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Imperialist competitive algorithm optimized artificial neural networks for UCAV global path planning

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ABSTRACT

Unmanned combat aerial vehicle (UCAV), owing to its potential to perform dangerous, repetitive tasks in remote and hazardous, is very promising for the technological leadership of the nation and essential for improving the security of society. A novel hybrid method for the globally optimal path planning of UCAV is proposed in this paper, which is based on an artificial neural network (ANN) trained by imperialist competitive algorithm (ICA). The comparative experimental results with artificial bee colony (ABC) algorithm show that our proposed approach can not only reduce the uncertainty of the evolutionary computation caused by the probability model, but also avoid falling into local point with much quicker speed.

1. Introduction

Unmanned combat aerial vehicle (UCAV) is an unmanned aerial vehicle (UAV) that is designed to deliver weapons and attack targets without an onboard pilot. UCAV has the potential to perform dangerous, repetitive tasks in remote and hazardous environments, and has been one of the inevitable trends of the modern aerial weapon equipment [1]. Path planning is to generate a space path between an initial location and the desired destination that has an optimal or near-optimal performance under specific constraint conditions. The key techniques of the UCAV path planning include the information acquisition and the processing of the terrain and the enemy, the establishment of the threat model, the design of the planning algorithm and the path tracking control.

At present, due to the inherent technical idea of the fetters, there are very few intelligence elements in the newly-developed UCAV [2,3]. Based on the different task requirements and the battlefield environment, series of algorithms have been proposed to solve this complicated optimization problem, such as A* algorithm, evolutionary computation [1], particle swarm optimization (PSO) [4] and ant colony optimization (ACO) [5]. The processing algorithms given in Refs. [4,5], which are easily affected by constraint conditions, and the ability of anti-interference is rather weak. In this work, a novel approach based on artificial neural network (ANN) is proposed for UCAV global path planning problem, and imperialist competitive algorithm (ICA) has been applied to train the networks.

ICA was firstly proposed to solve the continuous optimization problems by Esmaeil and Lucas [6], which is a new bio-inspired computing algorithm for optimization of problems. While PSO, ACO and other swarm intelligence are designed by mimicking the natural behaviors, ICA was inspired by the imperialistic competition mechanism. The major advantage of ICA lies in that the weaker empire is assumed to be collapsed in the imperialistic competition process, and as a result the probability of finding the optimal parameters is significantly increased, which efficiently avoid local optimum to a large extent. ICA has been successfully used in image processing field [7], and ICA can also be adopted to optimize the flight path effectively. In this work, we mainly focus on UCAV path planning in two dimensions, just like our newly published work [8].

In this paper, we mainly focused on a novel type of artificial neural network trained by ICA, and utilize this hybrid method to solve UCAV global path planning problem. The remainder of this paper is organized as follows. Section 2 describes the environment modeling by artificial neural network, and the threat resources and collision energy function in UCAV global path planning are also given in this section. Section 3 specifies the optimization of neural network using the ICA. Then, in Section 4, comparative experimental results with ABC algorithm are given to verify the effectiveness of our proposed approach. Our concluding remarks are contained in Section 5.

2. Environment modeling by artificial neural network

Modeling of the threat sources is the key task issue in UCAV optimal path planning. In our model, we define the starting point

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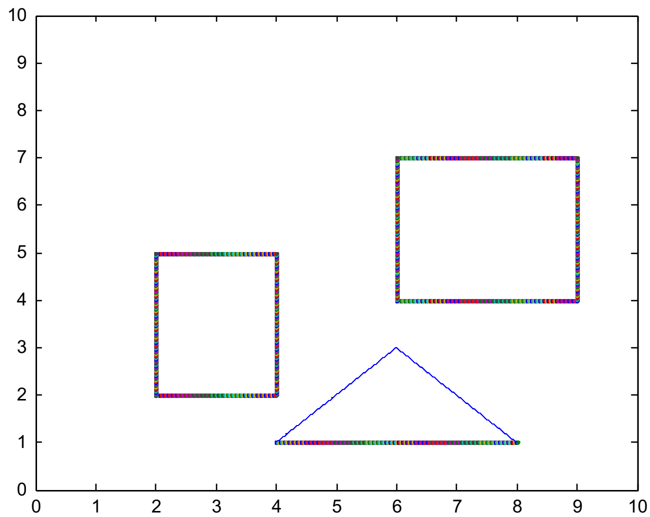

Fig. 1. Restriction condition of various obstacles.

as S and the target point as T, as is shown in Fig. 1. The flight task is to generate an optimal path between S and T considering all these threatening area. In the discussion, the UCAV is regarded as an agent and the obstacles should be expanded according to the radius of the UCAV [9].

The restriction condition of the obstacles can be represented by inequalities (1)–(3). Where x and y are any point in the workspace [10]. Inequalities of the obstacles are shown as follows:

$$\begin{cases} y-1>0 \\ -x-y+9>0 \\ -x-y-3>0 \end{cases} \tag{1}$$

$$\begin{cases} x-2>0 \\ -x+4>0 \\ y-2>0 \\ -y+5>0 \end{cases} \tag{2}$$

$$\begin{cases} x-6>0 \\ -x+9>0 \\ y-4>0 \\ -y+7>0 \end{cases} \tag{3}$$

In order to quantify the collision between the path and the obstacles, a hierarchical network model is established, which is well suitable for optimization design in accordance with the principle of artificial neural network, i.e. the collision penalty function. The neural network used to calculate the collision penalty function is shown in Fig. 2. The two nodes of the input layer represent the coordinates of the points along the path. The eleven nodes of the medium layer represent the eleven restrict conditions of the obstacles. The outputs of the nodes of the top layer represent the collision energy function corresponding to each obstacle [11].

The calculation of the collision energy function of the obstacles can be conducted according to the network. The collision energy function of the first obstacle can be calculated with the following equations [12]:

$$C_1 = f(T_1) \tag{4}$$

$$T_1 = \sum_{m=1}^{M} O_{Mm} + \theta_T \tag{5}$$

$$O_{Mm} = f(I_{Mm}) \tag{6}$$

$$I_{Mm} = \omega_{xm} X_i + \omega_{ym} Y_i + \theta_{Mm} \tag{7}$$

where C_1 is the output of the nodes of the top layer, T_1 is the input of the nodes of the top layer, M is the number of obstacle sides (see Fig. 1), θ_T is the threshold of the nodes of the top layer (which is equal to $-(N-0.5)$, and N is the number of inequalities), O_{Mm} is the output of the mth node of the medium layer, I_{Mm} is the input of the mth node of the medium layer, θ_{Mm} is the threshold of the mth node (equal to the constant term in inequalities), ω_{xm} and ω_{ym} are the coefficients of the restriction conditions of the connection of the middle and the top layers, respectively.

The membership function between the middle layer and the top layer is S-shaped function, whose equality $f(x)$ can be obtained by the following equation:

$$f(x) = \frac{1}{1+e^{-x/T}} \tag{8}$$

In this equation, the function parameter T influences the shape of the penalty functions.

Let (x_i,y_i) denote the coordinate of any point in the workspace of the UCAV. We assume that the speed of the obstacle remains the same, V_K, during the time between t_i and t_{i+1}. The x-axis component of the speed is v_{kx}, while the y-axis component of the speed is v_{ky}. Therefore, θ_{im} can be presented by function (9), and the expression between t_i and t_{i+1} satisfies function (10).

$$\begin{aligned} &\theta_{1m} = -(2+V_{kx}t_i), \quad \theta_{2m} = 4+V_{kx}t_i \\ &\theta_{3m} = -(6+V_{ky}t_i), \quad \theta_{4m} = 8+V_{ky}t_i \\ &\theta_{5m} = -(7+V_{kx}t_i), \quad \theta_{6m} = 9+V_{kx}t_i \\ &\theta_{7m} = -(2+V_{ky}t_i), \quad \theta_{8m} = 4+V_{ky}t_i \end{aligned} \tag{9}$$

$$t_{i+1} = t_i + \frac{\sqrt{(x_{i+1}-x_i)^2 + (y_{i+1}-y_i)^2}}{v(t_i)} \tag{10}$$

To accelerate the search speed of the algorithm, the line ST is set to be the x axis, and take the coordinate transformation on each discrete point $(x(K),y(K))$ according to Eq. (1), where θ is the angle that the original x axis contra rotates to parallel segment ST, K is the number of obstacles, and (x_s,y_s) represents the coordinates in the original coordinate system. The updated discrete point can be calculated by the following equation:

$$\begin{bmatrix} x'(K) \\ y'(K) \end{bmatrix} = \begin{bmatrix} \cos\theta & \sin\theta \\ -\sin\theta & \cos\theta \end{bmatrix} \begin{bmatrix} x(K)-x_s \\ y(K)-y_s \end{bmatrix} \tag{11}$$

3. Artificial neural network based on ICA

3.1. The basic principle of ICA

The optimization problem can be easily described as to find an argument x whose relevant cost $f(x)$ is optimum, and it has been extensively applied in many different situations, such as industrial planning, resource allocation, scheduling, pattern recognition, and so on. Different bio-inspired computing methods have been proposed to solve the optimization problem. For example, GA is a particular bio-inspired computing algorithm that evolves a population of candidate solutions to a given problem, using operators inspired by natural genetic variation and natural selection. PSO is another example which simulates the social behavior of animals. The inspiration source of ICA was first proposed by inspiration of imperialistic competition mechanism [6].

Similar to other bio-inspired computing algorithms that start with initial populations, ICA also begins with initial empires. Any individual of an empire is called a country. There are two types of countries; colony and imperialist state that collectively form

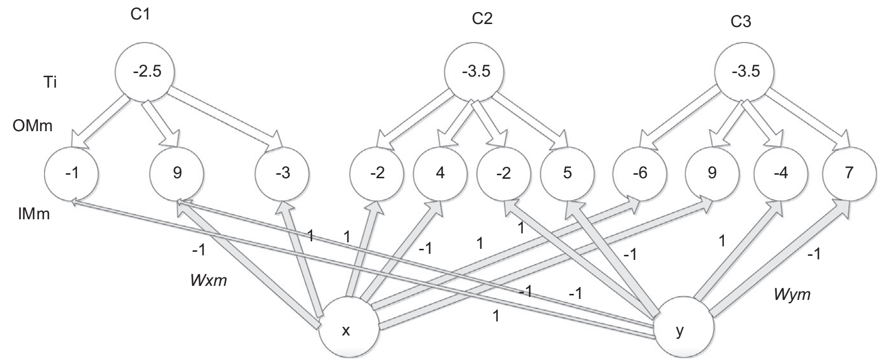

Fig. 2. Architecture of artificial neural network.

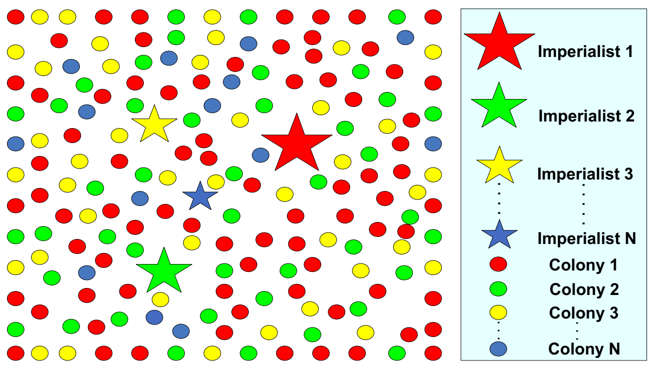

Fig. 3. The initial empires.

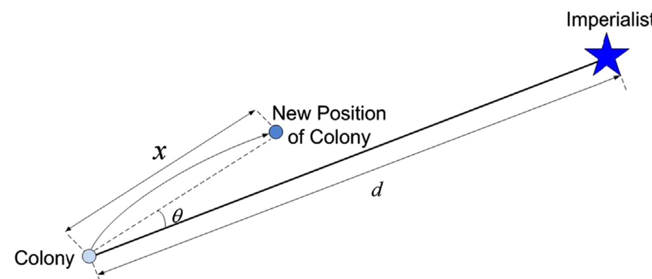

Fig. 4. Movement of colonies toward their relevant imperialist in random.

empires. Imperialistic competitions among these empires form the basis of the ICA. During this competition, weak empires collapse and powerful ones take possession of their colonies. Imperialistic competitions converge to a state in which there exists only one empire and its colonies are in the same position and have the same cost as the imperialist, which represents the best found solution of the matching problem.

First, initialize a number of countries which represent possible solutions of the matching problem, and select those with relatively high fitness to be the imperialist states, while the rest forms the colonies of these imperialists. As is shown in Fig. 3, the bigger empires have greater number of colonies while weaker ones have less [13].

Then, after forming initial empires, the colonies in each of them start moving toward their relevant imperialist country, and the moving model is shown in Fig. 4 [13]. While moving toward the imperialist, a colony might reach to a position with higher cost than that of imperialist. In this case, the imperialist and the colony change their positions. Then the algorithm will continue by the imperialist in the new position and then colonies start moving toward this position. After the exchanging step, calculate the total power of each empire, which depends on both the power of the imperialist country and the power of its colonies. Then, in the imperialistic competition process, all empires try to take the possession of colonies of other empires and control them. The imperialistic competition gradually brings about a decrease in the power of weaker empires and an increase in the power of more powerful ones, which is modeled by just picking some (usually one) of the weakest colonies of the weakest empires and making a competition among all empires to possess these (this) colonies. And when an empire loses all of its colonies, it is assumed to be collapsed.

After a while all the empires except the most powerful one will collapse and all the colonies will be under the control of this unique empire. In this ideal new world all the colonies have the same positions and same costs and they are controlled by an imperialist with the same position and cost as themselves, which means the algorithm converges to the best solution [8].

3.2. ICA-based ANN optimization

The objective of learning method is to develop the artificial neural network satisfying the criteria of accuracy as well as simplicity in complexity. As required, the overall model has to provide an accurate input–output mapping. This is achieved by minimizing the objective function which reflects the accuracy criterion, root-mean-square error (RMSE). As far as the structure of the artificial neural network is concerned, there are two components to be considered (optimized), in essence, the number of fuzzy rules, and the weight of each rule in consequent part.

In order to obtain the globally optimal parameters of the network, Imperialist competitive algorithm is applied to the artificial neural network system. Fig. 5 shows the optimization procedure of ICA-based artificial neural network optimization.

Step 1: Initialize a number of countries with the parameters of the artificial neural network and membership function, which include the number of rules and the weight of each rule in consequent part. We can get results with these initialized parameters of the network. Those with relatively high fitness will be the imperialist states, while the rest form the colonies of these imperialists. The number of colonies belong to each imperialist, which is related to the probability. The probability can be calculated according to the equation below:

$$P = \frac{Norm\_Imperialist\_Cost}{\sum_{i=1}^{m} sum(Norm\_Imperialist\_Cost)} \tag{12}$$

where *Norm_Imperialist_Cost* denotes the fitness of each imperialist state, m is the number of imperialist states.

Step 2: In the imperialistic competition process, the colonies start moving toward their relevant imperialist countries.

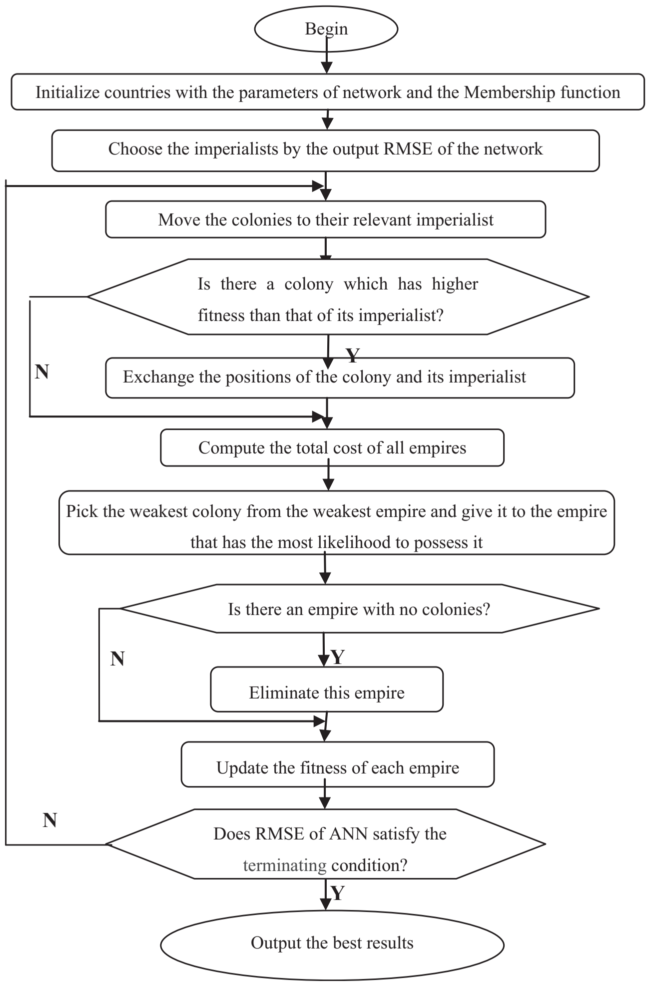

Fig. 5. The flowchart of ICA-based artificial neural network optimization.

In some cases, a colony might reach to a position with higher cost than that of the relevant imperialist, and as a result the imperialist and the colony change their positions. All empires try to take possession of colonies of other empires and control them. The imperialistic competition gradually brings about a decrease in the power of weaker empires and an increase in the power of more powerful ones, which is modeled by just picking some (usually one) of the weakest colonies of the weakest empires and making a competition among all empires to possess these (this) colonies.

Step 3: When an empire loses all of its colonies, it will be collapsed and becomes a colony of the strongest imperialist. In the end, all the empires except the most powerful one will collapse and all the colonies will be under the control of this unique empire. In this ideal new world all the colonies have the same positions and same costs and they are controlled by an imperialist with the same position and cost as themselves, which means that the algorithm converges to the best solution [6].

Step 4: In the imperialistic competition process, the parameters are optimized. If the maximum number of steps of the competition has been completed, or the maximum fitness value changes in a small range, the algorithm terminates. The fitness function is chosen to be a weighted sum of the threat and fuel costs:

$$J = kJ_t + (1-k)J_f \tag{13}$$

where k is a variable between 0 and 1, which gives the designer certain flexibility to dispose relations between the threat exposition degree and the fuel consumption. When k approaches 1, a shorter path is necessary to be planned, and less attention is paid to the radar's exposing threats. Otherwise, when k is more approaching 0, it requires avoiding the threat as far as possible on the cost of sacrificing the path length. The optimized path is found only when function J reaches its minimal value [8].

Step 5: Calculate the similarity value of the new colony, and in the moving process, if the colony reaches to a position with higher similarity value than that of its imperialist, change the positions between them.

Calculate the total power of the empires according to the following equation:

$$Tf_n = fitness(imperialist_n) + \xi mean\{fitness(colonies\_of\_empire)\} \tag{14}$$

where Tf_n is the total cost of the nth empire, and ξ is a positive number which is considered to be less than 1. A little value for ξ causes the total power of the empire to be determined by just the imperialist and increasing it will add to the role of the colonies in determining the total power of an empire. The value of 0.1 for ξ is a proper value in most of the implementations.

Step 6: Conduct the imperialistic competition work by just picking one of the weakest colonies of the weakest empires and making a competition among all empires to possess this colony.

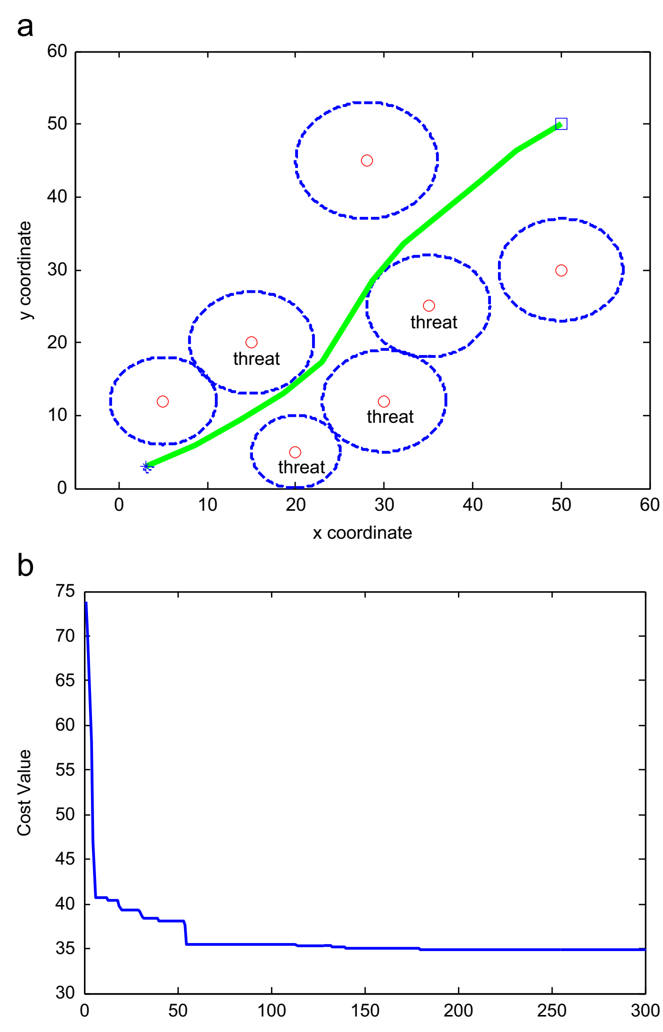

Fig. 6. The path planning result of condition 1. (a) UCAV global path planning by ABC Based ANN and (b) the evolution curve of ICA.

Step 7: If the RMSE of ANN satisfies the terminating condition or $NC < NC_{max}$, go to Step 2. Otherwise, output the optimal results.

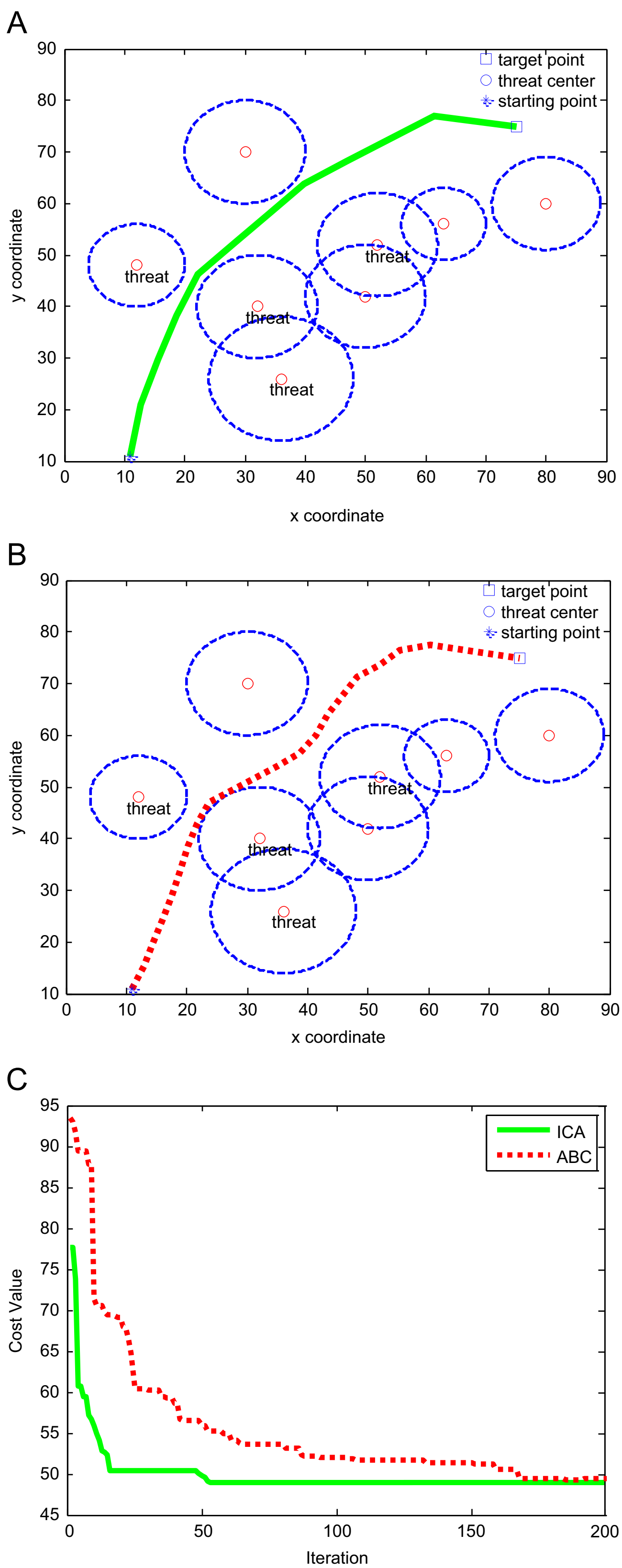

Fig. 7. Comparative results for UCAV global path planning of condition 2. (a) The global path planning result of ICA based ANN, (b) the global path planning result of ABC algorithm and (c) the evolution curves comparison of ICA and ABC.

4. Experimental results

In order to investigate the feasibility and effectiveness of the proposed method in this paper, series of comparative experiments with ABC algorithm have been conducted under complex combating field environments.

The algorithm was implemented in a Matlab 2010 programming environment on an Inter Core 2 PC running Windows 7, the hardware is a laptop with processing frequency of 2.3 GHz and 4 GB RAM. The initial parameters of ICA algorithm were set as: $NumOfCountries = 100$, $NumOfImper = 10$, $NumOfColony = 90$, $Nc_{max} = 300$, $\zeta = 0.1$.

Set the coordinates of the starting point as (3, 3), and the target point as (50, 50) in Fig. 6. Fig. 6(a) shows the UCAV path planning results in two-dimension space. The evolution curve presented in Fig. 6(b) shows the convergence curve of ICA. The symbol "⁎" denotes the starting point, the "○" denotes the threaten area, and the symbol "□" denotes the target point.

Set the coordinates of the starting point as (11, 11), and the target point as (75, 75) in Fig. 7. Fig. 7(a) shows the UCAV global path planning result of ICA based ANN in two-dimension space. Fig. 7(b) shows the UCAV global path planning result of ABC. The evolution curve presented in Fig. 7(c) shows the convergence curve of ICA based ANN.

From the experimental results presented in Figs. 6 and 7, it is obvious that the achieved path in Figs. 6(a) and 7(a) obviously maintains a favorable performance. In contrast of the results of ABC algorithm, our algorithm shows slight differences due to the calculating complexity. It is obvious that our proposed hybrid method can find a more feasible and global path for the UCAV than ABC approach. Furthermore, the successful rate of our method shows that ICA can find the feasible and optimal matching more stable and much quicker than the ABC algorithm.

5. Conclusion and future work

This paper presented a hybrid algorithm based on artificial neural network and ICA for UCAV global path planning problem in complicated combat field environment, and the comparative simulation experiments show that this hybrid method is more feasible and effective than ABC algorithm in UCAV two-dimension global path planning.

Our future work will focus on applying our proposed hybrid method to solve UCAV global path planning and re-planning problems in three-dimension. In addition, our proposed method will be also applied in multiple UCAV formation and close formation [14], which is another key issue in the near future.

Acknowledgments

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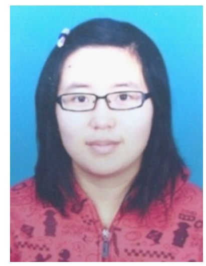

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