Research Article

Target Threat Assessment in Air Combat Based on Improved Glowworm Swarm Optimization and ELM Neural Network

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Target threat assessment technology is one of the key technologies of intelligent tactical aid decision-making system. Aiming at the problem that traditional beyond-visual-range air combat threat assessment algorithms are susceptible to complex factors, there are correlations between assessment indicators, and accurate and objective assessment results cannot be obtained. A target threat assessment algorithm based on linear discriminant analysis (LDA) and improved glowworm swarm optimization (IGSO) algorithm to optimize extreme learning machine (ELM) is proposed in this paper. Firstly, the linear discriminant analysis method is used to classify the threat assessment indicators, eliminate the correlation between the assessment indicators, and achieve dimensionality reduction of the assessment indicators. Secondly, a prediction model with multiple parallel extreme learning machines as the core is constructed, and the input weights and thresholds of extreme learning machines are optimized by the improved glowworm swarm optimization algorithm, and the weighted integration is carried out according to the training level of the kernel. Then, the threat assessment index functions of angle, speed, distance, altitude, and air combat capability are constructed, respectively, and the sample data of air combat target threat assessment are obtained by combining the structure entropy weight method. Finally, the air combat data is selected from the air combat maneuvering instrument (ACMI), and the accuracy and real-time performance of the LDA-IGSO-ELM algorithm are verified through simulation. The results show that the algorithm can quickly and accurately assess target threats.

1. Introduction

With the continuous development of airborne radar technology and the increasing lethality of air-to-air missiles, the beyond-visual-range air combat has gradually developed into one of the main combat methods of modern air combat [1]. Target threat assessment is an important link in the decision-making process of air combat beyond the visual. The purpose is to predict the threat level of each batch of incoming targets to our aircraft based on the battlefield situation information and determine the threat order of the targets. It is helpful for our pilots to make reasonable decisions, take corresponding maneuvers, improve survivability, and win the initiative on the battlefield through accurate and reasonable assessment of enemy target threats [2]. Therefore, how to accurately and quickly threat assessment in a complex air combat environment is becoming a hot current topic.

The current methods used in air combat target threat assessment are mainly divided into two categories [3]. The one is based on the establishment of a specific threat assessment model; the other is an assessment method based on intelligent algorithms. The modeling method is to quantify the threat degree of the target by establishing a mathematical model of the target threat assessment index. The commonly used theories include attribute decision-making method, fuzzy reasoning, D-S evidence theory, grey correlation method, TOPSIS method, Bayesian network, and game theory. For example, a target threat assessment method based on fuzzy logic is proposed in literature [4, 5] by constructing the membership function of the threat assessment parameters. A target threat assessment model based on cloud model for the uncertainty of information is proposed in literature [6]. The Bayesian inference network is used to solve the problem of target threat assessment in literature [7]. A hybrid threat assessment method based on intuitionistic

fuzzy sets that can handle the uncertainty of information is proposed in literature [8]. A threat index method based on multiattribute decision-making theory for target threat assessment problem is proposed in literature [9]. The most representative and widely used method is the threat index method. The advantages of this modeling method are simple principle, easy to implement, accurate, and convincing evaluation results. However, the disadvantage is that the modeling is relatively complicated, the amount of calculation is large, and the algorithm execution time is long. In practical applications, it is difficult to meet the real-time requirements.

The evaluation method of intelligent algorithm is mainly to transform the target threat problem into a nonlinear prediction method, and the threat evaluation problem is equivalent to the prediction problem of multivariate function [10]. The assessment parameters are taken as input and the threat value of target as output, and the assessment model trained by the air combat data is used to predict the threat value of the target. For example, neural network and its improved algorithm are used for target threat assessment in literature [11, 12], and regression support vector machine is used for target threat assessment in literature [13]. A target threat assessment method based on fuzzy neural network is proposed in literature [14], which integrates the advantages of neural network and fuzzy theory to make the target threat assessment result more accurate and credible. In order to improve the accuracy of target threat assessment, a target threat assessment model based on gray wolf algorithm and wavelet neural network is proposed in literature [15], which improves the prediction accuracy and generalization ability of the model. The quantum computing characteristics of quantum evolutionary algorithm and the divide-and-conquer idea of cooperative coevolution evolutionary algorithm are combined to propose an improved differential evolution in literature [16]. The pricing problem of arithmetic average Asian barrier options in the continuous case is studied, and the corresponding reliability index is analyzed in literature [17]. To improve exploration ability, convergence accuracy, and convergence speed, an improved differential evolution algorithm with neighborhood mutation operators and opposition-based learning is developed in literature [18]. An improved quantum evolutionary algorithm (QEA) based on the niche coevolution strategy and enhanced particle swarm optimization (PSO) is designed in literature [19]. Neural network is used to approximate the unknown nonlinear term in the system in literature [20]. The advantage of the evaluation method using intelligent algorithms is that it does not require complex evaluation process modeling. On the contrary, the machine learning algorithm is used to explore the intrinsic relationship between the threat value target and the evaluation parameter, which makes the calculation of the evaluation process easier, thereby reducing the evaluation time and improving the efficiency. However, the disadvantage is that the above methods rely on the experience of experts to determine the weight of threat assessment indicators, which are highly subjective and cannot truly reflect the complex nonlinear relationship between threat assessments. At the same time,

the lack of available air combat training data leads to insufficient training of neural networks and the difficulty of determining the structure of the neural network, and it is easy to fall into local extreme values. Through the above analysis, the current existing threat assessment methods have some shortcomings. Therefore, it is urgent to find a threat assessment method with high accuracy and good real-time performance.

In order to improve the accuracy and real-time performance of target threat assessment, an air combat target threat assessment model based on improved glowworm swarm optimization algorithm to optimize ELM neural network is proposed in this paper. Firstly, the training data is dimensionally reduced and classified by linear discriminant analysis (LDA) so that the redundancy and correlation between indicators are eliminated, and the training data is divided into medium range and long range according to the target distance. Then, an ELM neural network that optimizes input weights and thresholds is constructed using the improved glowworm swarm optimization algorithm with linearly decreasing inertia weights, so as to well overcome the shortcomings of traditional BP neural network such as slow training speed and easy to fall into local minimums [21]. On this basis, the ELM grouped multitask learning algorithm is adopted to improve the learning effect of the training data. In this method, a hypersphere multitask learning model is proposed to optimize the integration of multiple ELMs, which effectively improves the generalization ability of ELM neural network and greatly improves the robustness of ELM. In addition, the structure entropy weight theory is used to preprocess the training data, which effectively improves the objectivity and credibility of the training samples and improves the accuracy of the target threat assessment model.

The main contributions of this paper are as follows: (1) linear discriminant analysis can effectively reduce and classify the training sample data, improve the quality of data, and eliminate the correlation between parameters; (2) an ELM neural network using IGSO optimizes the weights and thresholds between the input layer and the hidden layer; results are presented to demonstrate its performance, effectiveness, and faster adaptation capability and accuracy; and (3) the hypersphere multitask learning algorithm is used to carry out the weighted integration of the independent parallel training ELM neural network, and the experiment shows that the method can effectively improve the prediction speed and accuracy of IGSO-ELM.

The paper is organized as follows. Section 2 presents a background on linear discriminant analysis method. Section 3 describes the improved glowworm swarm optimization algorithm. Section 4 describes the ELM neural network. Section 5 establishes target threat assessment model based on IGSO-ELM. The experimental results are presented and analyzed in Section 6. Section 7 presents concluding remarks.

2. Linear Discriminant Analysis Method

Linear discriminant analysis (LDA) is a linear classification statistical method for feature extraction in multivariate

statistics. The purpose of this method is to extract the most discriminant low-dimensional features from the high-dimensional feature space. These features are used to gather all samples of the same category and separate samples of different categories as much as possible, which is to choose the feature that maximizes the ratio of the dispersion between the classes of the samples to the dispersion within the classes. The Fisher criterion function is used in the linear discriminant analysis method. The definition of the Fisher criterion function is

$$J(\mathbf{w}) = \operatorname{argmax} \frac{|\mathbf{w}^T \mathbf{S}_b \mathbf{w}|}{|\mathbf{w}^T \mathbf{S}_w \mathbf{w}|} = [w_1, w_2, \dots, w_d], \quad (1)$$

where $\mathbf{S}_b$ and $\mathbf{S}_w$ are the interclass dispersion matrix and the intraclass dispersion matrix of the sample, and their definitions are as follows:

$$\begin{aligned} \mathbf{S}_b &= \sum_{i=1}^c \frac{N_i}{N} (\bar{x}_i - \bar{x})(\bar{x}_i - \bar{x})^T, \\ \mathbf{S}_w &= \sum_{i=1}^c \sum_{j=1}^{N_i} \frac{1}{N} (x_{ij} - \bar{x}_i)(x_{ij} - \bar{x}_i)^T, \end{aligned} \quad (2)$$

where N is the number of all samples; c is the number of sample categories; $N_i (i = 1, 2, \dots, c)$ is the number of samples in the i th category; $x_{ij} (i = 1, 2, \dots, c; j = 1, 2, \dots, N_i)$ is the j th sample in the i th category; $\bar{x}$ is the average of all samples; and $\bar{x}_i (i = 1, 2, \dots, c)$ is the mean value of the sample of the i th category.

The LDA method is used to find a vector set $\mathbf{w} = [w_1, w_2, \dots, w_d]$ by solving the optimal value of formula (1), so that after the samples are projected on the vector, the sample dispersion of different categories is as large as possible, and the sample dispersion within each category is as small as possible.

In formula (1), $J(w)$ is the generalized Rayleigh entropy, which can be solved by Lagrange multiplier method. Let the denominator be equal to a nonzero constant, let $\mathbf{w}^T \mathbf{S}_w \mathbf{w} = C \neq 0$, and define the Lagrange function as

$$L(w, \lambda) = \mathbf{w}^T \mathbf{S}_b \mathbf{w} - \lambda (\mathbf{w}^T \mathbf{S}_w \mathbf{w} - C), \quad (3)$$

where λ is the Lagrange multiplier. Taking the partial derivative of w in formula (3),

$$\frac{\partial L(w, \lambda)}{\partial w} = \mathbf{S}_b \mathbf{w} - \lambda \mathbf{S}_w \mathbf{w}. \quad (4)$$

Let the partial derivative of formula (4) be zero, and $\mathbf{S}_b \mathbf{w}^* - \lambda \mathbf{S}_w \mathbf{w}^* = 0$ is obtained, namely,

$$\mathbf{S}_b \mathbf{w}^* = \lambda \mathbf{S}_w \mathbf{w}^*, \quad (5)$$

where $\mathbf{w}^*$ is $\mathbf{w}$ when $J(w)$ reaches the maximum value. When $\mathbf{S}_w$ is nonsingular, multiply both sides of formula (5) by $\mathbf{S}_w^{-1}$ to get

$$\mathbf{S}_w^{-1} \mathbf{S}_b \mathbf{w}^* = \lambda \mathbf{w}^*. \quad (6)$$

To sum up, when $\mathbf{S}_w$ is a nonsingular matrix, mathematically solving formula (6) is equivalent to solving the eigenvalue problem of $\mathbf{S}_w^{-1} \mathbf{S}_b$, so that the maximum transformation matrix $\mathbf{w}$ of $J(w)$ is composed of eigenvectors corresponding to the first m maximum eigenvalues of $\mathbf{S}_w^{-1} \mathbf{S}_b$.

3. Improve Glowworm Swarm Optimization Algorithm

3.1. Glowworm Swarm Optimization Algorithm. The glowworm swarm optimization algorithm is a new swarm search stochastic optimization algorithm proposed by Yang Xin She, a scholar in Cambridge, UK, simulating the luminous behaviour of glowworm in reality [22]. The bionic principle is as follows: the point in the search space simulates the individual of the glowworm, each glowworm individual carries the respective luciferin, and the value of the luciferin can measure the advantages and disadvantages of the individual position, which is the advantages and disadvantages of the solution. At the same time, each individual has its own perception range, which is also called decision range. Individuals can only look for excellent individuals (individuals with a high luciferin value) and move them thereon within a certain perceptual range. In the end, the optimization is implemented by repeated selection to move in the search space.

In the GSO algorithm, each glowworm i is defined by the current position $x_i(t)$ and the luciferin value allied $l_i(t)$ at time t , and $f(x_i(t))$ represents the value of objective function at agent i 's location at time t . During the execution of the algorithm, each glowworm transmits information to neighborhood within its regional decisions. Under the initial conditions, the target function definition domain is used as the initialization decision scope of the GSO algorithm and then updates the decision domain range by:

$$r_d^i(t+1) = \min \{r_s, \max \{0, r_d^i(t) + \beta(n_t - |N_i(t)|)\}\}, \quad (7)$$

where $r_d^i(t)$ represents the variable neighborhood range associated with glowworm i at time t . The variable is bounded by a radial sensor range ($0 < r_d^i < r_s$); $N_i(t) = \{j : d_{ij}(t) < r_d^i; l_i(t) < l_j(t)\}$ is the set of neighborhood of glowworm i at time t ; $d_{ij}(t)$ represents the Euclidean distance between glowworm i and j at time t . n_t represent a parameter being used to control the number of neighbors, and β is a constant parameter.

According to the concept of GSO algorithm, each glowworm will be attracted to their neighbors that glow brighter. Consequently, during the movement phase, glowworm used a probabilistic mechanism to move towards their neighbor having a higher intensity of luciferin than theirs. For each

glowworm i , the probability of movement towards a neighbor is given by

$$p_{ij}(t) = \frac{l_j(t) - l_i(t)}{\sum_{k \in N_i(t)} l_k(t) - l_i(t)}. \quad (8)$$

Then, the discrete time model of the glowworm movement can be stated as

$$x_i(t+1) = x_i(t) + s \left(\frac{x_j(t) - x_i(t)}{\|x_j(t) - x_i(t)\|} \right), \quad (9)$$

where $s(>0)$ represents the step size and $\|\cdot\|$ is the Euclidean norm operator. Then, $x_i(t) \in R^m$ represent the location of glowworm i at time t in the m -dimensional real space R^m .

After glowworm i moved to a new location, the luciferin update rule is given by

$$l_i(t) = (1-\rho)l_i(t-1) + \gamma f(x_i(t)), \quad (10)$$

where $\rho \in (0, 1)$ is the luciferin decay constant, γ is the luciferin enhancement constant.

In the neighbor set, when the glowworm i finds a glowworm j with a higher luciferin value and if the distance between the glowworm i and the glowworm j at this time is less than the radial sensor range, the glowworm i selects the glowworm j with the probability $p_{ij}(t)$ (calculated by formula (8)) and moves in that direction. Then, update the position according to formula (9) and calculate the objective function value of the new position. Finally, the luciferin value is updated according to formula (10).

3.2. Improved Glowworm Swarm Optimization Algorithm. In the later iteration of the standard glowworm swarm optimization algorithm, since the glowworm has gradually moved to the vicinity of the local or global extreme point, the distance between the glowworms gradually reduced at this time. According to the position update formula (9), the gradual increase in the attraction between glowworms will cause the individual glowworms to move too long and to not reach or miss the optimal position, causing the problem of oscillation near the extreme point.

On the basis of the standard glowworm swarm optimization algorithm, an improved glowworm swarm optimization algorithm based on linearly decreasing weight function is proposed in this paper; the location update formula becomes:

$$x_i(t+1) = w(n)x_i(t) + s \left(\frac{x_j(t) - x_i(t)}{\|x_j(t) - x_i(t)\|} \right), \quad (11)$$

$$w(n) = w_{\max} - (w_{\max} - w_{\min}) \times \frac{n}{n_{\max}}$$

where $w_{\max}$ and $w_{\min}$ are the maximum and minimum weights, respectively. n and $n_{\max}$ are the current and maximum iteration steps, respectively.

The influence of the glowworm previous position information on the current position can be controlled by the inertial weight. The weight determines the distance the glowworm moves and balances the global optimization and local search capabilities of the glowworm swarm optimization algorithm. When the weight value is larger, the current position of glowworm will have a greater influence on the next position to be moved. The attractiveness of glowworm is relatively small, and the global search ability is enhanced, while the local search ability is relatively weakened. Conversely, the current position of the glowworm will have less influence on the next position to be moved, and the attraction between the glowworm will be relatively large. The global search capability is weakened, while the local search capability is relatively enhanced. Therefore, by adjusting the value of inertia weight $w(n)$, the glowworm swarm optimization algorithm can have a strong global search ability in the early stage of search, which is helpful to accelerate the global convergence speed. At the later stage of the search, the weight gradually decreases with the iteration, and the search area of the individual glowworm also becomes smaller, but the local search ability is enhanced. The search ability of glowworm near the extreme points is enhanced to avoid repeated oscillations caused by excessive moving distance.

4. ELM Neural Network

4.1. Introduction of ELM Neural Network. Extreme learning machine (ELM) is a machine learning algorithm based on a single-hidden-layer feedforward neuron network proposed by Professor G.B. Huang of Nanyang Technological University in 2004 [14]. The characteristic of the extreme learning machine algorithm is that the hidden-layer node parameters are randomly selected without adjustment during the training process. The neural network only sets the number of neurons in the hidden layer to obtain the unique optimal solution. The output weight of the network is the least-square solution obtained by the least-square loss function, which is ultimately reduced to the Moore-Penrose generalized inverse problem for solving a matrix. In this way, the process of determining network parameters does not require any iterative steps, thereby greatly reducing the adjustment time of network parameters. Compared with traditional training methods, the extreme learning machine has the advantages of fast learning speed and better generalization performance [23, 24].

Consider standard single-hidden-layer feedforward neural networks (SLFNs) with L hidden nodes, n input neurons, m output neurons, and activation function $g(x)$. Given N arbitrarily different training samples $\{(\mathbf{x}_j, \mathbf{t}_j)\}_{j=1}^N$, where $\mathbf{x}_j = [x_{j1}, x_{j2}, \dots, x_{jn}]^T \in \mathbf{R}^n$ is the n dimension input vector of the j th sample and $\mathbf{t}_j = [t_{j1}, t_{j2}, \dots, t_{jm}]^T \in \mathbf{R}^m$ is the corresponding expected output vector, then the network can be mathematically modeled as

$$f_j(x) = \sum_{i=1}^L \beta_i g(\mathbf{w}_i \mathbf{x}_j + \mathbf{b}_i) \quad j = 1, 2, \dots, N, \quad (12)$$

where $\mathbf{w}_i = [w_{i1}, w_{i2}, \dots, w_{in}]^T$ is the weight vector connecting the i th hidden neuron and the input neurons, $\beta_i = [\beta_1, \beta_2, \dots, \beta_L]^T$ is the weight vector connecting the i th hidden neuron and the output neurons, b_i is the bias of the i th hidden neuron, and $g(\mathbf{w}_i \mathbf{x}_j + \mathbf{b}_i)$ denotes the output function of the i th hidden node which is bounded.

The output of the neural network can also be expressed as follows:

$$\mathbf{H}\beta = \mathbf{T}, \quad (13)$$

where $\mathbf{H}$ is the output matrix of hidden layer, β is the output weight matrix of the hidden layer, and $\mathbf{T}$ is the expected output.

$$\begin{aligned} \mathbf{H} &= [\mathbf{h}(\mathbf{x}_1)^T, \dots, \mathbf{h}(\mathbf{x}_N)^T]^T \\ &= \begin{bmatrix} g(w_1 x_1 + b_1) & \cdots & g(w_L x_1 + b_L) \\ \vdots & \ddots & \vdots \\ g(w_1 x_N + b_1) & \cdots & g(w_L x_N + b_L) \end{bmatrix}_{N \times L}, \quad (14) \\ \mathbf{T} &= [t_1, t_2, \dots, t_N]^T. \end{aligned}$$

The hidden node parameters (w_i, b_i) remain fixed after being randomly generated. The training of a SLFNs is equivalent to finding a least-square solution $\hat{\beta}$ of the linear system $\mathbf{H}\beta = \mathbf{T}$. That is,

$$\|\mathbf{H}\hat{\beta} - \mathbf{T}\| = \min_{\beta} \|\mathbf{H}\beta - \mathbf{T}\|. \quad (15)$$

The smallest norm least-square solution of the above linear system is

$$\hat{\beta} = \mathbf{H}^+ \mathbf{T}. \quad (16)$$

where $\mathbf{H}^+$ represents the Moore-Penrose generalized inverse of the hidden-layer output matrix $\mathbf{H}$.

4.2. LDA-ELM Algorithm. ELM neural network has the advantages of strong generalization ability, fast calculation speed, and simple structure, but some researchers have found that the robustness of ELM caused by input variables has become the bottleneck for further development of ELM. Beyond-visual-range air combat is an extremely complex confrontation process. The complex electromagnetic environment will cause great noise interference to the situation data obtained by our airborne sensors. These high-dimensional mixed data will increase the training error of the ELM neural network and reduce the accuracy of the prediction. A LDA-ELM algorithm model is proposed in this paper, and the steps of which are as follows: first, the original data is dimensionally reduced and classified through the LDA method to reduce the correlation between the input data and ensure that the input variables are highly correlated with the output. Then, the kernel

based on the ELM neural network is trained independently and in parallel. Finally, a hypersphere multitask learning algorithm is adopted to integrate the kernel according to its training degree, and the final prediction result is obtained.

As shown in Figure 1, when mixed data with noise enters the LDA-ELM model, it will first be cleaned by the LDA algorithm to eliminate the correlation between the data as much as possible, which greatly improves the reliability of the original data. Then, the processed data is sent to different ELM kernels for training in parallel. Finally, the weights of well-trained kernels will be increased and the weights of poorly trained kernels will be reduced, and the output results of different kernels will be selectively and optimally integrated.

Suppose there are N ELM neural network kernels, and each ELM neural network can be regarded as a learning task. The training samples are all taken from the same sample space $\mathbf{X} \times \mathbf{Y} \subset \mathbf{R}^d \times \mathbf{R}$. Each learning task has m training samples. Therefore, the learning task can be expressed as for N decision functions $h_1, h_2, \dots, h_N$ and look for the function $h(x_i) \approx y_i$. In this paper, a hypersphere ε -insensitive loss function is proposed and extended to a regularized form, and then an ELM-based hypersphere multitask learning model can be obtained:

$$\min \sum_{j=1}^N \|\beta_j\|^2 + C \sum_{i=1}^m \xi_i \quad (17)$$

$$\text{s.t. } \|\mathbf{y}_i - \mathbf{W}h(\mathbf{x}_i)\|^2 \leq \varepsilon + \xi_i, \quad \varepsilon, \xi \geq 0, i = 1, 2, \dots, m, \quad (18)$$

where $\mathbf{y}_i = [y_{i1}, y_{i2}, \dots, y_{iN}]$ is the target output, β_j is the model output weight of the j th task. $\mathbf{W} = [\beta_1, \beta_2, \dots, \beta_N]^T$ is the output weight matrix of the learning task. C is the regularization parameter, which is used to balance the generalization ability represented by $\sum_{j=1}^N \|\beta_j\|^2$ and the fitting error represented by $\sum_{i=1}^m \xi_i$. It can be seen that the hypersphere ε -insensitive loss function is adopted in formula (17), and the samples within the hypersphere with radius ε surrounded by all tasks are not punished. The obtained constraint conditions include T learning tasks into the same decision model. The advantage of formula (17) is that it provides a new channel for information sharing and migration among tasks through constraint conditions and loss functions and carries out an overall assessment of learning risks of multiple tasks. This indirectly promotes knowledge sharing based on the existing algorithm form of information transmission using model parameters. At the same time, the constraint conditions adopted in formula (17) can avoid the repeated calculation loss between different tasks. Therefore, this constraint is more suitable for solving multitasking learning problems than the traditional equality constraint or single task constraint.

FIGURE 1: Block diagram of the LDA-ELM model.

Lagrange method is used to solve formula (17). Build minimization optimization goals:

$$L = \sum_{j=1}^N \|\beta_j\|^2 + C \sum_{i=1}^m \xi_i - \sum_{i=1}^m \alpha_i \{ \varepsilon + \xi_i - \|\mathbf{y}_i - \mathbf{W}h(\mathbf{x}_i)\|^2 \} - \sum_{i=1}^m \mu_i \xi_i, \quad (19)$$

where α_i and $\mu_i (i = 1, 2, \dots, m)$ are Lagrange multipliers.

Formula (19) can be solved by iterative reweighted least-square method. The solution of this method in each iteration depends on the solution of the last iteration. Compared with the conventional quadratic algorithm, this method has been proved to have less time and space complexity and guarantees better convergence. After the output weight of each task is obtained by the above method, a new network is obtained by integrating several good kernels with weight. The network can eliminate the bad effects caused by the poorly trained kernel under the condition of high-dimensional mixed data, and the independent and parallel training of the kernel can maintain a very high computing speed, ensure the maximum generalization performance of the algorithm, improve the robustness of ELM to the greatest extent, and improve the accuracy of threat prediction.

5. Target Threat Assessment Model Based on IGSO-ELM

5.1. Construction of Target Threat Assessment Index System. With the further development of airborne fire control radar technology, airborne photoelectric detection technology and medium-range and long-range air-to-air missiles, beyond-visual-range air combat has replaced traditional air combat as the main combat method for destroying enemy aircraft to seize air supremacy. The traditional threat estimation model of short-range air combat cannot be used to describe the characteristics of beyond-visual-range air combat. Therefore, based on the analysis of the air-to-air missile attack zone, the new threat function is evaluated and con-

structed, and the threat estimation model of beyond-visual-range air combat is improved in this paper. Through the establishment of target threat assessment model, the situation parameters acquired by airborne radar and other airborne equipment in air combat are linked with the comprehensive threat index. Thus, a sample database with air combat situation parameters as the input of ELM neural network and comprehensive threat index as the output of ELM neural network is obtained (data construction of air combat threat target samples is described in Section 5.3). This sample database is the basis of ELM neural network training. Therefore, the target threat assessment model determines the rationality of the sample data, which is of great significance for practical application.

The air combat situation of the fighter on both sides is shown in Figure 2 [25]. D_{ij} is the target line between our fighter U_i and the enemy fighter T_j . h_{ji} is the height difference between the enemy and our fighter. v_i and v_j are the speed vectors of our fighter and enemy fighter, respectively. φ and θ are the azimuth angles of our fighter and enemy fighter, respectively. q is the entrance angle of our fighter. The abovementioned angle direction stipulates that the right deviation relative to the target line is positive, and the left deviation is negative, so there are $0 \leq |\varphi| \leq \pi$ and $0 \leq |\theta| \leq \pi$.

Aiming at beyond-visual-range air combat with two-aircraft head-on flight, the mutual firing of missiles based characteristics in this paper; the main research objects are the air combat capability of the aircraft, the attack area of the airborne missile, the inescapable area, and the search area of the airborne radar, as well as the instantaneous geometric situation of both sides in the air battle. The expressions of air combat speed threat index T_{ij}^v , angle threat index T_{ij}^a , height threat index T_{ij}^h , distance threat index T_{ij}^r , and air combat capability threat index T_{ij}^c are established, respectively.

(1) Speed threat index T_{ij}^v

$$T_{ij}^v = \begin{cases} 0.1, & v_j < 0.6v_i, \\ -0.5 + \frac{v_j}{v_i}, & 0.6v_i \leq v_j \leq 1.5v_i, \\ 1.0, & v_j > 1.5v_i \end{cases} \quad (20)$$

(2) Angle threat index T_{ij}^a

Azimuth threat function

$$T_{ji}^a = \begin{cases} 0.3 \left(1 - \frac{|\varphi| - \varphi_{MAmax}}{\varphi_{Rmax} - \varphi_{MAmax}} \right), & \varphi_{MAmax} \leq |\varphi| \leq \varphi_{Rmax}, \\ 0.8 - \frac{|\varphi| - \varphi_{MEmax}}{2(\varphi_{MAmax} - \varphi_{MEmax})}, & \varphi_{MEmax} \leq |\varphi| \leq \varphi_{MAmax}, \\ 1 - \frac{|\varphi|}{5\varphi_{MEmax}}, & 0 \leq |\varphi| \leq \varphi_{MEmax}, \\ 0, & |\varphi| > \varphi_{Rmax}, \end{cases} \quad (21)$$

FIGURE 2: Air combat situation map.

where φ_{Rmax} is the maximum search azimuth angle of the enemy fighter radar; φ_{MAmax} is the maximum off-axis launch angle of the enemy fighter air-to-air missile; and φ_{MEmax} is the cone angle of the no-escape zone.

Entrance angle threat function

$$T_{ji}^q = \begin{cases} \frac{|q|}{50^\circ}, & |q| < 50^\circ, \\ 1 - \frac{|q| - 50^\circ}{130^\circ}, & 50^\circ \leq |q| \leq 180^\circ \end{cases} \quad (22)$$

The angle threat index

$$T_{ji}^a = (T_{ji}^\varphi)^{a_1} (T_{ji}^q)^{a_2}, \quad (23)$$

where $a_1 \geq 0$ and $a_2 \leq 1$ are weighting coefficients, which are used to measure the importance of azimuth and entry angles. This paper takes $a_1 = a_2 = 1$.

(3) Height threat index T_{ij}^h

$$T_{ji}^h = \begin{cases} 1, & h_{ji} < -5\text{km}, \\ 0.5 - 0.1h_{ji}, & -5\text{km} \leq h_{ji} < 5\text{km}, \\ 0.1, & h_{ji} \geq 5\text{km} \end{cases} \quad (24)$$

(4) Distance threat index T_{ij}^r

$$T_{ji}^r = \begin{cases} 0, & D_{ji} \geq D_{Rmax}, \\ 0.5e^{\frac{D_{ji} - D_{MAmax}}{D_{MAmax} - D_{Rmax}}}, & D_{MAmax} \leq D_{ji} < D_{Rmax}, \\ 2^{\frac{D_{ji} - D_{MEmax}}{D_{MAmax} - D_{MEmax}}}, & D_{MEmax} \leq D_{ji} < D_{MAmax}, \\ 1, & D_{MEmin} \leq D_{ji} < D_{MEmax}, \end{cases} \quad (25)$$

where D_{Rmax} is the maximum detection range of the radar. D_{MAmax} and D_{MAmin} are the maximum and minimum attack distances of the missile, respectively. D_{MEmax} and D_{MEmin} are the maximum and

minimum nonescape area distances of the missile, respectively.

(5) Air combat capability threat index T_{ij}^c

According to reference [26], the air combat capability of the fighter aircraft can be described with 7 parameters. The air combat capability index is as follows:

$$C = \left[\ln B + \ln \left(\sum A_1 + 1 \right) + \ln \left(\sum A_2 \right) \right] \varepsilon_1 \varepsilon_2 \varepsilon_3 \varepsilon_4, \quad (26)$$

where B is the maneuverability performance. A_1 is the fire-power performance. A_2 is the detection performance. ε_1 is the handling performance. ε_2 is the survival performance. ε_3 is the voyage coefficient, and ε_4 is the electronic counter-measure performance. The value of C can be obtained by looking up the table. Based on the comprehensive consideration of the air combat capabilities of both sides, the air combat capability threat function is constructed as follows:

$$T_{ji}^c = \begin{cases} 0, & \frac{c_j}{c_i} < 0.3, \\ 0.25, & 0.3 \leq \frac{c_j}{c_i} < 1, \\ 0.5, & \frac{c_j}{c_i} = 1, \\ 0.75, & 1 < \frac{c_j}{c_i} < 1.5, \\ 1, & \frac{c_j}{c_i} \geq 1.5. \end{cases} \quad (27)$$

Based on the air combat capability of the enemy and air combat situation, the comprehensive threat index is solved by the direct linear weighting method:

$$T_{ji} = w_1 T_{ji}^c + w_2 T_{ji}^a + w_3 T_{ji}^r + w_4 T_{ji}^v + w_5 T_{ji}^h, \quad (28)$$

where T_{ji} represents the comprehensive threat index of the j th enemy fighter against the i th our fighter. $w_i (i = 1, 2, 3, 4, 5)$ represents the weight that reflects the importance of each threat index in the comprehensive threat index, and its value is directly related to the contribution of the individual threat index to the comprehensive threat index. Therefore, it is a necessary prerequisite to determine the weight of each threat index for threat assessment.

5.2. The Structure Entropy Weight Method Determines the Index Weight. In the threat assessment process, the target threat index needs to be weighted to measure its importance. The usual weighting methods include subjective weighting method and objective weighting method. The subjective weighting method is a weighting method based on the experts' opinions and the subjective experience of decision-makers, including the Delphi method, AHP method, and importance ranking method. The subjective weighting method is relatively simple to calculate and mainly reflects

the experience and preference of the decision-makers. However, this type of weighting method only considers the preferences of decision-makers and expert opinions but ignores the objective authenticity of the collected information, which leads to certain limitations in practical applications.

The objective weighting method is a weighting method based on the underlying laws existing in the original data and the degree of influence on the evaluation results. There are principal component analysis method and factor analysis method in statistical analysis, entropy weight method based on physics, and deviation maximization method of multiattribute decision-making, etc. The objective weighting method does not change with the will of the decision-maker, and the weight coefficient is obtained from the original data mining and analysis, which has strong objectivity. However, it usually requires the aid of mathematical models and theoretical methods to calculate, which will lead to relatively complicated calculation. At the same time, the attribute weight will change with the data information collected, resulting in the method which is more sensitive to the data information.

Considering the defects of subjective weighting method and objective weighting method, the structure entropy weight method is selected in this paper to determine the target attribute weight [26, 27]. It is a weight coefficient structure analysis method that combines qualitative analysis and quantitative analysis. The idea is through the analysis of system indicators and their interrelationships, they are decomposed into several independent hierarchical structures. The Delphi expert survey method of collecting expert opinions is combined with the fuzzy analysis method to form a "typical ranking" for the importance of indicators. Quantitative analysis of the uncertainty of the "typical ranking" structure is carried out by using the theory of directness, and the calculation of the direct value and the analysis of "blindness" are carried out. Through statistical processing of the potential deviation data, the relative importance of the indicators at the same level can be obtained. Finally, the importance value of the indicators at each level is determined. This is the indicator weight. The steps are as follows.

Step 1. Collect expert opinions and form a "typical ranking."

By consulting experts in the field of air combat and reviewing relevant documents, the importance of each target threat assessment index is determined. The target threat matrix is constructed, and the "typical ranking" of experts is finally formed. Assuming that k experts participate in the consultation survey, each threat index constitutes an indicator set, denoted as $T = [T_1, T_2, T_3, T_4, T_5] = [T^c, T^a, T^r, T^v, T^h]$. Each expert evaluates each threat index and obtains the evaluation weight matrix of various threat index as $A(A = a_{ij})_{k \times 5}$, where $i = 1, 2 \dots k$ and $j = 1, 2, 3, 4, 5$. Among them, a_{ij} represents the i th expert's evaluation of the importance of the j th evaluation index, as shown in Table 1:

Step 2. "Blindness" analysis of "typical ranking".

Because the experts participating in the survey have deviations in their understanding of the importance of threat indicators, the ranking of the importance of threat indicators might be different from the real situation, resulting in noise and uncertainty in the data. It is necessary to correct the result of "typical ranking" of experts and use the entropy weight method in information theory to calculate the entropy value of each index, so as to reduce the uncertainty of "typical ranking" of experts and make the importance of each index judged by experts more real.

For the qualitative and quantitative transformation of the ranking number a_{ij} in Table 1, the membership function of the qualitative ranking transformation is defined as

$$\mu(a_{ij}) = \frac{\ln(m - a_{ij})}{\ln(m - 1)}, \quad (29)$$

where m is the conversion parameter amount, $m = j + 2$ and $m = 7$. Through formula (29), the ranking matrix A can be quantitatively transformed into the corresponding membership matrix B , where $b_{ij} = \mu(a_{ij})$.

The "unanimous view" of k experts on the indicator μ_j is called the average degree of awareness, which is recorded as b_j , so

$$b_j = \frac{(b_{1j} + b_{2j} + \dots + b_{kj})}{k}. \quad (30)$$

"Knowledge blindness" is the uncertainty caused by the expert's cognition of the factor μ_j , denoted as Q_j ; then,

$$Q_j = \left| \frac{[(\max(b_{1j}, b_{2j}, \dots, b_{kj}) - b_j) + (\min(b_{1j}, b_{2j}, \dots, b_{kj}) - b_j)]}{2} \right|. \quad (31)$$

The overall knowledge of the k experts on the indicator μ_j is recorded as x_j ,

$$x_j = b_j(1 - Q_j), \quad x_j > 0. \quad (32)$$

The evaluation vector $\mathbf{X} = (x_1, x_2, \dots, x_5)$ of all the experts on each index.

Step 3. Normalization.

In order to get the weight of the indicator μ_j , normalize $x_j = b_j(1 - Q_j)$; let

$$w_j = \frac{x_j}{\sum_{j=1}^5 x_j}. \quad (33)$$

Obviously, $w_j (j = 1, 2, \dots, 5) > 0$ and $\sum_{j=1}^5 w_j = 1$. $\mathbf{W} = [w_1, w_2, \dots, w_5]$ is the weight vector of the index set $\mathbf{T} = [T_1, T_2, T_3, T_4, T_5] = [T^c, T^a, T^r, T^v, T^h]$ formed by the threat index. $\mathbf{W}$ is the overall judgment of the consistency of the

TABLE 1: Expert opinion evaluation form.

Expert number	T^c	T^a	T^r	T^v	T^h
Expert 1	a_{11}	a_{12}	a_{13}	a_{14}	a_{15}
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
Expert i	a_{i1}	a_{i2}	a_{i3}	a_{i4}	a_{i5}
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
Expert k	a_{k1}	a_{k2}	a_{k3}	a_{k4}	a_{k5}

importance of the index set T by k “expert opinions,” which conforms to the wishes or cognition of the k expert groups.

5.3. Data Construction of Air Combat Threat Target Samples. The distance between the enemy and our fighters is generally used as the basis for classifying the types of air combat, which is divided into close-range air combat within 10 km and beyond-visual-range air combat beyond 10 km. In beyond-visual-range air combat, air combat in the range of 10 km to 100 km is called medium-range air combat, and air combat over 100 km is called long-range air combat. Therefore, beyond-visual-range air combat includes two types: medium-range and long-range air combat. In this paper, 100 sets of air combat situation data are selected as the training samples of the neural network. The situation data includes the distance between the two fighters, the altitude difference, the speed ratio, the attack range of the missiles carried by the enemy fighters, and the azimuth angle of our fighters. Threat indices T^v , T^a , T^h , T^r , and T^c can be calculated based on the air combat situation data and the established air combat threat assessment function. The status and influence of each threat index are different under different types of air combat. In medium-range air combat, the difference of angle and height between fighters is the most important, while in long-range air combat, the performance of weapons play a vital role. Therefore, by combining the threat index with the weight of the threat assessment index determined based on the structure entropy weight method, the comprehensive threat index T of the enemy fighters to our fighters can be calculated. Based on the above process, the air combat situation parameters D_{ji} , h_{ji} , v_j/v_i , $\varphi_{R \max}$, $\varphi_{MA \max}$, $\varphi_{ME \max}$, and q can be used as the input of the ELM neural network, and the comprehensive threat index T of the enemy fighters can be used as the output of the new ELM neural network sample.

5.4. Target Threat Assessment Model Structure and Algorithm Flow. In traditional threat assessment methods, the types of midrange and long-range beyond-visual-range air combat are not distinguished but a unified threat assessment is carried out. This will lead to the disadvantage of increasing the redundancy between indicators and weakening the generalization ability of neural network. Aiming at the above shortcomings, an air combat target threat assessment model based on the linear discriminant analysis method and improved glowworm swarm optimization algorithm to optimize extreme learning machine combined with threat index method is constructed in this paper. This model

can classify and reduce the dimensionality of air combat situation data and carry out multitask grouping training on the extreme learning machine, so as to evaluate the target threat in air combat quickly and accurately. The evaluation model is shown in Figure 3, and the specific implementation steps are as follows [28].

Step 1. Construct an air combat target threat assessment sample.

Firstly, the combat trajectory extracted from ACMI (air combat maneuvering instrument) system is used to obtain the necessary situation information and other flight data parameters from the trajectory. Then, a threat assessment system based on the threat index method is constructed, which includes five indicators of speed, distance, angle, altitude, and air combat capability. Finally, in order to reduce the influence of human subjective factors and obtain more reasonable threat assessment index weights, a structure entropy weight method that combines subjective and objective valuation methods is adopted in this paper. The purpose is to determine the weight of the five evaluation indicators and finally obtain the comprehensive threat index T .

Step 2. Air combat target evaluation model based on LDA-IGSO-ELM.

The target threat index is processed, and the discriminant analysis method is used to classify and reduce the dimensionality of the original index. According to the distance and angle between air combat enemy and our fighters, the index data is divided into medium and long range, and the correlation between the original evaluation indices is eliminated, and the dimensionality of the data is reduced.

The ELM neural network is constructed, and its input weights and thresholds are optimized by the improved glowworm swarm optimization algorithm, as shown in Figure 4.

Based on the two types of sample data constructed in Step (1), the ELM neural network is trained by grouping multitask. The ELM neural network takes the integrated variable processed by the LDA algorithm as the input and the target threat value as the output.

A target threat assessment model based on the linear discriminant analysis method, improved glowworm swarm optimization algorithm, and ELM algorithm is established in this paper. The model contains two levels: in the first layer, the threat assessment system constructed by the threat index method and the comprehensive threat index obtained by the structure entropy weight method are used to construct the sample data. In the second layer, the target threat assessment model of LDA-IGSO-ELM is constructed by analyzing and determining the index factors that affect the target threat value. First, the linear discriminant analysis method is used to extract the low-dimensional features with the most discriminative ability from the high-dimensional feature space from the situation data. These features can help gather all samples of the same category together and separate samples of different categories as much as possible, so as to realize the classification of situational data and eliminate the correlation and redundancy between the data. On

FIGURE 3: Structure diagram of target threat assessment model.

FIGURE 4: The optimization process of ELM neural network by IGSO algorithm.

this basis, the improved GSO algorithm is used to optimize the ELM grouping hypersphere multitask learning algorithm, so as to realize the multitask learning ability of the ELM and improve the prediction and robustness of the ELM neural network. Finally, the result of the training sample after mathematical statistical analysis is used as the input variable of the ELM neural network model, and the target threat assessment value is used as the output variable.

From the LDA-IGSO-ELM target threat assessment flow chart, it can be seen that the threat assessment model constructed in this paper can be used to train and evaluate midrange and long-range beyond-visual-range air combat in groups based on the characteristics of modern beyond-visual-range air combat. On the basis of constructing the threat assessment model, the structure entropy weight method is introduced to weaken the subjectivity of solving the threat index weight in the model, which has a great improvement in performance compared with the single threat assessment mathematical model and intelligent algorithm. The traditional mathematical model of threat assessment is combined with the ELM neural network in this paper. Using the self-learning and associative storage advantages of the neural network, the current enemy-to-us air combat situation parameters are taken as the input of the network, and the threat value of the target is obtained directly through the ELM neural network. There is no need to repeat the specific processes of obtaining threat index, determining weight, and obtaining comprehensive threat index in the traditional mathematical evaluation model. Therefore, the method proposed in this paper can simplify the computational complexity of target threat assessment and improve the timeliness of assessment, which has profound significance for target threat assessment in complex air combat environment.

6. Experimental Simulation and Verification

In this paper, the air combat confrontation process data extracted from ACMI (air combat maneuvering instrument) is used for air combat target threat assessment analysis and simulation. Two sets of midrange and long-range one-to-one beyond-visual-range air combat data were selected. Each set of air combat time was 500 s, and the sampling time of the sample was 0.5 s, so a total of 4000 air combat sample points are extracted. The 4000 air combat sample point data are divided into training sample data and test sample data. Among them, the first 3800 data are used as training samples, and the remaining 200 data are used as algorithm test samples.

6.1. Optimization and Verification of Training Parameters Based on Structure Entropy Weight Method. Taking medium-range air combat and long-range air combat in the beyond-horizon air combat mode as examples, through consultation with 10 experts and scholars in the field, the importance of each threat index was evaluated (important degree is divided into 9 levels, level 9 is the most important, and level 1 is the least important), and expert opinions are obtained as shown in Tables 2 and 3.

TABLE 2: Expert opinion evaluation form in medium-range air combat mode.

Expert	Medium range (12 km)					Medium range (60 km)				
	T^v	T^a	T^h	T^r	T^c	T^v	T^a	T^h	T^r	T^c
1	2	8	5	1	3	4	6	3	9	2
2	1	9	4	3	2	3	5	4	8	1
3	1	7	3	2	4	2	6	4	8	3
4	3	8	6	1	2	5	4	7	9	2
5	2	9	5	3	1	4	6	7	9	3
6	2	9	4	3	1	5	7	6	8	2
7	1	6	4	2	3	3	5	6	7	1
8	3	7	6	1	2	4	7	5	8	2
9	2	8	5	4	1	3	7	6	9	1
10	2	7	5	3	1	4	8	6	9	3

TABLE 3: Expert opinion evaluation form in long-range air combat mode.

Expert	Long range (110 km)					Long range (140 km)				
	T^v	T^a	T^h	T^r	T^c	T^v	T^a	T^h	T^r	T^c
1	8	5	6	9	7	6	1	2	9	4
2	7	5	4	8	6	7	1	3	9	6
3	6	1	2	9	7	5	2	3	8	4
4	4	2	5	7	6	5	3	1	8	6
5	7	1	2	6	5	5	3	4	8	7
6	7	3	4	9	8	5	2	1	9	6
7	5	4	6	8	7	4	1	2	7	8
8	7	1	2	9	8	6	3	4	8	5
9	5	2	1	6	7	4	3	2	8	9
10	6	1	2	7	4	5	4	3	9	8

Comprehensive consideration of the multiple-expert evaluation can reduce the single expert subjectivity and one-sidedness of the evaluation. For different air combat modes, the weights of each threat index are obtained by the analytic hierarchy process of expert assignment and the structure entropy weight method of subjective and objective fusion, respectively. The comparison results are shown in Table 4.

The conclusion can be drawn from the above table: in the midrange air combat mode, when the distance between the two fighters is 12 km, the weight ranking result of the structure entropy weight method is $w_2 > w_3 > w_4 > w_1 > w_5$, and the weight ranking result of the analytic hierarchy process is $w_4 > w_2 > w_3 > w_1 > w_5$. When the distance between the two fighters is 60 km, the weight ranking of the structure entropy weight method is $w_4 > w_2 > w_3 > w_1 > w_5$, and the weight ranking of the analytic hierarchy process is $w_4 > w_1 > w_5 > w_3 > w_2$. In long-range air combat, when the distance between the two fighters is 110 km, the ranking of the structure entropy weight method is $w_4 > w_5 > w_1 > w_3 > w_2$, and the weight ranking result of the analytic hierarchy process is $w_1 > w_5 > w_4 > w_3 > w_2$. When the distance

TABLE 4: Comparison of weights between AHP and structure entropy in different air combat modes.

Air combat mode	Weight	AHP	Structure entropy
Medium range (12 km)	w_1	0.1269	0.1616
	w_2	0.2585	0.2806
	w_3	0.1458	0.2362
	w_4	0.3523	0.1676
	w_5	0.1165	0.1540
Medium range (60 km)	w_1	0.2647	0.1702
	w_2	0.0975	0.2197
	w_3	0.1197	0.2181
	w_4	0.3749	0.2856
	w_5	0.1432	0.1064
Long range (110 km)	w_1	0.3157	0.2247
	w_2	0.1087	0.1049
	w_3	0.1279	0.1679
	w_4	0.1998	0.2675
	w_5	0.2479	0.2350
Long range (140 km)	w_1	0.2712	0.2264
	w_2	0.1058	0.1298
	w_3	0.1252	0.1421
	w_4	0.2963	0.2643
	w_5	0.2015	0.2374

between the two fighters is 140 km, the ranking of the structure entropy weight method is still $w_4 > w_5 > w_1 > w_3 > w_2$, and the result of the weight ranking of the analytic hierarchy process is $w_4 > w_1 > w_5 > w_3 > w_2$.

By consulting experts and relevant literature, it is found that in midrange air combat, the angle advantage of enemy fighters will lead our fighters to be in the attack zone of enemy air-to-air missiles. The enemy fighters with a high degree of advantage has a greater potential energy, and it is easy to convert the height advantage into the angle and speed advantage, so that the air-to-air missile has a greater initial launch speed and thus improves the hit rate. This will cause our fighters to become passive and increase the degree of threat to us. Therefore, the angle threat and the high threat have a great influence on the target threat. In long-range air combat, the distance between enemy fighters and our fighters becomes the main factor affecting threat assessment. In addition, the air combat capability of the enemy fighter will directly determine the enemy's radar detection, electronic countermeasures, and missile launch capabilities. Therefore, the threat of air combat capability has a greater impact on threat assessment than the threat of speed. By comparing the ranking results of the two methods, it is found that the weight ranking results obtained by the structure entropy weight method are consistent with this conclusion. Therefore, the weight optimization based on the structure entropy weight method analyzes the "blind-

FIGURE 5: Test results of the number of hidden-layer nodes.

ness" of experts in the index evaluation, which can effectively reduce the impact of randomness and subjectivity on threat assessment indicators. It is more objective and reasonable to use the weights obtained by this method as training parameters.

6.2. Determination of Hidden-Layer Nodes in ELM Neural Network. The choice of the number of nodes in the hidden layer of the ELM neural network is very important. In order to improve the network performance and reduce the system error of the network, more hidden-layer nodes are often selected. However, if there are too many hidden-layer nodes in ELM, the network structure will be more complex. On the one hand, it increases the learning and training time of the network and reduces the real-time performance of the algorithm. On the other hand, too many nodes will lead to the training easily falling into the local minimum point without the optimal advantage, and overfitting is easy to occur. If the number of hidden-layer nodes is too small, it is difficult for the ELM neural network to learn samples. At the meantime, the generalization ability becomes weak, and the network performance will be poor. However, there is no scientific and universal method to determine the number of hidden-layer nodes of ELM neural network in theory. Therefore, the optimal number of hidden-layer nodes should be determined by testing and experimentation under the comprehensive consideration of the complexity and error of the network structure [29]. According to the Kolmogorov theorem, for a neural network with a single hidden layer, the number of input-layer nodes n_1 , the number of output layer nodes m , and the number of hidden-layer nodes n_2 satisfy the $n_2 = \sqrt{n_1 + m + 1} + a$ relationship, where a is a constant between [1, 10]. In this paper, the number of nodes in the input layer of the neural network is $n_1 = 5$, and the number of nodes in the output layer is $m = 1$, in order to ensure that the ELM neural network not only has good generalization performance but also has better training time and test accuracy. Based on the idea of node construction method and deletion method, the test samples are used to find the number of hidden-layer nodes in the range of [3, 30], which makes the error performance of ELM neural network the best.

In the test simulation experiment, the ELM neural network randomly generates the weight ω and the threshold β , and the activation function is selected as the Logsig function $g(x) = 1/(1 + e^{-x})$. Then, the training samples are used

FIGURE 6: Comparison of the evolution process of IGSO and GSO algorithms.

to train the ELM neural network with different numbers of hidden-layer nodes, and the test sample is predicted and the predicted mean square error (MSE) is output. The computational formula of MSE is shown in the following formula:

$$\text{MSE} = \frac{1}{N} \sum_{i=1}^N (t_i - \hat{t}_i)^2, \quad (34)$$

where N is the number of test samples and t_i and $\hat{t}_i$ are the true threat value and predicted threat value of the i th sample, respectively. The test results are shown in Figure 5.

It can be seen from Figure 5 that as the number of hidden-layer nodes increases, the prediction accuracy of the test set of the ELM neural network shows a trend of first rising and then falling. When the number of hidden-layer nodes is 18, the ELM neural network has the best prediction performance, so the number of hidden nodes is set to 18.

6.3. Convergence Analysis of IGSO-ELM Algorithm. The average of the 100 training data prediction errors is used as the fitness value of the individual glowworm. The relationship between the fitness value of the GSO algorithm and the IGSO algorithm to optimize the ELM neural network and the evolutionary algebra is analyzed and compared. The result is shown in Figure 6.

It can be seen that the improved glowworm swarm optimization algorithm converges to the best fitness value 0.0143 when it evolves to the 40th generation, and the fitness value basically stabilizes. The standard glowworm swarm optimization algorithm tends to be stable around the 70th generation with a fitness value of 0.0145. Through comparison, it can be seen that the convergence speed of the IGSO algorithm is significantly higher than that of the GSO algorithm.

The IGSO algorithm can find the optimal weight and threshold of the ELM neural network faster and has a strong optimization ability. This is because the global convergence speed of the glowworm swarm optimization algorithm is accelerated by the variable inertia weight. At the same time, the local search ability near the extreme point is enhanced, which prevents the glowworm from oscillating repeatedly near the extreme point. Finally, the optimization speed has been improved. Obviously, the improved glowworm swarm optimization algorithm is used to optimize the ELM neural network, which promotes the accuracy of the target threat assessment results and avoids the problem of algorithm performance degradation caused by randomly generating neural network connection weights. It makes up for the shortcomings of the standard glowworm swarm optimization algorithm that is easy to fall into the local optimal value, making the air combat threat assessment under the beyond visual range more reasonable and accurate.

6.4. Comparative Analysis of Target Threat Assessment Accuracy. In order to compare and verify the strong performance of the proposed algorithm model in air combat target threat assessment, LDA-IGSO-ELM algorithm is compared with the ELM, BP, IGSO-ELM, LDA-ELM, and LDA-BP algorithm in simulation experiments. For the purpose of controlling variables, the numbers of neurons in the hidden layer of the ELM neural network and the BP neural network are both 18, and the activation functions are both Logsig functions. The experimental results are shown in Figure 7. It can be seen that the LDA-IGSO-ELM algorithm proposed in this paper has the best threat assessment effect, the prediction error is the smallest, and the error does not exceed 0.015. The errors of the other five algorithms are relatively large, and the effect of threat assessment is relatively poor compared to the LDA-IGSO-ELM algorithm. Through the

FIGURE 7: Continued.

(c)

(d)

FIGURE 7: Continued.

(e)

(f)

FIGURE 7: Simulation results of test samples: (a) LDA-IGSO-ELM prediction; (b) GSO-ELM prediction; (c) ELM; (d) LDA-BP prediction; (e) LDA-ELM prediction; (f) BP prediction.

TABLE 5: Comparison of prediction errors of multiple algorithms.

Algorithms	MAE/ 10^{-3}	MSE/ 10^{-5}	MAPE/ 10^{-2}	NMSE/ 10^{-2}	Time (s)
ELM	9.8613	81.9537	5.6153	57.9945	8.3228
BP	-24.7193	156.7659	6.9669	110.9353	6.5854
LDA-ELM	4.5405	38.9052	3.5047	27.5313	5.2916
LDA-BP	-2.9644	29.2936	3.6192	20.7296	4.1345
GSO-ELM	1.1232	8.4076	1.8038	5.9496	4.5633
LDA-IGSO-ELM	0.9597	2.1586	1.0988	1.5276	3.2457

comparison, it can be seen that LDA can effectively reduce the dimensionality and classification of the data samples of target threat assessment and eliminate the confusion between the data. ELM neural network multitask group training can reduce the influence of noisy sample data on the prediction results and improve the accuracy of prediction. The weights and thresholds between the input layer and the hidden layer of the ELM neural network are optimized by the improved glowworm swarm optimization algorithm, which promotes the accuracy of the target threat assessment results and avoids blindness caused by randomly generating weights and thresholds. As a result, the overall performance of the network is improved.

In order to further test the evaluation effect of LDA-IGSO-ELM algorithm, mean absolute error (MAE), mean square error (MSE), mean absolute percentage error (MAPE), and normalized mean square error (NMSE) are used to evaluate the performance of this algorithm. The mean square error (MSE) has been defined in Section 6.2, and the other three statistical errors are specifically defined as

$$\begin{aligned}
 \text{MAE} &= \frac{1}{N} \sum_{i=1}^N |t_i - \hat{t}_i|, \\
 \text{MAPE} &= \frac{1}{N} \sum_{i=1}^N \left| \frac{t_i - \hat{t}_i}{t_i} \right|, \\
 \text{NMSE} &= \frac{\sum_{i=1}^N (t_i - \bar{t})^2}{\sum_{i=1}^N (t_i - \bar{t})^2},
 \end{aligned} \tag{35}$$

where N is the number of samples, t_i is the true threat value, $\hat{t}_i$ is the predicted threat value, and $\bar{t}$ is the average value of the true threat value. From the above definition formula, the results in Table 5 are obtained. It can be seen that the MAE, MSE, MAPE, and NMSE errors of the LDA-IGSO-ELM algorithm proposed in this paper are better than the other five algorithms, which shows that the algorithm in this paper has higher accuracy and the best effect in threat assessment.

By observing the prediction errors in Table 5 and comparing ELM neural network and BP neural network, it can be seen that the four errors of ELM neural network are better than those of BP neural network, which indicates that the shortcomings of BP neural network have been effectively avoided by ELM neural network and the prediction accuracy has been further improved. This is attributed to the idea of

error back propagation adopted by the BP neural network. When the output layer of forward propagation cannot get the expected output, it needs to constantly calculate the error of the output layer and reverse correct the weight. However, the ELM neural network randomly generates the connection weight between the input layer and the hidden layer and the threshold value of the neurons in the hidden layer, which does not need to be adjusted in the training process. The unique optimal solution can be obtained only by setting the number of neurons in the hidden layer. Compared with the BP neural network algorithm, the ELM neural network has faster learning speed and better generalization performance. Then, by observing the prediction errors of LDA-ELM and LDA-BP, it can be found that their error values are improved compared with ELM and BP, indicating that after dimension reduction and classification of learning samples by LDA, the characteristics of learning samples are more obvious, which is helpful to improve the generalization ability of neural network on sample features. Finally, by comparing the prediction errors of LDA-IGSO-ELM, GSO-ELM, and LDA-ELM, it can be seen that the glowworm swarm optimization algorithm controls the influence of glowworm's previous position information on the current position through inertial weight, which determines the distance that glowworm moves and strengthens the global optimization and local search ability of the glowworm swarm optimization algorithm. In the early stage, the global search ability of glowworms is stronger, while in the later stage, the local search ability is enhanced. IGSO can effectively and quickly find the optimal weight of ELM neural network, which improves the rapidity and accuracy of the algorithm.

Figure 8 shows the execution time of 6 algorithms. The training time of the GSO-ELM algorithm is 4.5633 s, which is longer than the 3.2457 s used by the LDA-IGSO-ELM algorithm. This is because the LDA algorithm successfully eliminates the correlation and redundancy between variables by preprocessing the original evaluation data, which enhances the generalization ability of ELM neural network, and grouping learning also effectively improves the training efficiency of the ELM neural network. The training time of the LDA-ELM algorithm is 5.2916 s, which is also longer than the LDA-IGSO-ELM algorithm. The analysis shows that the basic ELM neural network randomly generates weights and thresholds, so the parameters are not the optimal choice and have some irrationality. However, the ELM neural network optimized by the improved glowworm swarm

FIGURE 8: Comparison of training time of various algorithms.

optimization algorithm can quickly find the optimal weight and threshold value, effectively avoiding the randomness of the initial ELM neural network weight and threshold value, improving the overall performance of the ELM neural network, and reducing the increase of training time caused by blindly searching for the optimal parameters. Therefore, the execution time of LDA-IGSO-ELM algorithm is shorter, which can meet the real-time requirements of air combat threat prediction.

7. Conclusions

In this paper, a target threat assessment algorithm based on linear discriminant analysis (LDA) and improved glowworm swarm optimization algorithm (IGSO) is proposed to optimize the extreme learning machine (ELM) based on the characteristics of modern beyond-visual-range air combat. The main conclusions are as follows:

- (1) Linear discriminant analysis can be used to effectively classify and reduce the dimension of threat assessment indicators, eliminate the correlation between the assessment indicators, and greatly improve the reliability of the assessment indicators
- (2) The improved glowworm swarm optimization algorithm can be well used to optimize the weights and thresholds between the input layer and the hidden layer of the ELM neural network, thus effectively improving the training time and prediction accuracy of the model
- (3) The independent parallel training ELM neural network is weighted and integrated through the hypersphere multitask learning algorithm, which can be effectively used to improve the prediction speed, improve the robustness of the model, and improve the prediction accuracy

- (4) Threat assessment sample data constructed by structure entropy weight method not only contains the subjective experience and professional knowledge of experts but also can maintain objective authenticity, so the sample has a high credibility

Finally, the simulation results show that the LDA-IGSO-ELM algorithm can quickly and accurately solve the problem of threat assessment, so as to provide effective support for firepower allocation and maneuver decision.

Data Availability

The data used to support the findings of this study were related to secrets. Requests for data will be considered by the corresponding author in the future if necessary.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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