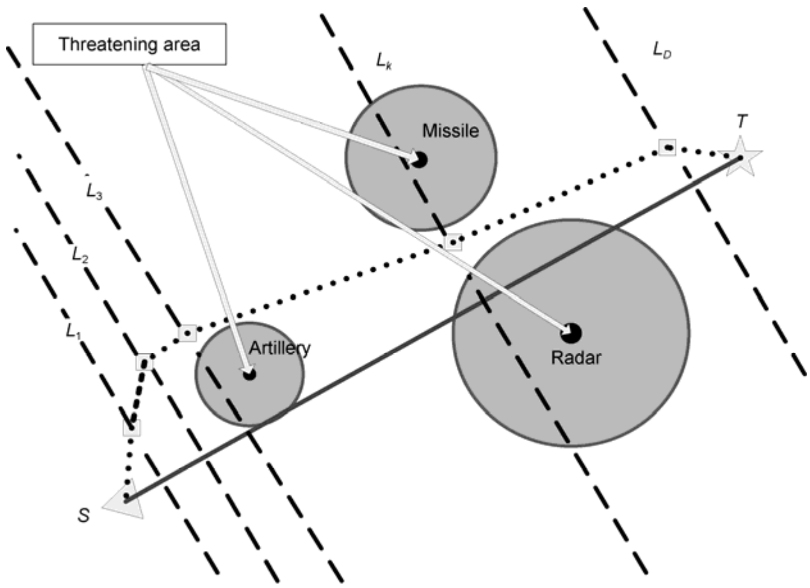

Figure 1 Typical UCAV battle field model.

2.2 Performance evaluation function of route optimization

The performance indicators of the UAV route mainly include the threat cost and the fuel consumption, and the calculating formulas of which are presented as follows [9]:

$$\min J = \int_0^L \left[kw_t + (1-k) w_f \right] \mathrm{d}s, \tag{3}$$

where J is the total cost for traveling along the trajectory, L is the total length of the generated path, and w_t and w_f are variables which denote the threat cost and fuel cost of each line segment on the route respectively, w_t is close related with the current path point and w_f can be considered equal to the length of path. While k is a adjustment coefficient between 0 and 1, which gives the designer certain flexibility to dispose relations between the threat exposition degree and the fuel consumption. When k is more approaching 1, a shorter path is needed to be planned, and less attention is paid to exposure to threats. Otherwise, when k is more approaching 0, it requires avoiding the threat as far as possible on the cost of more fuel consumption.

2.3 Cost of the threats

The cost factor of the i-th segment can be expressed as:

$$w_i = kw_{t,i} + (1-k) w_{f,i}, \quad (0 \leqslant k \leqslant 1), \tag{4}$$

where $w_{t,i}$ and $w_{f,i}$ denote the same with w_t and w_f , and k is the adjustment coefficient in eq. (3).

Assume that there is no inter-relationship between each threat. To simplify the calculations, a computationally more efficient and acceptably accurate approximation to the exact solution is adopted. In this paper, the threat cost of each edge connecting two discrete points was calculated at five points along it instead of calculating at all the points along it, as is shown in Figure 2. If the i-th edge is within the effect range, the threat cost is given by the expression

$$w_{t,L_{ij}} = \frac{L_{ij}^5}{5} \sum_{k=1}^{N_t} t_k \times \left(\frac{1}{d_{0.1,k}^4} + \frac{1}{d_{0.3,k}^4} + \frac{1}{d_{0.5,k}^4} + \frac{1}{d_{0.7,k}^4} + \frac{1}{d_{0.9,k}^4} \right), \tag{5}$$

where N_t is the number of threatening areas, L_{ij} is the sub-path length connected the i-th and the j-th discrete points, $d_{0.1,i,k}$ is the distance from the 1/10 point of L_{ij} to the k-th threat center, and t_k is the threat level of k-th threat.

3 Principle of basic GSA

Gravitation is the tendency of masses to accelerate toward each other. It is one of the four fundamental interactions in nature. Every particle in the universe attracts every other particle, as is shown in Figure 3. The gravitational force between two particles is directly proportional to their masses and inversely proportional to the square of the distance between them R according to Newton's Law of Gravitation (Substantial experiments show that superior result will be seen in GSA if R^2 was replaced with R [4, 6]):

$$F = G\frac{M_1 M_2}{R^2}, \tag{6}$$

where F is the magnitude of the gravitational force, G is gravitational constant, M_1 and M_2 are the mass of the first and the second particle respectively, and R is the distance between two particles.

According to newton's law of motion, when a force, F, is applied to a particle, its acceleration, a, depends only on the force and its mass, M, which can be expressed by

$$a = \frac{F}{M}, \tag{7}$$

where a is the acceleration of the particle under the action of force, F, and M represents the inertia mass of the particle.

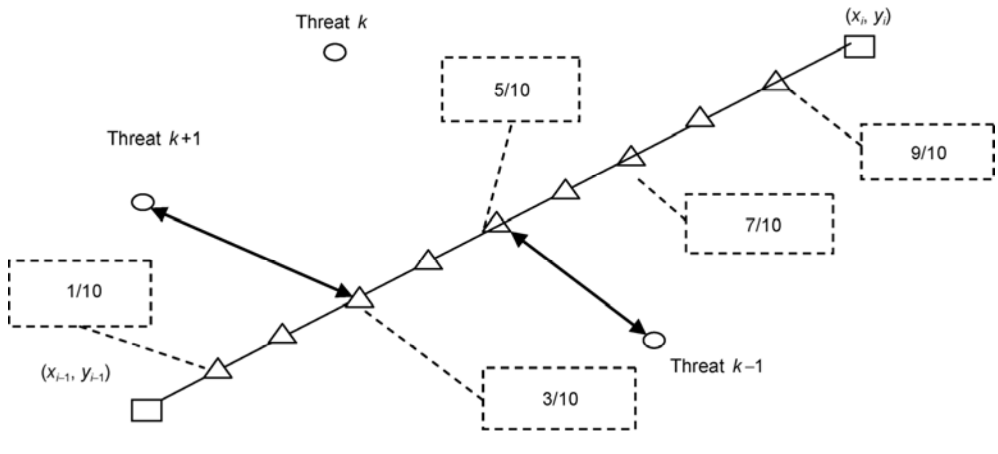

Figure 2 Calculation of the threats cost.

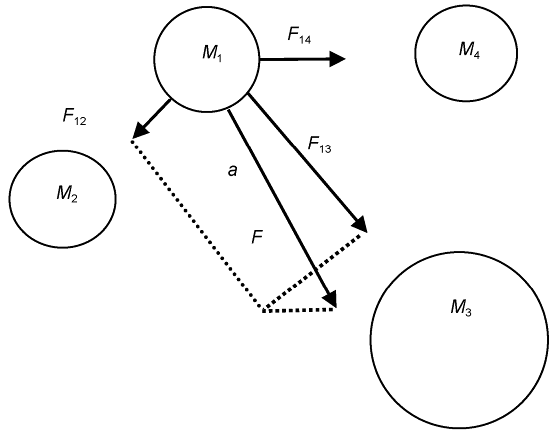

Figure 3 The law of gravity.

To describe the GSA, consider a system with N particles in a D-dimension search space:

$$X = (x_1, x_2, \cdots, x_N).$$

And position of the i-th particle is defined as follows:

$$X_i = (x_i^1, x_i^2, \cdots, x_i^d, \cdots, x_i^D), \quad \text{for } i = 1, 2, \cdots, N,$$

where x_i^d is position of the i-th mass in the d-th dimension and D is dimension of the search space.

The gravitational force that the j-th particle applied on the i-th particle at a specific time "t" can be defined as

$$F_{ij}^d(t) = G(t) \frac{M_{pi}(t) M_{aj}(t)}{R_{ij}(t) + \varepsilon} \left(X_j^d(t) - X_i^d(t) \right), \tag{8}$$

where M_{aj} is the active gravitational mass related to agent j, M_{pi} is the passive gravitational mass related to agent i, $G(t)$ is gravitational constant at time t, ε is a small constant, and $R_{ij}(t)$ is the Euclidian distance between two agents i and j at time t.

$G(t)$ is gravitational constant at time t

$$G(t) = G_0 \exp\left(-\alpha \times \frac{t}{T} \right), \tag{9}$$

where G_0 is the initial value of gravitational constant and we choose it as 100 in this work, and by adjusting α different gravitational constants will be got to control the search accuracy, while T represent the maximum iteration number.

$R_{ij}(t)$ is the Euclidian distance between two agents i and j at time t and it can be expressed as following:

$$R_{ij}(t) = \left\| X_i(t), X_j(t) \right\|_2. \tag{10}$$

To give a stochastic characteristic to our algorithm, we suppose that the total force acts on agent i in a dimension d be a randomly weighted sum of d-th component of the forces exerted from other agents in the GSA:

$$F_i^d(t) = \sum_{j=1, j \neq i} \text{rand}_i \times F_{ij}^d(t), \tag{11}$$

where rand_j is a random number in the interval [0,1], and F_{ij}^d is the force acting on agent i from agent j.

Acceleration of agent i at time t can be expressed as following:

$$a_i^d(t) = \frac{F_i^d(t)}{M_i(t)}, \tag{12}$$

where M_i represents the inertia mass of agent i.

Furthermore, the next velocity of an agent is considered as a fraction of its current velocity added to its acceleration. Therefore, its position and its velocity could be calculated as follows:

$$v_i^d(t+1) = \text{rand}_j \times v_i^d(t) + a_i^d(t), \tag{13}$$

$$x_i^d(t+1) = x_i^d(t) + v_i^d(t+1), \tag{14}$$

where rand_j is a uniform random variable in the interval [0, 1].

Gravitational and inertia masses are simply calculated by the performance evaluation function. We update the gravitational and inertial masses by the following equations:

$$M_{ai} = M_{pi} = M_{ii} = M_i, \quad i = 1, 2, 3, \cdots, N;$$

$$m_i(t) = \frac{\text{fit}_i(t) - \text{worst}(t)}{\text{best}(t) - \text{worst}(t)}, \tag{15}$$

$$M_i(t) = \frac{m_i(t)}{\sum_{j=1}^{N} m_i(t)}, \tag{16}$$

where $\text{fit}_i(t)$ represent the fitness value of the agent i at time t.

Worst(t) and best(t) are defined as follows (for a minimization problem in UAV path planning):

$$\begin{aligned} \text{best}(t) &= \min_{j \in \{1,2,\cdots,N\}} \text{fit}_j(t), \\ \text{worst}(t) &= \max_{j \in \{1,2,\cdots,N\}} \text{fit}_j(t). \end{aligned} \tag{17}$$

4 Improved gravitational search algorithm

4.1 Idea of memory and social information

For both GSA and PSO, the optimization value are generally obtained by agent movements in the global search space, however the movement strategies are different. In the searching procedure of GSA, the agent direction is calculated based on the overall force obtained by other agents, while GSA is memory-less and only the current position of the agents plays a role in the updating procedure. However, PSO uses a kind of memory and social information among agents [4] (respectively due to the best position of an individual and the best position agents have ever reached). And the searching strategy of PSO are expressed as:

$$v_i^d(t+1) = wv_i^d(t) + c_1\text{rand}_j\left(p_{\text{best}}^d - x_i^d(t)\right) + c_2\text{rand}_k\left(g_{\text{best}}^d - x_i^d(t)\right), \tag{18}$$

$$x_i^d(t+1) = x_i^d(t) + v_i^d(t+1), \tag{19}$$

where rand_j, rand_k are two random variables in the range [0, 1], c_1 and c_2 are positive constants, w is the inertia weight, p_{best} is the best previous position of the i-th particle and g_{best} is the best previous position all the agents have ever reached.

In this work, the basic GSA model is improved by adopting the idea of memory and social information of PSO. This scheme has a novel moving strategy in the searching space, obeying the law of gravity and receiving guide of memory and social information. The velocity updating equation can be defined as:

$$v_i^d(t+1) = \text{rand}_i v_i^d(t) + a_i^d(t) + c_1\text{rand}_j\left(p_{\text{best}}^d - x_i^d(t)\right) + c_2\text{rand}_k\left(g_{\text{best}}^d - x_i^d(t)\right), \tag{20}$$

where rand_i, rand_j, rand_k are random variables in the range [0, 1], c_1 and c_2 are variables in the range [0, 1]. We can balance the effectiveness of "law of gravity" and effectiveness of "memory and social information" through c_1 and c_2.

4.2 Optimized solution saving strategy

Selecting operation of the proposed method adopts the "survival of the fittest" strategy with reference to DE [11]. That is to say, to decide whether or not it should become a member of generation t+1, the trial vector new_i^t is compared to the target vector current_i^t using the greedy criterion. If the trial vector has less or equal objective function value than the corresponding target vector, the trial vector will replace the target vector and enter the population of the next generation. Otherwise, the target vector will remain in the population for the next generation. The selection procedure can be expressed by the following equation:

$$\text{path}_i^{t+1} = \begin{cases} \text{new}_i^t, & f(\text{new}) < f(\text{current}), \\ \text{current}_i^t, & \text{others}. \end{cases} \tag{21}$$

4.3 Weight-based principle

A heavy mass has a large effective attraction radius and hence a great intensity of attraction. Therefore, agents with a higher performance have a greater gravitational mass. As a result, the agents tend to move toward the best agent. Hence, agents with heavy inertia mass move slowly and search the space more locally. To have a faster convergence, we modified the principle of updating the inertial masses. With the weight-based principle, agents with heavy inertia mass become heavier, and those with small inertia mass become smaller. In this way, search ability of GSA has been enhanced.

After updating the inertia mass of agents according to original GSA, weight value K_i will be added to every agent in each iterative process. Weight value K_i is defined as follows:

$$K_i(t) = \frac{C_{\min}M_{\min} - C_{\max}M_{\max}}{M_{\min} - M_{\max}} - M_i, \tag{22}$$

where K_i represents the weight value added to the inertia mass of the i-th agent, $C_{\max}$ and $C_{\min}$ are respectively maximum and minimum weight value, while $M_{\max}$ and $M_{\min}$ are respectively maximum and minimum inertia mass of each agent.

4.4 Procedures of IGSA for path planning

The implementation procedure of our proposed improved GSA approach to UAV path planning can be shown with Figure 4.

The detailed procedure of our proposed improved GSA approach to UAV path planning can be described as follows.

Step 1. Initialize the detailed information about the path planning task according to the environmental modeling. In order to simplify the calculation, conduct the coordinate transformation on discrete points related with the task according to eqs. (1), (2). Divide segment ST into D equal portions, engendering a collection of discrete points, we take it as $P=\{p_1, p_2, \cdots, p_D\}$.

Step 2. Radomly initialize N flight paths within the bound of the battlefield.

Step 3. Calculate the cost of each path formed by relative parameters based on eqs. (3)–(5), and update the gravitational constant $G(t)$, minimum cost best(t) and maximum cost worst(t) according to eq. (9) and (17), then apply the weight-based principle to update the inertia mass of each agents.

Step 4. Calculate the acceleration of the agents in different directions based on eq. (11) and (12).

Step 5. Calculate velocity of the agents based on the principle (eq. (20)) introduced the idea of memory and social information with reference to PSO.

Step 6. Update the agents' position and execute selection using the greedy criterion (eq. (21)) to enhance the evolution direction.

Step 7. Repeat from Step 3 to Step 6 until the stopping criteria is reached.

Step 8. Transform the path to the original coordinates system, and output the result.

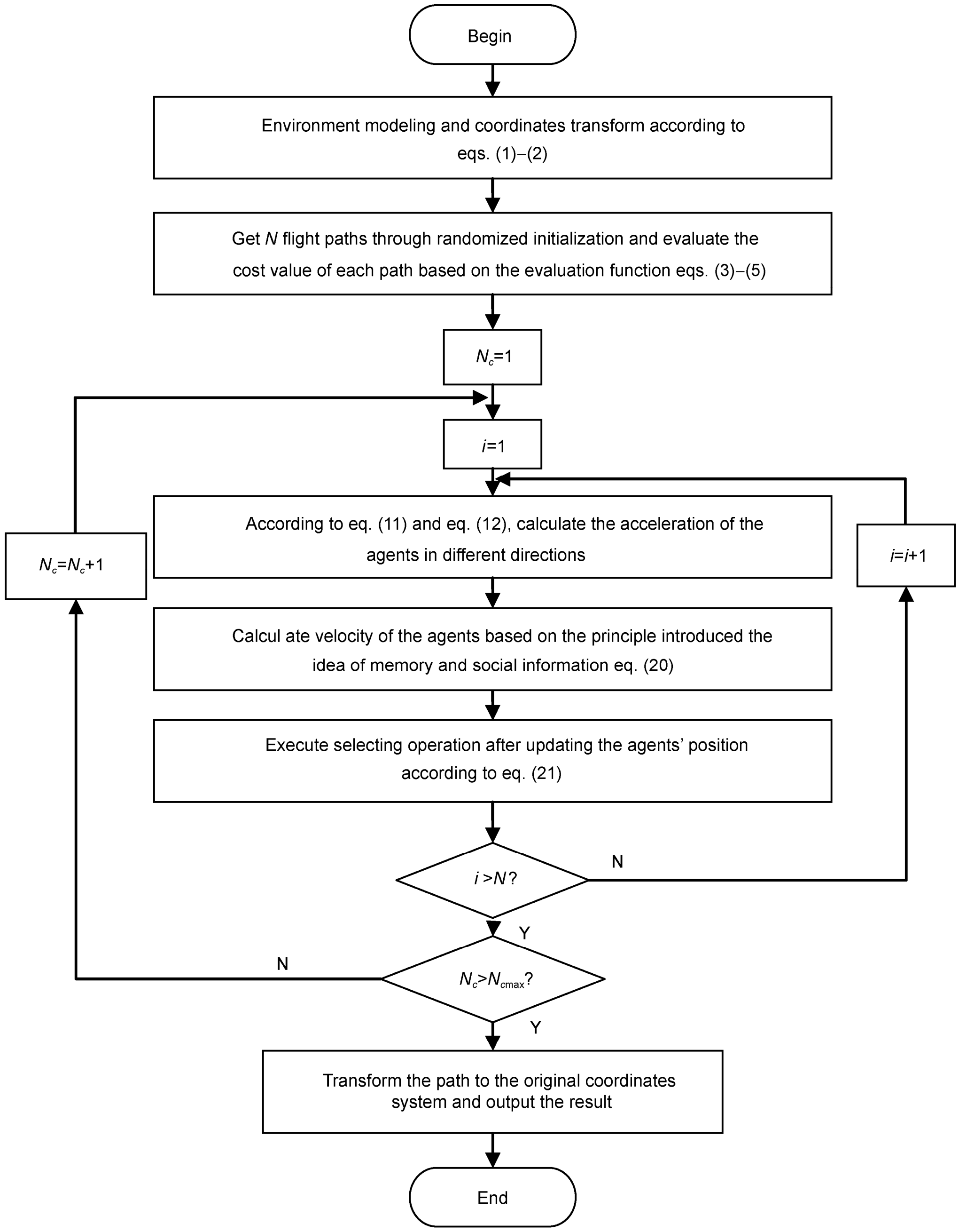

Figure 4 The procedure of our proposed IGSA.

5 Experimental results

In order to investigate the feasibility and effectiveness of the improved Gravitational Search Algorithm to UAV path planning, a series of comparative experiments with other methods have been conducted under complicated combating environments. The experiments are conducted with windows XP, and Matlab (ver 7.6). The detailed information about the path planning task, such as the coordinates of threat centers, threat radius and threat levels are set as follows.

The initialization of the parameters of our improved Gravitational Search Algorithm: In all cases, population size is set to 50 (N=50). Dimension is 15 (D=15), $N_{c\max}$=200. For the velocity updating formula, we have c_1=c_2=0.5, and the maximum and minimum weight value $C_{\max}$=5, $C_{\min}$=1 respectively. There are some threatening areas in the mission region, such as radars, missiles, and anti-aircraft artillery. The comparative experimental results (contains path planning result and evolution curves of the original GSA, the improved GSA and PSO) are shown in Figures 5 and 6.

It is noted that the "IGSA1" in Figure 5 represents the

Table 1 Task configuration of UAV

Starting point	Threat center	Threat radius	Threat level
[10, 10]	[45, 52]	13	2
Target	[17, 40]	13	10
[55, 100]	[28, 70]	10	1
k	[38, 26]	10	2
0.5	[58, 80]	16	5

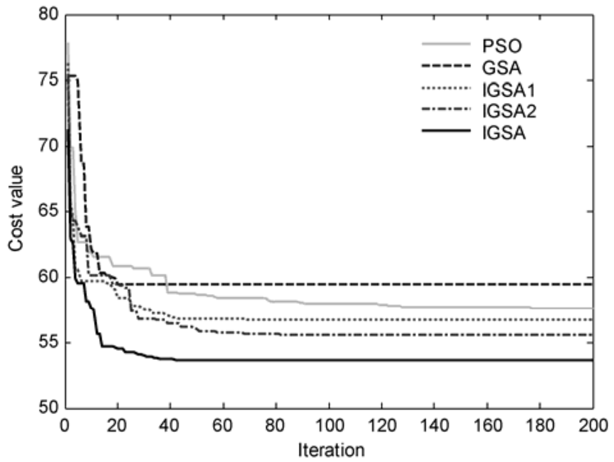

Figure 5 The comparative evolution curves of PSO, GSA and the improved GSA.

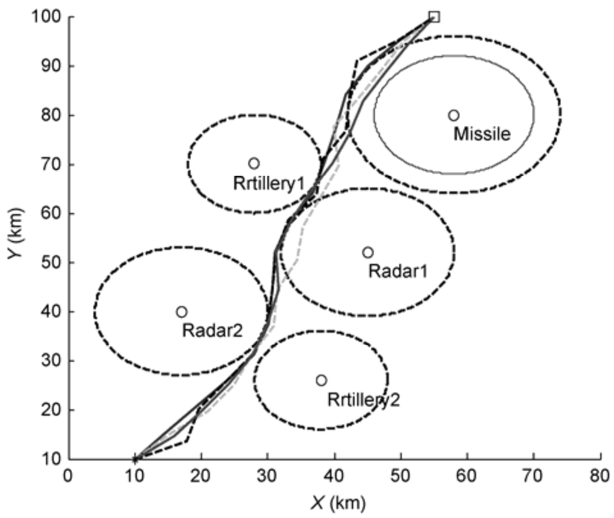

Figure 6 Path planning results of PSO, GSA and the improved GSA.

mation, while the "IGSA2" denotes the scheme with a weight-based principle and optimized solution saving strategy assigned to the original GSA.

It turns out our method can work better than the original GSA and PSO. As is shown in Figures 5 and 6, the path our scheme generated can bypassed the threat in the battlefield successfully, apparently showing that our method can find the feasible and optimal path for UAV more stable than basic GSA and PSO, and can effectively solve the path planning problem of UAV in complex combat field environment.

When the threaten radius reduced, we can recalculate the path according to the changed information. The simulation results can also be shown in Figure 6, which shows the feasibility of our IGSA under different combat field environment.

From the above experimental results, it is obvious that our improved gravitational search algorithm could jump out of the local optimum as well as speeding up the process of finding the optimal parameters. The experiments show that our proposed method is a more feasible and effective approach in solving UAV path planning problems, especially in complicated environments.

6 Conclusion

In this paper, a novel improved gravitational search algorithm is proposed. The idea of memory and social information of PSO is applied into GSA, and better performance can be attained in this way. Then, a weight-based GSA is proposed to improve the global searching ability by properly adjusting the inertia masses of agents. The optimized solution saving strategy was used during the operation of selecting with reference to differential evolution algorithm. The detailed procedure of the proposed approach for UAV path planning is also given in detail. The comparative experimental results show that our proposed method is more feasible and effective than other methods in UAV path planning.

Our future work will focus on the exact application of our proposed method in UAV path planning, re-planning and flight controller design [12]. Multiple robots and multiple UAVs coordinated control is also another hot issue in this field.

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