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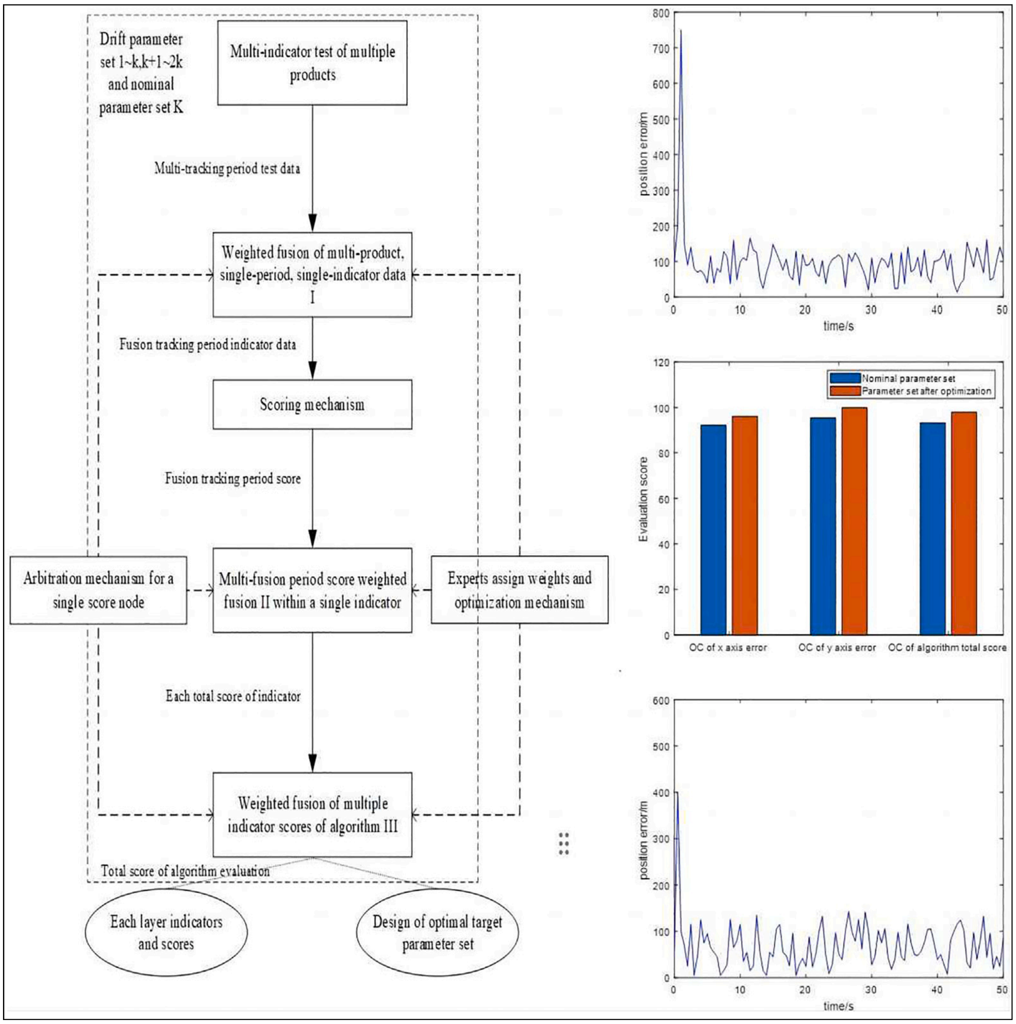

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Highlights

Weighted fusion excludes hardware influence on software evaluation

The subjective-objective weight design enhances accuracy of evaluation optimization

Parameters with highest evaluation score are found and hence improve existing algorithm

Hu et al., iScience *26*, 108550
December 15, 2023 © 2023 The Authors.
https://doi.org/10.1016/j.isci.2023.108550

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Compound weighted fusion evaluation and optimization of intelligent tracking algorithm in radar seeker

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SUMMARY

This paper designs a hierarchical weighted fusion evaluation/optimization scheme for the radar seeker neural network (NN) tracking algorithm. The first weighted fusion of closed-loop performance index is carried out to exclude the hardware influence on algorithm evaluation. Then, according to different tracking scenarios, the tracking index is divided into different periods; a single period score is given by a linear-nonlinear hybrid scoring mechanism. Furthermore, in a single index, the internal scores of different time periods are weighted and fused for the second time to obtain the index overall score. Finally, the third weighted fusion of the multi-index scores obtains the comprehensive score of the algorithm. We design the parameter evaluation case sets and repeat the aforementioned compound weighting; hence the case with the highest comprehensive score is obtained. Finally, the algorithm is optimized by the highest-score case. The experiment using fuzzy NN radar seeker verifies the effectiveness of the method.

INTRODUCTION

In the increasingly complex battlefield environment, the increasingly neural network (NN) recognition-tracking algorithm of radar seeker and the high complexity of its parameters and structure make related performance evaluation increasingly difficult.[1–4] The traditional software evaluation does not consider the special performance index of NN, nor does it involve the closed-loop parameters of radar tracking; therefore, it is not suitable for the fast development of intelligent tracking algorithm of radar seeker.[5–8] This paper is committed to providing a comprehensive and effective closed-loop evaluation scheme to realize the local and overall performance evaluation of the radar seeker intelligent tracking algorithm under multiple operating conditions and segmentation.

The research work on the evaluation of the intelligent tracking algorithm of the radar seeker is less concerned; however, the intelligent tracking algorithm design develops rapidly.[9–12] In Sadhu et al.,[13] the radar seeker anti-jamming evaluation system is given, but it is only limited to anti-jamming performance evaluation, not for intelligent algorithms. In Wang et al.,[14] the evaluation scheme of the intelligent filtering algorithm is further given; the gray correlation method is used to eliminate the subjectivity of the weight design, but it is only for the anti-jamming performance of the radar. Xie et al.[15] provide ideas for the design of initial weights in the evaluation of the radar seeker intelligent algorithm, and this study will also be used in this paper to eliminate subjectivity.

The aforementioned references show that there is a lot of research and cognitive space for radar seeker algorithm evaluation. However, with the increasing complexity of algorithms and the requirements of special seekers, the performance evaluation is becoming important.[16–19] In Loran et al.,[17] two object-oriented ship detectors based on the faster region-based convolutional NN (R-NN) were presented; R-NN was trained on thousands of real X-band airborne rangecCompressed radar data containing several ship signals. In Garry et al.,[20] a number-adaptive filtering technique was proposed to mitigate the effects of disturbance; hence, a number of spectral and spatially diverse wave signals were considered to evaluate suppression performance. In Baghdadi et al.,[21] synthetic aperture radar observations had been used to estimate soil moisture and surface roughness; hence, the surface backscattering models were evaluated. In Zhang et al.,[22] the autocorrelation and cross-correlation sidelobe was derived and integrated into evaluation theory for the orthogonality of polyphase codes. In Li et al.,[23] an abnormal region detection algorithm based on visual attention mechanism was proposed and evaluated in ground-penetrating radar. However, the aforementioned evaluation methods of radar guidance system seldom consider the particularity of NN tracking. In this paper, a special evaluation and optimization scheme is designed for NN tracking algorithm of radar seeker.

NN recognition and tracking algorithm develops rapidly in motion control. Through training, NN can make the controller lock the target and adjust the actuator for accurate tracking.[24–27] But the relevant assessment techniques are rarely studied. In Qiao et al.,[27] an extensive dataset of low-resolution and super-resolution image pairs was provided and used to evaluate the deep-learning super-resolution models in terms of signal-to-noise ratio and upscaling factor. In Huang et al.,[28] a review of the current research effort into making deep NNs safe

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https://doi.org/10.1016/j.isci.2023.108550

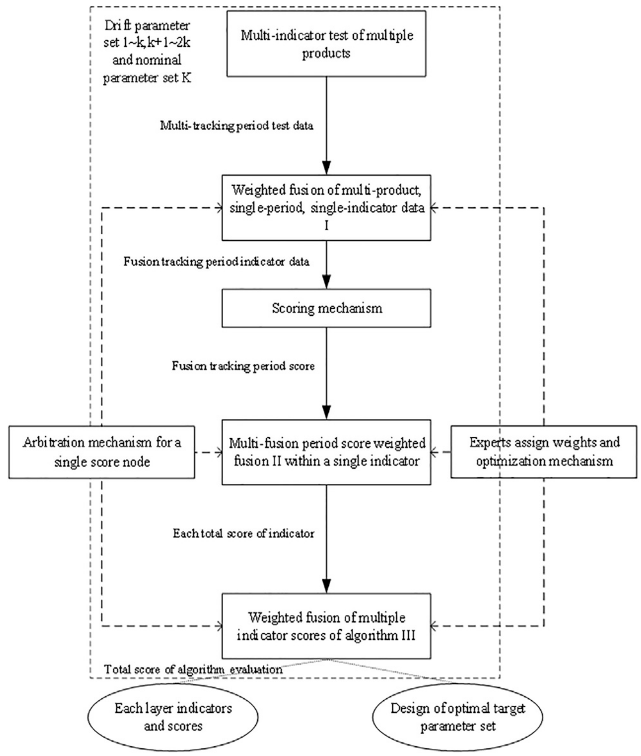

Figure 1. Evaluation scheme of intelligent tracking algorithm of radar seeker.

and trustworthy was conducted, by focusing on four aspects: verification, testing, adversarial attack and defense, and interpretability. In the study by Lei,[29] based on the features obtained, the MATLAB NN toolbox trained BP NN and evaluated the established continuous movement control model. In A Obed et al.,[30] a novel controller of PID control dynamic wavelet network model was proposed to control the servo motor; the authors evaluated the performance of the intelligent control with tracking error and response time. However, the aforementioned evaluation technologies do not consider the particularity of radar seeker and do not give the optimization direction after evaluation. This paper will focus on solving these two problems.

This paper considers the special target tracking scenarios, and index of radar seeker, hierarchical evaluation, and optimization scheme of seeker NN tracking algorithm are designed based on the aforementioned research, so as to create conditions for continuous improvement and evaluation of algorithm performance and seeker overall performance. Therefore, the main contributions are as follows.

(1) We set arbitration for each weighting calculation to ensure that the evaluation is meaningful. If the local score is too low, it will be directly stopped to continue the weighted fusion and the total score will be judged to be 0.
(2) The subjective-objective weight design. Weight ranges are found by objective gray correlation, and then the subjective expert value setting based on extreme expert/clique elimination finally determines the weight values in the three-layer evaluation. It eliminates the defect that objectivity lacks judgment experience and subjectivity is emotional.
(3) Taking the fuzzy NN algorithm as the evaluation object, the NN tracking algorithm with the highest comprehensive evaluation score is found by designing the evaluation use cases based on the algorithm parameters, so as to provide reference for improving the existing seeker software.

The structure of this paper is as follows: Firstly, we introduces the compound weighted fusion evaluation method, which includes the main method of weighted fusion, the assignment mechanism, the weighting mechanism, and the arbitration mechanism to ensure the objectivity of fusion. Then we introduces the NN tracking algorithm of radar seeker, which is the evaluation optimization object of the method. Thirdly, we presents the simulation and evaluation results of the algorithm. Finally, we summarizes the full text.

RESULTS

Theory and design

Overall scheme

The overall evaluation scheme of the radar seeker NN tracking algorithm designed in this paper is shown in Figure 1. The main contents of the scheme include the following steps.

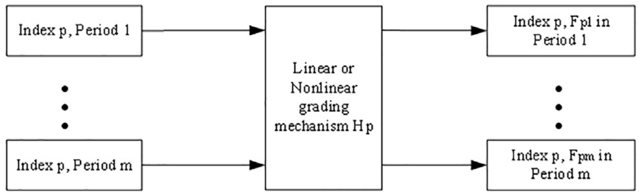

Figure 2. Tracking period scores under multi-index linear-nonlinear mechanism.

Step 1: the radar seekers to be evaluated under different storage/transportation environment are selected for evaluation. Real-time collection of performance index data and according to the tracking scenarios divided into different periods.
Step 2: same period and index data weighted fusion. The first layer of weighted fusion is to avoid the algorithm evaluation being affected by hardware environment. According to the physical characteristics of different index, the initial scoring mechanism is selected and the score of any index in any fusion period is obtained.
Step 3: multiple fusion periods score fusion within the same index. The second layer of weighted fusion aims to obtain the overall score of each index as a result of the overall evaluation of a single index.
Step 4: NN algorithm multi-index score weighted fusion. The third layer of weighted fusion is to obtain the total score of the NN tracking algorithm for the target to be evaluated, and the weight is still given by expert optimization mechanism.

The optimization objective shows the overall or local optimization direction of the evaluated intelligent algorithm, that is, the intelligent learning parameter set that gets the highest total score or the highest score of a certain index. Each of the following sub-sections is a detailed description of each module in Figure 1. This paper first introduces multi-layer compound evaluation and optimization and then introduces the key techniques to ensure objectivity: arbitration and mixed weight design mechanism.

Fusion scoring mechanism

The first layer of weighted fusion in Figure 1 (multi-indicator test of multiple products) is to integrate the performance index data of the same intelligent tracking algorithm under different hardware environment characteristics, so as to eliminate the interference of radar seeker hardware. The following two layers of weighting calculation are also the content of the main evaluation scheme.

Evaluation index set Z:{index 1 … p} covers common performance index of radar seeker, including position errors, response time, steady-state variance, resolution, etc. The division of the time period is related to the common target tracking conditions of the radar seeker. Time period set is marked as S:{period 1, period 2 …, period m}. The weighted fusion structure of multi-products, multi-time periods, and multi-index is shown in Equation 1. W(·) is the weight, which is assigned different values by the experts. The weighting mechanism is a weight selection method with optimization attributes, and it is common to have an algorithm to eliminate extreme experts. Weighted fusion function of the first layer is

$$x(z_p, s_m) = \sum_{i=1}^{n} X(z_p, b_{ni}, s_m) W(z_p, b_n, s_m) \quad \text{(Equation 1)}$$

where $z_1, \ldots, z_p, b_1, \ldots, b_p, s_1, \ldots, s_m$ are the element marker symbols in the weight variables of index set Z, standard set B, and time period set S, respectively. For example, z_p, b_1, and s_m respectively represent index p, production 1, and tracking period m, so $W(z_p,b_1,s_m)$ represents the corresponding weight.

The first layer of weighted fusion requires an additional initial scoring process to provide a basis function for the next layer of weighted fusion. In this paper, multiple scoring mechanisms are mixed. Figure 2 is a simple scoring structure. The specific mechanism to be used depends on the characteristics of index set Z.

The grading function includes smooth linear function, smooth nonlinear function, and non-smooth nonlinear function. Classical evaluation methods often use comments in this step, but this paper chooses to replace comments with scores, which also creates conditions for the generation of multi-layer compound evaluation index.

(1) Smooth linear function. Let ϑ be the indicator value and Θ be the score; then the corresponding relation of smooth linearity is

$$\Theta = Hi(\vartheta) = a\vartheta + b \quad \text{(Equation 2)}$$

where a and b are the real numbers and constants, ϑmin, ϑmax, Θmin, and Θmax are the minimum and maximum values of index after repeated experiments, and their corresponding scores.

(2) Smooth nonlinear function. ϑ is set as the index value, and Θ is the score; then the corresponding relation is

$$\Theta = Hi(\vartheta) = a_\tau \vartheta^\tau + a_{\tau-1}\vartheta^{\tau-1} + \cdots + a_1\vartheta + b \quad \text{(Equation 3)}$$

where b, a_1, ..., a_τ are the real constants; τ is a positive integer, and its minimum value is 2. Any smooth nonlinear function can be represented by adjusting the parameters of Equation 3. The significance of the nonlinear scoring function is that the change of the performance index in a certain interval will accelerate or slow down the change of the score to reflect the greater or lesser impact of the interval on the score.

(3) Non-smooth nonlinear function. This kind of grading function can be subdivided into continuous and discontinuous non-smoothing functions. Expert direct scoring belongs to the generalized non-smooth nonlinear scoring function. The non-smooth nonlinear correspondence is as a piecewise function:

$$\Theta = \mathrm{Hi}(\vartheta) = \begin{cases} a_{1,\tau}\vartheta^{\tau} + a_{1,\tau-1}\vartheta^{\tau-1} + \cdots + a_{1,1}\vartheta + b_1, & \vartheta \in [\vartheta_{\min}, \vartheta_1) \\ \vdots \\ a_{\sigma,\tau}\vartheta^{\tau} + a_{\sigma,\tau-1}\vartheta^{\tau-1} + \cdots + a_{\sigma,1}\vartheta + b_\sigma, & \vartheta \in [\vartheta_{\sigma-1}, \vartheta_{\max}] \end{cases} \quad \text{(Equation 4)}$$

where $\vartheta_1 \sim \vartheta_{\sigma\text{-}1}$ are the piecewise points in the intervals of the independent variables of the performance index. The functions within the intervals are continuously derivable, while the functions between the intervals are not (either continuous or discontinuous). Therefore, the aforementioned three categories of scoring mechanisms basically cover all scoring methods.

After scoring by the scoring mechanism, the score in the fusion period is also a function. It is necessary to convert the scoring function into score value and finally form a single period score F_{ij}, index i = 1 ..., p, period j = 1 ... m. Take the mean of score Θ as $J_{\Theta,ij}$ and the variance as $\sigma_{\Theta,ij}$. Then the total score of a single tracking period can be calculated as

$$F_{ij} = W(J_{\Theta,ij})J_{\Theta,ij} + W(\sigma_{\Theta,ij})\sigma_{\Theta,ij} \quad \text{(Equation 5)}$$

where $W(J_{\Theta,ij})$ and $W(\sigma_{\Theta,ij})$ are the weights of mean and variance values, and the weighting mechanism is consistent with the expert weighting optimization mechanism shown in Figure 1.

In conclusion, the weighted fusion of the first layer including a scoring mechanism set can obtain the index score of a single period, which creates conditions for the weighted fusion of the second layer to obtain the total score of a single index.

The second layer of weighted fusion is to obtain the total score of a single index based on the scores of the fusion periods. The fusion algorithm is as follows:

$$F_i = \sum_{j=1}^{m} W(z_i, r_j)F_{ij} \quad \text{(Equation 6)}$$

where $W(z_i,r_j)$ represents the weight of index i and fusion period j, i = 1, ..., p, j = 1, ..., m.

The third layer weighted fusion is to obtain the total score of radar seeker intelligent tracking algorithm based on multiple index score weighted. The fusion algorithm is as follows:

$$F = \sum_{i=1}^{p} W(z_i)F_i \quad \text{(Equation 7)}$$

where $W(z_i)$ represents the global weight of index i = 1 ..., p.

Remark 1: "closed loop" means that the physical performance index of the radar seeker with an intelligent tracking algorithm is used instead of the direct software logic and calculation performance to indirectly evaluate the quality.

If the military only pays attention to a certain indicator i, the weight of the remaining index in Figure 2 can be set as 0, namely

$$\begin{cases} W(z_i) = 1 \\ W(z_1) = 0 = W(z_2) = \cdots = W(z_{i-1}) = W(z_{i+1}) = \cdots = W(z_p) \end{cases} \quad \text{(Equation 8)}$$

Furthermore, (7) degenerates into (6) and continues to reflect the closed-loop performance of the algorithm.

Parameter optimization design

This section repeats the aforementioned three-layer compound evaluation process, but the evaluated intelligent tracking algorithm adopts the drift parameter sets different from the nominal parameter set proposed in Figure 1, to design parameter optimization strategies and optimize the intelligent learning parameters.

Definition 1: nominal parameters refer to the learning parameters when parameter changes are not considered in the evaluation. They are the existing parameters to be optimized.

If the evaluation score of a drift parameter set is better than that of the nominal set, it can be regarded as the optimization target. Set drift total parameter set C:{parameter set 1, parameter set 2 ..., parameter set k, parameter set k+1, parameter set 2k}. The scores of fusion periods, the total score of single index, and the total score of algorithm under each parameter set can be obtained by repeated evaluation. Due to the similar topology structure of weighted fusion, only the total weighted method of algorithm is shown in Figure 3.

Let the symbol of each parameter set be described as parameter set 1 = C_1, parameter set 2 = C_2, ..., parameter set 2k = C_{2k}, nominal parameter set K=C_K. Set

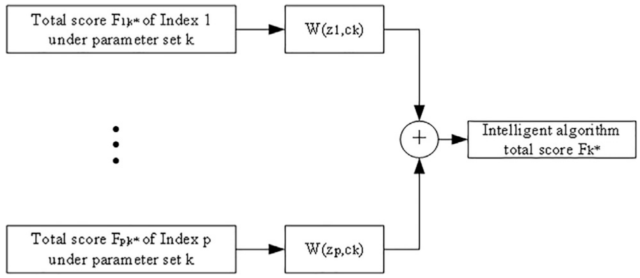

Figure 3. Total score of weighted fusion evaluated under drift parameter set.

$$\begin{cases} C_1, C_2, \cdots, C_k < C_K \\ C_{k+1}, C_{k+2}, \cdots, C_{2k} > C_K \end{cases} \quad \text{(Equation 9)}$$

where the set defines the following operations.

Definition 2: let q = 1 …, v represents parameter number in parameter set C_l, v is the parameter number, l is the parameter set number.

$$C_l = \{s_{lq}\} = \{s_{l1}, \cdots, s_{lv}\} \quad \text{(Equation 10)}$$

s_{lq} can represent any learning parameter in the drift parameter set whose superiority is to be verified. Then, if (10) is satisfied,

$$\sum_{lq=1}^{v} \mathrm{sgn}\{s_{l,q} - s_{l+1,q}\} > 0 \quad \text{(Equation 11)}$$

Thence $C_l > C_l + 1$. Therefore, the experimental significance of Equation 10 is to select the parameter sets that fluctuates up and down around the nominal parameter values; take k parameter sets less than C_K and take k parameter sets larger than C_K to form the drift parameter set C (this is a parameter selection sample pool for optimizing algorithm parameters) and then repeat the three-layer scoring evaluation process under each parameter set to obtain the score F_{1*}, …,F_{k*},F_{k+1*}, …,F_{2k*}.

Based on the aforementioned evaluation process and Equation 10, the overall optimization objective of parameters is set as

$$F_{max} = \max\{F_{1*}, \cdots, F_{k*}, F, F_{k+1,*}, \cdots, F_{2k,*}\} \quad \text{(Equation 12)}$$

Then the parameter local optimization objective can be set as

$$F_{i,max} = \max\{F_{i,1*}, \cdots, F_{i,k*}, F_i, F_{i,k+1,*}, \cdots, F_{i,2k,*}\} \quad \text{(Equation 13)}$$

The drift parameter set is the test case of the optimization evaluation method, and the details of parameter selection are related to the specific intelligent algorithm structure. In order to implement and verify the effectiveness of the evaluation and optimization scheme, a radar seeker NN algorithm will be introduced in the next section.

Weight criterion design

This study proposes an objective-subjective weighting optimization mechanism proposed in module "Experts assign weights and optimization mechanism" of Figure 1. The objective weighting mechanism sets the weight range, while the subjective weighting mechanism gives the specific weight values within the range.

$\gamma(X_i, X_j)$ is the gray correlation coefficient between the ith index and index j, and the specific definition of the corresponding gray correlation depth coefficient function q_{ij} is

$$q_{ij} \triangleq \frac{\gamma(X_i, X_j)}{\sum_{j=1}^{Q-1} \gamma(X_i, X_j)} \quad \text{(Equation 14)}$$

where Q is the total number of weights of all weighted fusion layers, whose expression will be given in the next section.

The objective weight model based on the gray correlation depth coefficient is as follows

Step 1: index weight expected change range constraint. The depth coefficient of gray correlation reflects the significance of the internal variation of sequence elements in the sequence set. The gray correlation depth coefficient can be introduced to determine the importance of different index according to the significance of such changes in different index, so as to determine the weight of each performance index. According to the aforementioned theory, the weight range of an index can be determined by the gray correlation depth coefficient. The weight change range is constrained as follows:

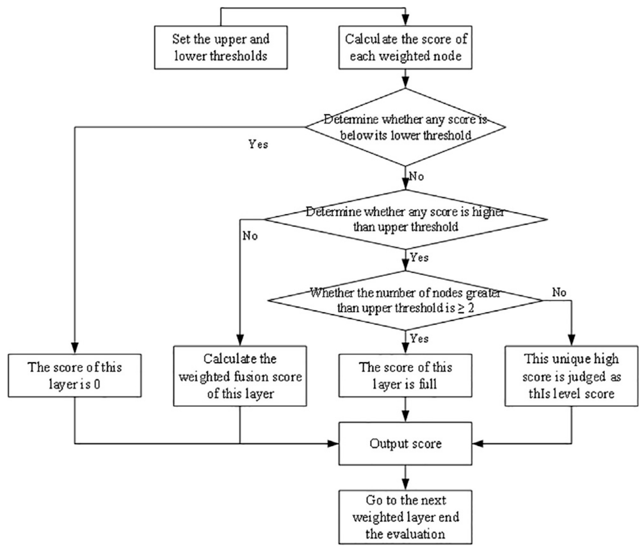

Figure 4. Flow chart of single-weighted layer arbitration mechanism.

$$W_{e,i} \subset \left[\min\left(q_{ij}\right), \max\left(q_{ij}\right)\right] \quad \text{(Equation 15)}$$

Step 2: fluctuation range constraint of index weight variance. The fluctuation range of index weight is also determined by the gray correlation depth coefficient. The constraint condition for introducing weight variance is as follows:

$$\frac{1}{Q^*}\sum_{i=1}^{Q^*}\left(W_i - \frac{1}{Q^*}\right)^2 \subset \left[\min(D(q_0)), \max(D(q_0))\right] \quad \text{(Equation 16)}$$

where $D(q_0)$ is the variance set of the full index gray correlation depth coefficient set q_0, and Q^* is to meet $Q^*<Q$. $D(q_0)$ can represent the fluctuation range of index weight, namely

$$D(q_0) = \frac{1}{Q}\sum_{j=1}^{Q-1}\left(q_{1j} - \frac{1}{Q}\right), \cdots, \frac{1}{Q}\sum_{j=1}^{Q-1}\left(q_{ij} - \frac{1}{Q}\right) \quad \text{(Equation 17)}$$

The objective weight design can only determine the weight range. On this basis, this study uses the expert judgment weight method to uniquely determine the weight. But experts will have subjective extreme opinions. In order to ensure the exclusion of extreme opinions, the subjective weight design needs to introduce the extreme expert elimination algorithm. The similarity coefficient between experts and expert groups can be obtained by calculating the similarity coefficient between experts with the help of cluster analysis. The smaller the similarity degree, the greater the deviation from expert groups, and the more extreme the expert opinions; its influence should be eliminated.

The specific steps are as follows

Step 1: invite an expert group composed of X experts; each expert $E_\iota(\iota = 1, 2, \ldots, X)$ determines Q index weight vectors according to the three-layer weighting scheme in Figure 1. $W_{e,\iota}=(W_{\iota1}, W_{\iota2}, \ldots, W_{\iota Q})(\iota = 1, 2, \ldots, X)$. According to the aforementioned setting of the number of indices and the number of time periods, Q satisfies

$$\begin{aligned} &Q = Q_1 + Q_2 + Q_3 + Q_4 = n \times p \times m + 3 \times p \times m \\ &Q_1 = n \times p \times m \\ &Q_2 = Q_3 = Q_4 = p \times m \end{aligned} \quad \text{(Equation 18)}$$

Then form the weight matrix as

$$W^*_{X\times Q} = \begin{bmatrix} W_{11} & W_{12} & \cdots & W_{1Q} \\ W_{21} & W_{22} & \cdots & W_{2Q} \\ \vdots & \vdots & & \vdots \\ W_{X1} & W_{X2} & \cdots & W_{XQ} \end{bmatrix} \quad \text{(Equation 19)}$$

Step 2: calculate the similarity coefficient between expert E_ι and expert E_π:

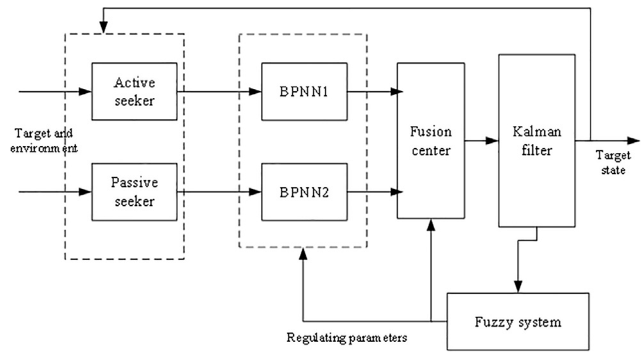

Figure 5. Overall structure of target tracking.

$$r_{\iota\pi} = 1 - \frac{1}{Q}\sum_{u=1}^{Q}\left|W_{e,\iota u} - W_{e,\pi u}\right| \quad \text{(Equation 20)}$$

Then form the matrix of similarity coefficient as

$$R_{X \times X} = \begin{bmatrix} r_{11} & r_{12} & \cdots & r_{1X} \\ r_{21} & r_{22} & \cdots & r_{2X} \\ \vdots & \vdots & & \vdots \\ r_{X1} & r_{X2} & \cdots & r_{XX} \end{bmatrix} \quad \text{(Equation 21)}$$

Obviously, the following conclusion holds: $r_{\iota\pi} = r_{\pi\iota}(\iota \neq \pi, \iota, \pi = 1, 2, \ldots, X)$, $r_{\iota\pi} = 1(\iota = \pi, \iota, \pi = 1, 2, \ldots, X)$.

Step 3: computing the similarity between expert E_i and expert group $\{E_1, E_2 \ldots, E_X\}$

$$g_\iota = \sum_{u=1}^{X} r_{\iota u} \quad \text{(Equation 22)}$$

Constitute the similarity vector $G=(g_1, g_2, \ldots, g_X)^T$, that is, sum the matrix of similar coefficients by row.

Step 4: eliminate extreme expert opinion. The expert opinions are screened according to the elimination ratio, and the expert opinions with low similarity are excluded. The 20% elimination ratio is adopted here.

Step 5: average the weight vector given by the remaining experts, namely, the final weight vector $W_e=(W_{e,1}, W_{e,2}, \ldots, W_{e,Q})$.

Arbitration mechanism for weighted fusion node

The arbitration mechanism corresponds to the module "Arbitration mechanism for single score node" in Figure 1. The mechanism of direct promotion and one vote rejection is introduced in weighted nodes of each level of performance index to correspond to the phenomenon that one single index data have a decisive status. The arbitration algorithm is executed as follows.

Step 1: design the upper threshold and lower threshold of each index in a single period, and design the upper threshold and lower threshold of each index in a full period.

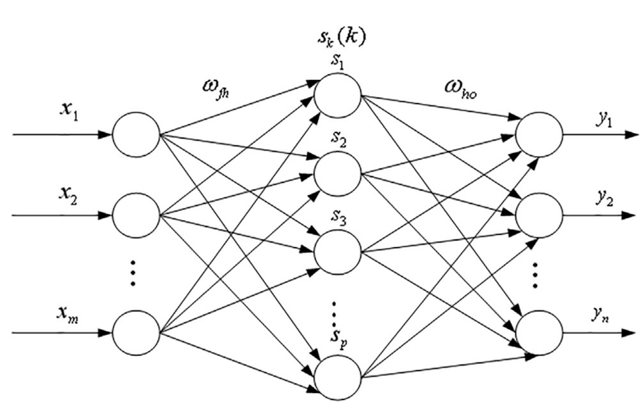

Figure 6. Structure diagram of BP NN.

Table 1. Fuzzy table of NN learning rate regulation

	Acceleration range a					
	0	(0, 15]	(15, 30]	(30, 45]	(45, 60]	(60, 75]
mobility Δ	0	very small	small	medium	large	very large
η	0.3	0.4	0.5	0.8	0.8	0.9

Step 2: calculate the score of a single index in a single period. If one score is lower than its lower threshold, the evaluation is terminated, and the total score of the radar seeker intelligent tracking algorithm is 0.

Step 3: if no score is lower than its lower threshold, judge whether any score is higher than its upper threshold. If no, this weighted fusion score will be performed; if yes, this weighted fusion score will not be performed and the score higher than the upper threshold will be directly judged as the weighted fusion score of the layer.

Step 4: calculate the score of single index in the whole period. If one score is lower than its lower threshold, the evaluation is terminated, and the total score of the radar seeker intelligent tracking algorithm is 0.

Step 5: if no score is lower than its lower threshold, judge whether any score is higher than its upper threshold. If no, the weighted fusion score will be performed. If yes, the score higher than the upper threshold will be directly judged as the weighted fusion score of the level, namely, the total score of comprehensive evaluation of the radar seeker intelligent tracking algorithm.

Finally, the arbitration mechanism assists the multi-layer weighted fusion agent architecture to complete the comprehensive evaluation. The flow chart of single-node arbitration mechanism for each weighted layer is shown in Figure 4.

Experimental model algorithm

The intelligent tracking algorithm introduced in this section is the evaluated object of the evaluation optimization method proposed in the previous section. In the experiment, the performance of the algorithm can be evaluated and optimized by selecting the parameters of the intelligent tracking algorithm described in this section and using the proposed evaluation optimization scheme. Therefore, it can be used to verify the ability of the evaluation optimization method to the intelligent tracking algorithm of complex parameters.

Seeker target tracking overall scheme

This section introduces an information fusion target tracking scheme of radar seeker based on BP NN and fuzzy system, which represents an advanced intelligent tracking algorithm; it is shown in Figure 5.

The information detected is divided into two categories through NN: target information and interference outfield value. The classified tracking information is sent to the fusion center, and then the information is fused. After fusion, the target trajectory can be obtained by filtering. Target maneuver parameters are extracted, and the learning rate of NN is adjusted by fuzzy system according to different motion states of the target.

BP NN algorithm

This section corresponds to the modules "BPNN1" and "BPNN2" in Figure 5. BP NN is a kind of multi-layer forward network, which is divided into input layer, hidden layer, and output layer. It is widely used in pattern recognition and data compression.[3]

Figure 6 shows a 3-layer forward BP NN, and the input layer neurons are $x_1, x_2, \ldots, x_m$, hidden layer neurons are $s_1, s_2, \ldots, s_p$, and the output layer neurons are $y_1, y_2, \ldots, y_n$. The weights from the input layer to the hidden layer and from the hidden layer to the output layer are ω_{fh} and ω_{ho}, respectively. The thresholds of the hidden layer neurons and output layer neurons are θ_f and θ_o, respectively. Nonlinear activation function $f^*(x) = \frac{1}{1+e^{-x}}$.

The input of the hidden layer neurons is

$$I_{n_h^1(k)} = \sum_{f=1}^{m} x_f \omega_{fh} - \theta_f \quad \text{(Equation 23)}$$

Table 2. Adjustment fuzzy table of fusion weights

	Distance range h/km					
	(60, ∞)	(50, 60]	(40, 50]	(30, 40]	(20, 30]	(0, 20]
R	very far	far	little far	little near	close	very close
Ratio α	0.2	0.5	1	2	3	4

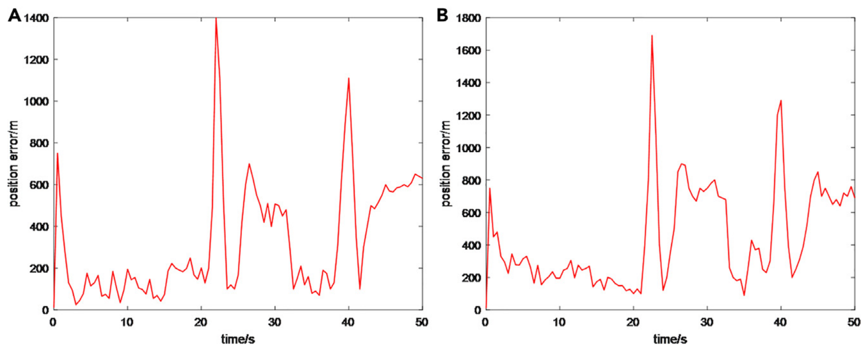

Figure 7. JPDA position errors in x and y directions
(A) x position error.
(B) y position error.

The output of hidden layer neurons is

$$s_h(k) = f^*\left(I_{n_h^1(k)}\right) = f^*\left(\sum_{f=1}^{m} x_f\omega_{fh} - \theta_f\right) \tag{Equation 24}$$

The input of neurons in the output layer is

$$I_{n_o^2(k)} = \sum_{h=1}^{p} \omega_{ho}s_h(k) - \theta_o = \sum_{h=1}^{p} \omega_{ho}f^*\left(\sum_{f=1}^{m} x_f\omega_{fh} - \theta_f\right) - \theta_o \tag{Equation 25}$$

The output of neurons in the output layer is

$$\begin{aligned} y_o(k) &= \frac{\alpha^*}{1+\alpha}f^*\left(I_{n_o^2(k)}\right) \\ &= \frac{\alpha^*}{1+\alpha}f^*\left(\sum_{h=1}^{p} \omega_{ho}f^*\left(\sum_{f=1}^{m} x_f\omega_{fh} - \theta_f\right) - \theta_o\right) \end{aligned} \tag{Equation 26}$$

where α is the fusion ratio between the active tracking NN and the passive tracking NN, and α^* satisfies $\alpha^* = 1$ or α. Set the expected output as d_o; then the error of output node o is

$$e_o(k) = d_o(k) - y_o(k) \tag{Equation 27}$$

The objective function of network training is

$$J(\omega) = \frac{1}{2}\sum_k\sum_o[e_o(k)]^2 = \frac{1}{2}\sum_k\sum_o[d_o(k) - y_o(k)]^2 \tag{Equation 28}$$

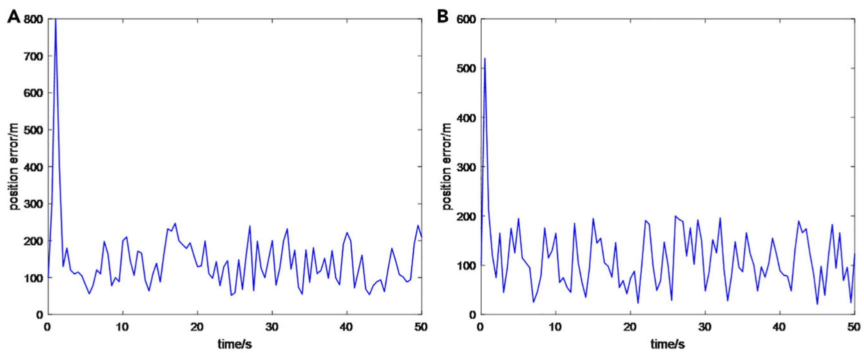

Figure 8. Position errors in x and y directions of the fuzzy NN algorithm
(A) x position error.
(B) y position error.

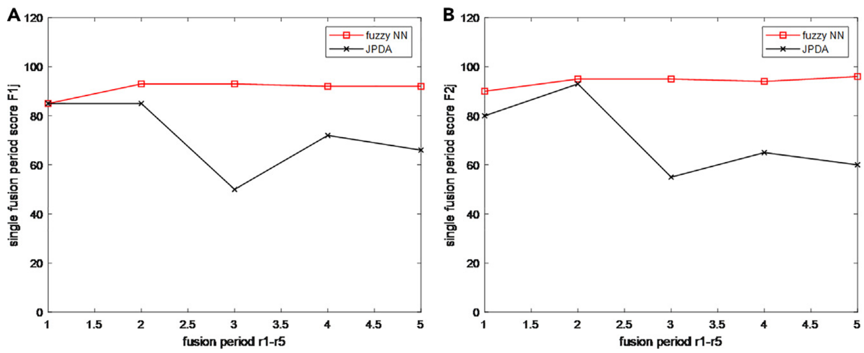

Figure 9. Comparison of weighted scores at the first layer
(A) Score of x axis position error.
(B) Score of y axis position error.

The minimum gradient rule is adopted to update the weight of the network. The weight adjustment from the hidden layer to the output layer is

$$\Delta\omega_{ho} = -\eta\frac{\partial J(\omega)}{\partial\omega_{ho}} = \eta\sum_k \delta_o(k)\cdot s_h(k) \quad \text{(Equtaion 29)}$$

The weight adjustment from the input layer to the hidden layer is

$$\Delta\omega_{fh} = -\eta\frac{\partial J(\omega)}{\partial\omega_{fh}} = \eta\sum_k \delta_h(k)\cdot x_f(k) \quad \text{(Equation 30)}$$

η is the learning rate, and

$$\delta_o(k) = e_o(k)\cdot f^{\dot{*}}\left[I_{n_o^2(k)}\right] \quad \text{(Equation 31)}$$

$$\delta_h(k) = f^{\dot{*}}\left[I_{n_h^1(k)}\right]\cdot\sum_o \omega_{ho}\delta_o(k) \quad \text{(Equation 32)}$$

The BP NN connected to the active radar seeker has 3 input neurons, which are two directional positions and one angle of the target. There are 2 neurons in the output layer. The output 0 represents the target, and the output 1 represents the interference field value. The input neurons of the BP NN connected to the passive radar seeker are 2, which are the position information of the two directions of the target, respectively. The number and functions of the output layer neurons is the same as that of the active seeker.

Fuzzy system

In this paper, the algorithm extracts the acceleration of the target and makes real-time fuzzy adjustment of the learning rate of the NN and the weight of the fusion center according to the maneuvering degree and distance of the target so that the system can track the target. The target

Table 3. Weight values in 1st layer weighted fusion

	z_1							z_2						
	b_1	b_2	b_3	b_4	b_5	b_6	b_7	b_1	b_2	b_3	b_4	b_5	b_6	b_7
s_1	0.25	0.2	0.15	0.1	0.1	0.1	0.1	0.25	0.2	0.15	0.1	0.1	0.1	0.1
s_2	0.3	0.25	0.2	0.1	0.05	0.05	0.05	0.3	0.25	0.2	0.1	0.05	0.05	0.05
s_3	0.35	0.3	0.2	0.05	0.04	0.03	0.03	0.35	0.3	0.2	0.05	0.04	0.03	0.03
s_4	0.35	0.25	0.2	0.1	0.04	0.03	0.03	0.35	0.25	0.2	0.1	0.04	0.03	0.03
s_5	0.35	0.25	0.2	0.1	0.04	0.03	0.03	0.35	0.25	0.2	0.1	0.04	0.03	0.03

Table 4. Weight values for whole periods of a single index (2nd layer)

	r_1	r_2	r_3	r_4	r_5
z_1	0.1	0.2	0.3	0.25	0.15
z_2	0.1	0.2	0.3	0.25	0.15

maneuvering degree Δ is blurred according to different ranges of target acceleration: "zero", "very small", "small", "medium", "large", and "very large". The corresponding NN learning rate η is shown in Table 1.

The proposed algorithm uses a fuzzy system to adjust the fusion weights in real time, which overcomes the shortcoming and does not change after the weights are determined. The weight of the information detected by the active-passive radar seeker in fusion center is adjusted by the distance of the target. According to different range h of the extracted target, the missile-target distance is set as R by the fuzzy method: "very far", "far", "little far", "little near", "close", and "very close". The fusion weight ratio α of the active-passive radar seeker of the corresponding fusion center is adjusted as shown in Table 2.

Remark 2: The fuzzy NN algorithm is the evaluation object. The evaluation scheme designs the evaluation use case by η, α, a, and h to determine the highest evaluation score. The radar seeker closed-loop indicators are position tracking errors.

Simulation evaluation analysis conclusions

In this section, simulation experiment is used to verify the effectiveness and superiority of the evaluation optimization scheme. The object to be evaluated is the intelligent fuzzy NN tracking algorithm described in Section 3.

Simulation experiment

The measured intelligent algorithm integrates the active-passive seeker information to track the target. The initial position of the target is (10 km, 50 km), and the initial speed of the target is (−50 m/s, −300 m/s); the target moves at a constant speed in 0~150 s, makes a slow turn with acceleration (5 m/s^2, 5 m/s^2) in 150–200 s, and moves at a constant speed in 200~210 s. It is fast turning with acceleration (−65 m/s^2, −65 m/s^2) in 210~220 s, in uniform motion in 220~320 s, medium and low speed turning with acceleration (20 m/s^2, −20 m/s^2) within 320~350 s, in uniform motion within 350~380 s, in 380~400 s with acceleration (−35 m/s^2, −35 m/s^2) to make a moderate speed turn, and finally in 400~500 s to do uniform motion. The JPDA algorithm and the proposed fuzzy NN are respectively used to track the target.

It can be seen from Figures 7 and 8 that the fusion position errors of JPDA algorithm are relatively large, which make it difficult to track the target effectively, while the proposed fuzzy NN algorithm can track the target accurately.

Evaluation and optimize design

In this section, the fuzzy NN tracking algorithm in the previous section is evaluated to verify the feasibility of the evaluation scheme and the consistency of direct comparison with simulation. The tracking period is divided into S: {s_1, s_2, s_3, s_4, s_5}, and the working condition is described as follows: s_1: 0~150 s, uniform and straight running; s_2: 150~200 s, slow turn; s_3: 210~220 s, fast turn; s_4: 320~350 s, medium-low speed turning; and s_5: 380~400 s, medium speed turn. In the first layer fusion weight setting, x axis position error index is z_1 and y axis position error index is z_2; there are 7 seekers with different storage/transportation environments. Weight distribution table is shown in Table 3.

In the second layer fusion weight setting, the five tracking periods are denoted as r_1~r_5, and the distribution weight follows a qualitative standard; that is, the higher the initial score in the period of bad working conditions, the higher the score in the whole period of single index is likely to be. Therefore, the 2nd layer weight allocation (single index) is shown in Table 4.

In the weight setting of the third layer fusion, the x axis position error and the y axis position error are not equally important to the algorithm evaluation, so the weights are 0.4 and 0.6 in Table 5.

The first layer of the hierarchical scoring fusion period score is shown in Figure 9. The first layer score of the fuzzy NN tracking algorithm in this paper is significantly higher than that of the JPDA, consistent with the curve comparison.

The comparative analysis results of the third layer evaluation are shown in Table 6. Combined with Figure 9 and Table 6, it can be seen that, under the condition that there is little difference in scores in the uniform motion tracking period, the scores in the first layer of turning environment are closer to the comprehensive scores, indicating that the scores in the extreme period have a greater impact on the overall scores, which is consistent with the realistic demand.

Table 6 also shows that the score of the evaluation scheme is consistent with the result of direct comparison between the simulation curves: the difference between the target uniform curves is small, and the difference between the fast turning curves is large, so the score difference

Table 5. Weight values in weighted fusion of whole algorithm (3rd layer)

	z_1	z_2
W(z_1)	0.4	0.4
W(z_2)	0.6	0.6

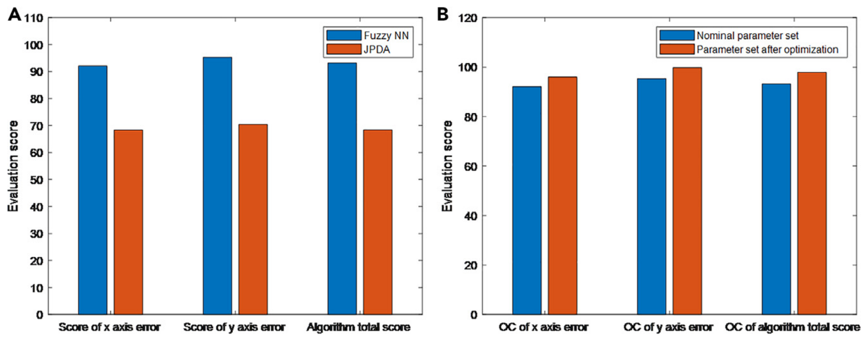

Figure 10. Comparisons of multi-algorithm evaluation and NN optimization
(A) Single index score and multiple index fusion total score.
(B) Fuzzy NN score optimization comparison (OC) before and after optimization.

between the uniform curves is small and the score difference between the fast turning curves is large. Therefore, the proposed evaluation scheme is valid.

In optimization design, the parameter set of evaluation use case needs to be determined first, and the nominal parameter set selected in this experiment is (η, α). The relationship between the evaluation case parameter set and the nominal parameter set is as follows:

$$(\eta^*, \alpha^*) = (\eta + \Delta\eta, \alpha / \Delta\alpha) \quad \text{(Equation 33)}$$

According to the aforementioned relationship, the six elements of η and α are set to increase or decrease equally; the range of $\Delta\eta$ is [−0.2, 0.2], and the range of $\Delta\alpha$ is [0.1, 5]. After repeated experiments, the optimization target parameter set (η^*, α^*)=(η+0.11, α/2) of the fuzzy NN intelligent tracking algorithm is locked. According to the order of the Tables 1 and 2, the values of the two parameters after the optimization are η^* = {0.19, 0.29, 0.39, 0.49, 0.59, 0.69} and α^* = {0.1, 0.25, 0.5, 1, 1.75, 2.5}. The total score of the optimized algorithm is 97.9, 4.7 points higher than the nominal score, and the comprehensive performance is improved by 5%.

Figure 10A more clearly shows the superior performance of fuzzy NN compared with traditional JPDA from the perspective of evaluation, and Figure 10B quantifies the improvement degree of the optimized algorithm compared with that before optimization

The tracking experiment of the optimized fuzzy NN algorithm is shown in Figure 11. It can be clearly seen with the naked eye that the tracking errors and response time are reduced, and the performance is greatly improved. This indirectly verifies the validity of the proposed evaluation optimization scheme.

In de Moura et al.,[31] an optimizer was also designed for fuzzy NN tracking algorithm. This study conducts a comparative analysis experiment with its method, and the experimental results are shown in Table 7.

The data unit is meter, consistent with Figure 11. $e_{x,m}$, $e_{y,m}$, $e_{x,a}$, $e_{y,a}$, $e_{x,s1}$~$e_{x,s5}$, and $e_{y,s1}$~$e_{y,s5}$ respectively represent the maximum x axis tracking error, the maximum y axis tracking error, the average x axis error, the average y axis error, the x axis tracking errors of the five time periods, and the y axis tracking errors of the five time periods. Since there is no evaluation process in de Moura et al.,[31] contrastive analysis can only use tracking errors as an index. Even if we only look at the tracking errors, the proposed evaluation optimization method can still reduce the average tracking errors by about 24% after optimizing by the method of de Moura et al.,[31] that is, 25~30 m, and the maximum errors by more. This indicates that the proposed evaluation optimization method not only has the ability to improve the performance of intelligent tracking algorithms but also has better improvement range under similar tracking algorithms and has more application value.

Conclusions

The influence of hardware environment on algorithm evaluation is excluded after weighted fusion of radar seeker performance index data with different environment and target characteristics. The linear-nonlinear hybrid scoring mechanism gives the effective single period score. Furthermore, the second layer of weighted fusion of different period scores within a single index is used to obtain the overall score of the index. Finally, the total score of the algorithm is obtained by the third layer weighted fusion of multiple index scores and provides a basis for evaluating the

Table 6. 3-layer evaluation and comparative analysis of two algorithms

	x axis position error (z_1) scores for each period					y axis position error (z_2) scores for each period					z_1 score	z_2 score	Total score
Algorithm comparison	F_{11}	F_{12}	F_{13}	F_{14}	F_{15}	F_{21}	F_{22}	F_{23}	F_{24}	F_{25}	F_1	F_2	F
FuzzyNN	85	93	93	93	92	90	95	95	94	96	92.1	94.3	93.2
JPDA	85	85	50	72	66	80	93	55	65	60	68.4	68.4	68.4
Differences	0	8	43	21	26	10	2	40	29	36	23.7	26	24.9

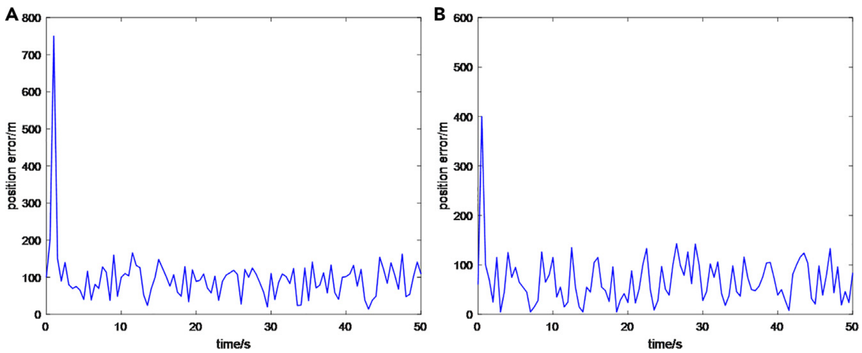

Figure 11. Position errors of the optimized fuzzy NN algorithm

(A) Score of x axis position error.

(B) Score of y axis position error.

overall and local performance of the algorithm. The parameter set with the highest total score is obtained; then optimization objective is set, finally improving the intelligent radar seeker algorithm. The proposed method not only constructs the evaluation system from local to global but also helps to optimize NN model parameters, thus improving the overall performance of the radar seeker. This method also applies to infrared and optical seekers. Subsequent research will focus on the evaluation and optimization of intelligent recognition algorithms.

Limitations of the study

The proposed evaluation and optimization based on weighted fusion require large-scale expert judgment and tracking data from different seeker hardwares. The two main disadvantages behind this are the following. (1) The design of weights requires time and cost, so it is not real time. (2) The data of different types of seeker need to be collected during verification, and the data processing workload is large. Actually, the proposed scheme cannot optimize algorithm in real time when the aircraft is working.

STAR★METHODS

Detailed methods are provided in the online version of this paper and include the following:

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- RESOURCE AVAILABILITY
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- METHOD DETAILS
  - Numerical analysis
- EXPERIMENTAL MEASUREMENTS

ACKNOWLEDGMENTS

The project was supported by the basic project of quality technology of CASIC Third Research Institute under Grant JR202210. This research was also supported by the Key Project of Science and Technology Committee of the Third Institute of CASIC.

AUTHOR CONTRIBUTIONS

K.H., J.W., and C.Y. conceived the research, performed the research, and wrote the manuscript. K.H. and Z.W. performed the research, revised the manuscript, and provided the fund support. Responsibilities of the corresponding author and lead contact K.H. are 1) supervising the work; 2) being responsible for all data, figures, and text; 3) ensuring that authorship is granted appropriately to contributors; 4) ensuring that all authors approve the content and submission of the paper as well as edits made through the revision and production processes; 5) ensuring adherence to all editorial and submission policies; 6) identifying and declaring conflicts of interest on behalf of all authors; 7) identifying and disclosing related work by any co-authors under consideration elsewhere; 8) arbitrating decisions and disputes and ensuring communication with the journal (before and after publication), sharing of any relevant information or updates to co-authors, and accountability for fulfillment of requests for reagents and resources.

DECLARATION OF INTERESTS

The authors declare no competing interests.

Table 7. Comparative analysis of performance with state-of-the-art method

	$e_{x,m}$	$e_{y,m}$	$e_{x,a}$	$e_{y,a}$	$e_{x,s1}$	$e_{y,s1}$	$e_{x,s2}$	$e_{y,s2}$	$e_{x,s3}$	$e_{y,s3}$	$e_{x,s4}$	$e_{y,s4}$	$e_{x,s5}$	$e_{y,s5}$
Method in de Moura et al.[31]	800.7	406.0	124.3	117.5	163.1	127.5	110.1	114.0	112.4	106.5	123.9	124.7	110.3	106.7
Proposed method	750.1	399.8	94.8	92.3	153.1	105.5	90.1	76.0	80.4	86.5	83.9	69.7	98.4	66.6

INCLUSION AND DIVERSITY

We support inclusive, diverse, and equitable conduct of research.

Received: March 20, 2023
Revised: October 10, 2023
Accepted: November 20, 2023
Published: November 23, 2023

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STAR★METHODS

KEY RESOURCES TABLE

REAGENT or RESOURCE	SOURCE	IDENTIFIER
Software and algorithms		
MATLAB	The MathWorks, Inc	R2020b
CST Studio Suite	Dassault Systemes	CST 2018
Other		
Vector Network Analyzer	Rohde&Schwarz	ZVA40

RESOURCE AVAILABILITY

Lead contact

Further information and requests for resources should be directed to and will be fulfilled by the lead contact, Kaiyu Hu (hukaiyuluran@126.com).

Materials availability

This paper did not generate new unique reagents.

Data and code availability

(1) Data reported in this paper will be shared by the lead contact upon request.
(2) This paper does not report original code.
(3) Radar seeker; intelligent tracking algorithm; weighted fusion evaluation; performance index

METHOD DETAILS

Numerical analysis

All the numerical analysis required for this work was conducted by MATLAB R2020b and CST Design Studio Suite 2021. Firstly, an oval slot was designed which its dispersion diagram was analyzed. The single oval slot was then modified through glide symmetry principle. The dispersion diagram of the modified unit cell was discussed in terms of minor and major radius of the oval slots. Moreover, the rotation of the single oval affected on the microwave band-width of seeker dual NN tracking algorithm.

EXPERIMENTAL MEASUREMENTS

In order to measure the characteristics of the proposed dual band filter, vector network analyzer (Rohde&Schwarz ZVA40) was used. The tracking algorithm was connected to the vector network analyzer using high frequency cable. Tracking signals on the x and y axes were eventually measured.