TEST Engineering & Management

July - August 2020
ISSN: 0193-4120 Page No. 4407 - 4416

A Gradient Boosting Decision Tree Method based Air Combat Style Predication

Lin Huo[1,a,*], Tingting Zhang[1], Simiao Fei[2], Cong Guan[3]
[1] School of Safety Engineering, Shenyang Aerospace University, Shenyang110135, China
[a] Liaoning Key Laboratory of Aircraft Safety and Airworthiness, Shenyang, China
[2] Shenyang Aircraft Design Institute, Shenyang 110035, China
[3] School of Artificial Intelligence, Nanjing University, Nanjing 210023, China
Corresponding author (Lin Huo, E-mail: huolin@buaa.edu.cn)

Article Info
Volume 83
Page Number: 574 - 585
Publication Issue:
July-August 2020

Article History
Article Received: *25 April 2020*
Revised: *29 May 2020*
Accepted: *20 June 2020*
Publication: *10 August 2020*

Abstract

The combat style of the air target plays a key role in the air combat strategy and combat result. If the combat style tendency of the air targets can be correctly predicted during the combat, a counter strategy in a targeted manner can be adopted to greatly improve the probability of winning the air combat. In the one-on-one air combat, the basic combat style includes three kinds of style characteristics: the moderate, the conservative and the radical. A new intelligent decision tree model based on the Gradient Boosting Decision Tree (GBDT) method is proposed in the article, which can effectively predict the combat style of target objects by using air combat simulation confrontation behavior data. Firstly, the Classification and Regression Tree (CART) is constructed to conduct Classification Regression and feature selection. Then three different styles Artificial Intelligence（AI）of air combat behavior data are generated by using evolutionary neural network technology. All parameters of neural network strategy are then coded by Genetic Algorithm in real number. And by designing different task target fitness functions, genetic evolution is carried out according to the fitness value. The further neural network strategy with the best fitness value is formed as the Artificial Intelligence（AI）for data collection. So the baseline objects of the moderate, the conservative and the radical style are generated and a large amount of confrontation date is obtained by fighting against each other in the air combat simulation environment. Finally, the LightGBM framework is used to process the large-scale confrontation data with a total training sample size of 180000.

Keywords: *Intelligent air combat, Gradient Boosting Decision Tree, Machine Learning, Classification and Regression Tree, Combat style prediction, LightGBM;*

1. Introduction

Predicting the combat style of the opponent air target is a key link in the air combat, and it is an important basis for formulating the combat strategy of air combat, which is very important for winning the victory of air combat[1]. Therefore, if we can correctly predict the combat style tendency of the air target in the air combat, we can take targeted countermeasures and thus greatly improve the possibility of victory in the air combat. At present, in one-to-one medium-range air combat, the basic combat style includes three characteristics: conservative, moderate, and radical. Conservative style focuses on defense and seeks for opportunities to shoot down targets under the premise of ensuring survival; Moderate style is a strategy to balance the relationship between offense and defense; Radical style is offensive and aims to quickly shoot down the target.

At present, there is no direct research on air combat style prediction in China. But in recent

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years, scholars have begun to pursue more efficient and more accurate identification of combat intention of air targets. Yin Xiang et al[2] established a mathematical model for the enemy combat intention recognition, and combined with Fisher and Bayes classification discrimination method, obtained target intention recognition rules; Zhou Wangwang et al[3] adopted the deep neural network model to solve some problems of air combat intention recognition caused by the lack of field experts' experience, and also achieved the goal of faster convergence speed and better recognition effect; Zhai Xiangyu et al[4] proposed a standardized fully connected network and residual network model to study the attribute factors that influence the analysis of target combat intention, and verified the feasibility of the method by simulation. In 2019, Hu Dashuai and other scholars applied the AlexNet convolutional neural network model in deep learning to air target coarse classification task[5]. The above research methods focus on Linear Discriminant Analysis[6], Logistic Regression Model[7], Bayesian Network[8], Neural Network[9], Decision Tree[10]. etc. Among them, Neural Network algorithms have strong self-learning ability, good adaptive ability and fault tolerance [20].

However, none of the above studies has carried out specific prediction research on the combat style category of air targets. For one-to-one medium-range long-range air combat, the input posture means that the state space can reach at most 200 dimensions and the high-level actions can reach at least 20. Because it is difficult to judge which dimensions are strongly related to the combat style by virtue of human experience. When the dimension of data set is more complex, the above algorithm cannot actively select and combine features, so its accuracy rate will be affected by irrelevant dimensions and even cause dimension disaster[11]. At the same time, there are many contingencies in the air combat behavior, resulting in a high proportion of abnormal points in the data of combat behavior. If the abnormal points are not removed in the data preprocessing, the accuracy of classification results will also be affected. For example, LR model which is very sensitive to feature combination, requires a large amount of human prior knowledge to obtain features, and the effect is not guaranteed.

Decision Tree is one of the most popular classification and regression methods in Machine Learning. Gradient Boosting Decision Tree (GBDT) has achieved great success in various machine learning and data mining challenges and has strong robustness for abnormal points and high model flexibility. Due to its flexible loss function mechanism, GBDT can handle any data-driven task with fast processing speed and good effect. Therefore, it is increasingly used to solve nonlinear and multi-parameter estimation and prediction problems. GBDT is a method to improve classifier performance by combining weak classifiers[12]. The core idea is to construct several CART decision trees in order, and the value classified by the T-th decision tree is the gradient of the loss function on the training set of the value classified by the T-1st tree. In the iterative learning of GBDT, if the strong learner of the last iteration training is $f_{t-1}(x)$, the objective function is $L\big(y, f_{t-1}(x)\big)$, the objective function of this iteration is $L\big(y, f_{t-1}(x)\big) = L\big(y, f_{t-1}(x) + h_t(x)\big)$ minimum, and get a new weak learner $h_t(x)$, fit a CART regression tree with a negative gradient of the objective function. GBDT method can effectively solve the problem of automatic feature selection and abnormal point processing, and also can avoid the problem of model over-fitting to some extent[13].

In this paper, three different types of air combat behavior data Artificial Intelligence (AI) are constructed based on the three types of air combat styles. Let these three AIs carry out a large number of one-to-one medium distance air combat confrontation, and record the confrontation behavior data. Then a new model which can effectively predict the target style is built by GBDT method, and the model is trained and verified by a large number of simulation confrontation behavior data.

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2. Gradient Boosting Decision Tree Method

As a traditional machine learning algorithm, the Gradient Boosting Decision Tree (GBDT) Method is the most suitable one to fit the real distribution. It is an algorithm to classify or regress data by using an addition model, constructing a linear combination of multiple basis functions and reducing residual errors generated in the training process. GBDT is an integrated learning Gradient Boosting algorithm, combined with the regression tree and enhanced algorithm framework. The model residual is reduced through iteration, that is, a weak classifier is generated in each iteration through multiple rounds of iteration. Each classifier is trained on the basis of the previous round of classifier residual, and has strong nonlinear processing and prediction abilities [14]..

Weak classifier generally selects simple model, low variance and high deviation. Because the training process is to improve the accuracy of the final classifier by reducing the deviation. Weak classifier generally chooses a Classification and Regression Tree (CART)that can both classify and regress[15].

2.1. Feature Selection Technology Based on CART

Each round of GBDT training is based on the residual of the previous round of training. The residual here is the negative gradient of the current objective function. Therefore, it is meaningful to subtract the output of the weak classifier after each iteration of training, so the regression form of CART is selected. CART as a weak classifier commonly used in GBDT, is a binary tree and can be used for classification and regression problems [16]. CART also plays a role in feature selection in GBDT method.

CART can be used for both classification and regression. The basic idea of applying the classification problem is to select the optimal feature and optimal cutting point according to the minimum Gini index criterion, and then construct the subnode in the way of binary tree, and then recursively expand the subnode until the whole decision tree is generated, and finally carry out necessary pruning to the decision tree; For regression we need to minimize the sample variance [17]. Because GBDT technology deals with both classification and regression problems, if CART is chosen as a weak classifier, CART regression tree form will be used. In essence, CART regression tree solves the regression problem that includes training samples. The training sample form is as follows:

$$D = \{(x_1, y_2), (x_2, y_2), \cdots (x_m, y_m)\} \qquad (1)$$

Where x_i is a n-dimensional vector. This study represents n-dimensional air combat situation information vector; y_i is the label of the sample. In the regression problem, the label y_i is a series of consecutive scalar values. In this study, it indicates whether it is the combat style of the enemy aircraft identified by the regression tree. If yes, y_i is 1, otherwise is 0.

The regression tree model can be expressed as:

$$h(x) = \sum_{m=1}^{M} c_m I(x \in R_m) \qquad (2)$$

The data space is divided into $R_1 \sim R_m$ regions, each of which is a fixed value c_m. When $x \in R_m, I(x \in R_m) = 1$, and the rest is $I = 0$. This can calculate the loss error of the output value and the label:

$$loss = \sum_{R_m} \sum_{x_i \in R_m} \left(y_i - h(x_i)\right)^2 = \sum_{R_m} \sum_{x_i \in R_m} \left(y_i - c_m\right)^2 \qquad (3)$$

The purpose of the CART regression tree is to constrain the number of leaf nodes while minimizing the loss error of the decision tree. Therefore, for each leaf node, the output value $c_m = avg\left((y_i | x_i \in R_m)\right)$, the loss error function reaches a minimum when c_m is the average of the sample labels of the root node.

On the other hand, we need to make each attribute partition of the decision tree, and also reduce the loss error of the model on the training set.

Initially, only the root node is included in the CART tree, and all samples are divided into root nodes.

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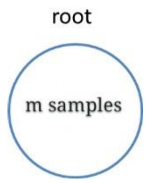

Fig 1 CART Root Node

In this case, the value of the root node is the average of all samples. Then, the loss error is:

$$loss = \frac{\sum_t^m (y_i - \hat{y})^2}{m} \qquad (4)$$

In the formula, $\hat{y}$ is the mean of all sample labels. At this time, the j dimension feature is selected from the n-dimensional features, and the value of the sample in the j dimension is selected from the m-samples: x_j as a criterion for division, when the j dimension of the sample i is less than or equal to x_j, the sample is divided into the left sub tree. Otherwise, it is divided into the right subtree. Through the above operations, the number of samples divided into the left subtree is m_1, and the number of samples divided into the right subtree is $m_2 = m - m_1$. The result of the division is as follows:

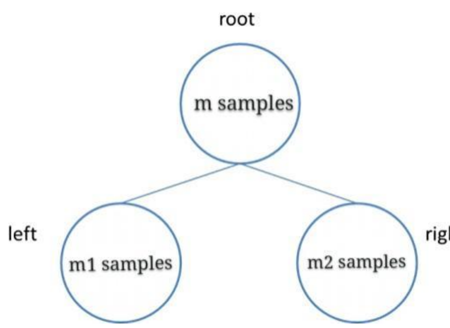

Fig2 CART Sub-nodes

If the left node has m_1 sample and the right node has m_2 samples, the loss function value is the sum of the loss function values of the left and right subtrees:

$$loss = \frac{\sum_{X^{(i)} \in left} \left(y_i - \hat{y}_1\right)^2}{m_1} + \frac{\sum_{X^{(j)} \in right} \left(y_j - \hat{y}_2\right)^2}{m_2} \qquad (5)$$

Where $\hat{y}_1$ is the mean value of the node labels in the left subtree, and the same reason $\hat{y}_2$ is the mean value of the node labels in the right subtree. Iterate through all the possible features and division methods, select the smallest $loss$ division as the final division, and select the optimal division for each leaf node traversing the division points in turn. Until there is only one sample left in the leaf node, the loss value no longer drops, and no features can be divided.

2.2. Based on GBDT classification technology

During the training, for each time slice of air combat behavior sample x, a classification regression tree is trained for each possible classification. In this study, the samples are divided into three categories: conservative, moderate and radical styles. For instance, air combat behavior sample x of a certain time slice belongs to category II. Then the classification result of the sample x can be represented by a three-dimensional vector [0, 1, 0]. 0 presents that the sample does not belong to the class, 1 presents that the sample belongs to the class. Since the sample already belongs to the moderate category, the vector dimension corresponding to the moderate category is 1, and the other positions are 0.

As there are three categories of combat styles in the sample, namely {Conservative, Moderate, Radical}, it is essentially to train three trees at the same time in each round of iterative training. If the target behavior data is labeled as belonging to the second category of moderate, whether the target behavior data x belongs to the first Conservative category , the first tree input is （x,0）. Whether the target behavior data x belongs to the second Moderate category, the second tree input is （x,1）. Whether the target behavior data x belongs to the third Radical category, the third tree input is （x,0）. The training process of each tree here is the CATR generation process described in section 2.1. Using the target behavior data samples, three regression trees can be solved to predict the three categories of target combat styles, and the three trees predicted values for the categories x are $f_1(x)$, $f_2(x)$ and $f_3(x)$[18].

So in this type of training, we follow the logistic regression of multiple classifications, using the $soft\max$ function to generate the probability, then the probability P_1 belonging to the first type of conservative style is:

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$$P_1 = \frac{e^{f_1(x)}}{\sum_{k=1}^{3} e^{f_k(x)}} \tag{6}$$

The input is the training set sample $D = \{(x_1, y_2), (x_2, y_2), \cdots (x_m, y_m)\}$, the maximum number of iterations T, the loss function L. The output is a strong learner $f_1(x), f_2(x)$, $f_3(x)$.

1. Initialize weak learner $f_{i0}(x)$, $i = 1,2,3$

2. For the number of iterations t = 1, 2 , ...T:

$$f_{i0}(x) = \underbrace{\arg\min}_{c} \sum_{j=1}^{m} L(y_j, c) \tag{7}$$

a. Calculate a negative gradient for the samples j=1, 2,...m

$$r_{tj} = \left[\frac{\partial L(y_j, f(x_j))}{\partial f(x_j)} \right]_{f_i(x) = f_{i,t-1}(x)} \tag{8}$$

b. Use (x_j, r_{ij}), $j = 1,2, \cdots m$, to fit the three CART regression trees, and obtain the t regression tree whose corresponding leaf node area is R_{tk}, $k = 1,2,\ldots,K_i$. Where K is the number of leaf nodes of the i-type regression tree t.

c. Calculate the best fit for leaf area $k = 1,2,\ldots,K_i$.

$$C_{tk} = \underbrace{argmin}_{c} \sum_{x_i \in R_{tk}} L(y_j, f_{i,t-1}(x_j) + c) \tag{9}$$

In the CART tree, for the sample x belonging to the root node R_{tk}, there is the same gradient value, and the gradient C_{tk}, which is the fastest drop in the loss function, is found by fitting.

Thus get the decision tree fitting function of this round:

Where $I(x \in R_{tk}) = 1$, when $x \in R_{tk}$.

$$h_t(x) = \sum_{k=1}^{K_i} c_{tk} I(x \in R_{tk}) \tag{10}$$

d. Update the strong learner

$$f_{it}(x) = f_{i,t-1}(x) + h_{it}(x) \tag{11}$$

[3] Get the expression of strong learner as follows, where $i = 1,2,3$

$$f_i(x) = f_{iT}(x) = f_{i0}(x) + \sum_{t=1}^{T} h_{it}(x) \tag{12}$$

3. Target combat style recognition based on GBDT

3.1. One-to-one medium-range air combat style AI construction

Three different styles AIs used to generate air combat behavior data are constructed using evolutionary neural network algorithms[19]. Some aircraft models are used to construct the simulation and the weapon is a general air-to-air missile. The state space uses a space of artificially refined 16-dimensional continuous quantities. The action space uses high-level actions including maneuver numbers and whether to launch a two-dimensional action space. The strategy adopts a five-layer fully-connected neural network, and the input-output layer is consistent with the state space action space dimension. The hidden layer is a fully-connected layer activated by 30 nodes Relu.

The Artificial Intelligence (AI) formation method adopts evolutionary neural network technology, and all the parameters of the neural network strategy are genetically coded by the genetic algorithm[20]. Different network parameters compete with the baseline opponents in the simulation environment, and different fitness values are obtained. The genetic evolution is based on the fitness value. Finally, the neural network strategy with the best fitness value is formed as the AI for collecting data.

Different kinds of styles are mainly guided by the design of the fitness function. The fitness function of radical style AI is designed to make the opponent's shot down fitness value higher. The fitness function of conservative style AI is designed lowest in the fitness value of the shot down by the opponent. The moderate style AI fitness function is designed as the average of the first two. Through large-scale simulation training, three different styles of air combat AIs are finally formed.

3.2. Confrontational behavior data collection

The confrontation data is derived from the behavior data of the trained three styles AIs against the baseline opponent 100 times, and the behavior data of each style AI confronting the other two AIs. In a total of 600 medium-distance air combat data, each style AI produced 200 battles, sampling 300 time segments per field. The sampling idea is to sample the key time segments with a probability of

1, if not enough 300, the non-critical time segments are sampled with a probability of 0.5. A critical time segment is defined as a time segment of the action number switch or a time segment in which the missile is fired.

The total training sample size is 180,000, which is cross-validated, with 0.8 as the training set, 0.1 as the verification set, and 0.1 as the training set.

3.3. Training and learning

GBDT algorithm uses a negative gradient as the information gain of the division. The shortcoming of the training process is that the calculation of the information gain which needs to scan all the samples to find the optimal division point. When there is large amounts of data or high feature dimensions, the efficiency and expansibility is difficult to satisfy.

LightGBM is an optimization framework of GBDT algorithm, with faster training efficiency, low memory requirement and higher accuracy. It can be used for parallel learning and suitable for large-scale data processing.

One of the optimization of GBDT by LightGBM is the histogram based decision tree algorithm, as shown in Figure 3. Firstly, the histogram based decision tree algorithm divided the continuous floating point eigenvalue (bin) into several integers and constructs a histogram with integer width. As the data is traversed, the discrete values are used as cumulative statistics for the indexes in the histogram. After traversing the data, the histogram accumulates the necessary statistics. Then, the optimal segmentation point is traversed according to the discrete value of the histogram.

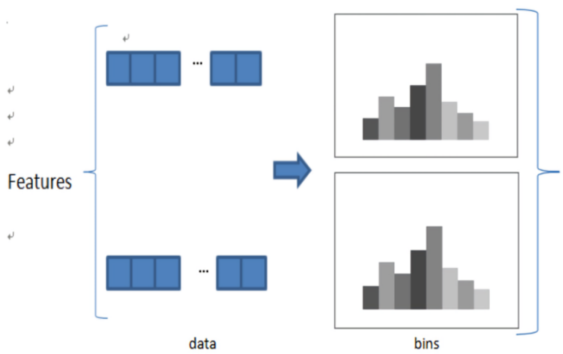

Fig 3 histogram algorithm

Most decision tree learning algorithms grow trees through horizontal growth strategies [21], as shown in the following figure:

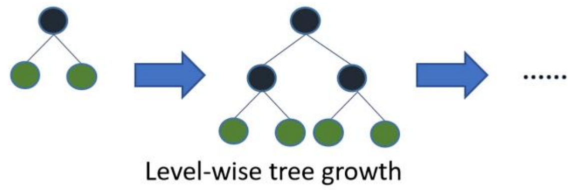

Fig 4 Level-Wise Tree Growth

Another optimization is Leaf-Wise growth strategy, with nodes with higher gain taking priority in growth [22], as shown in Figure 5. When growing the same leaf nodes, Leaf-Wise algorithm can reduce more losses than Level-Wise algorithm.

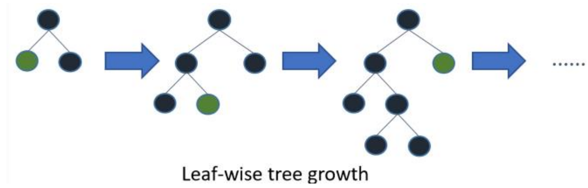

Fig 5 Leaf-Wise Tree Growth

When the data size is small, Leaf-Wise may cause over-fitting. Therefore, LightGBM can take advantage of the extra parameter max_depth to limit the depth of the tree and avoid over-fitting (tree growth is still through the Leaf-Wise strategy).

In order to prevent over-fitting and improve the generalization ability of the model, the number of leaves of LightGBM is set to 35, the learning rate is 0.05, the tree sampling ratio is 0.8, and the proportion of sub-samples used for training models to the entire sample set is 0.9.

4. Simulation and experimental analysis

When classifying data with the GBDT algorithm, we combine the actions of height, speed, acceleration, and attack area with weapon operations and maneuver operations into a one-dimensional data vector, then add classification style labels to the data samples. to train the GBDT model.

Table 1 Model input data dimension

Coad	Meaning	Sample 1	Sample 2	Sample 3
V_b_0	speed	1034.614849	1292.750830	1315.200934
H_b_0	Height	9.267653	7.811261	6.509195
ACC_b_0	Acceleration	0.000000	0.000000	0.000000
R_0	Distance	60.628563	83.345497	68.792374
Raero_EST_b_0	Maximum attack area	72.2845	71.2678	72.2678
Ropt_EST_b_0	Optimal attack area	47.6423	45.3736	46.1325
:	:	:	:	:
Action	Maneuvering action number	2	1	1
Shoot	Whether to launch missiles	1	0	0
Label	Style category	[1,0,0]	[0,1,0]	[0,0,1]

The prediction model outputs the classification results in the form of probability. So the model outputs the probability values of conservative, moderate and radical target styles, and selects the maximum probability as the prediction result, that is $y_{t-pre} = argmaxf_t(x_i)$.

In the training model stage, 180,000 samples were used for training, 80% samples were used as the training set, 10% samples were used as the verification set and 10% samples were used as the test set. Each data set is constructed by simple random sampling method. In the training process, the prediction speed of the model is temporarily ignored, and the prediction accuracy of the model is only considered. The training results are shown in the figure below.

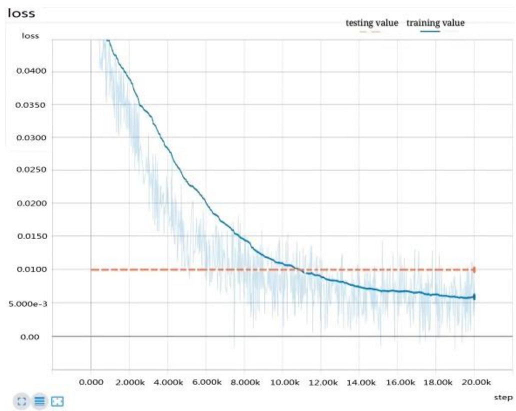

Fig 6 Training Set Loss Function Value Decrease

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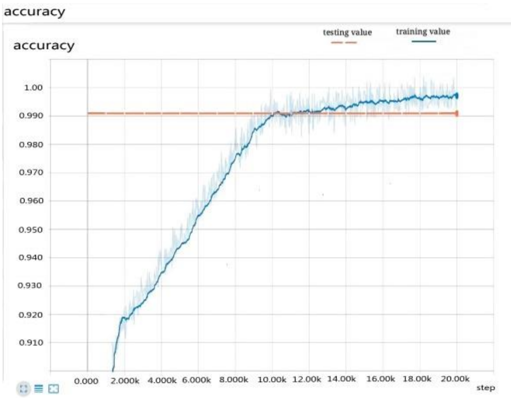

Fig 7 Training Set Prediction Accuracy Improvement

In addition, due to the timing problem of the target style prediction, the faster the target style prediction is completed, the more time is left for us to improve our strategy to counter the other side. Therefore, this study verifies the prediction efficiency of the model. In the application of the model, we choose 0.7 as the confidence level. In other words, only when the sliding average of the three styles cumulative output probability of the model exceeds 0.7, can the target object be considered as belonging to this style, that is to say:

$$y_{t-pre} = \begin{cases} m_a, m_a > 0.7 \\ None, else \end{cases} \qquad (13)$$

Among them $m_a = argmax \frac{1}{t} \sum_{t=0} f_t(x_i)$

The recognition results of three targets styles are shown in the following figure.

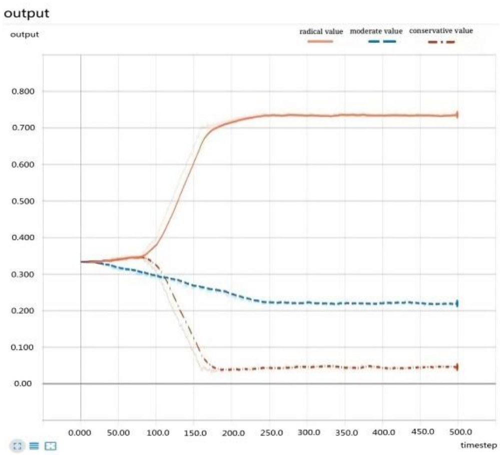

Fig 8 Radical Style Target Recognition

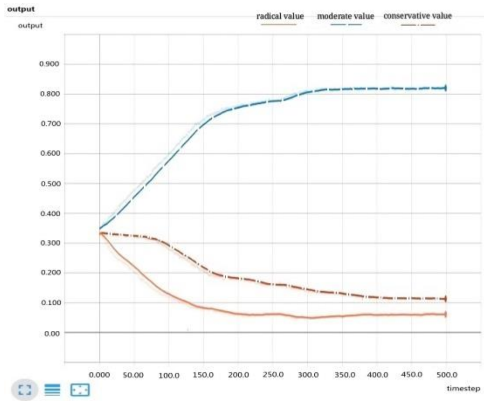

Fig 9 Moderate Style Opponent Recognition

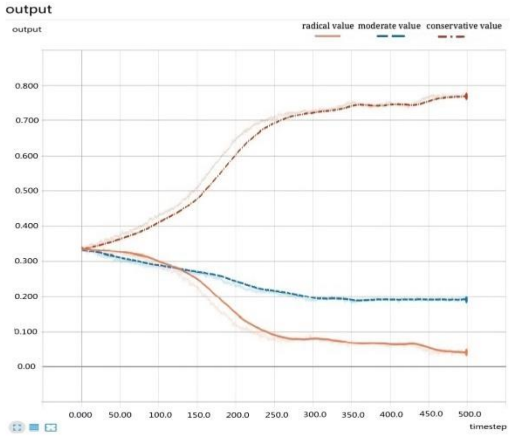

Fig 10 Conservative Style Opponent Recognition

After the parameters adjustment and training in the verification set and the training set, the performance loss value of the model in the training set finally stabilized at 0.0056, 99.68% accuracy, and the loss value of the trained model in the test set reached 0.00994, 99.09% accuracy.

5. Conclusions

Through one-to-one medium-range air combat simulation and experimental analysis, Gradient Boosting Decision Tree method (GBDT) can be used to effectively predict the combat style of the opposing air target within an acceptable time. From the perspective of the air combat countermeasure mechanism, the air target combat style is not only conservative, moderate, and radical. This paper does not make a further detailed classification of combat styles, because a more detailed classification of styles involves a more systematic prior knowledge of air combat and corresponding AI design. However, the method described in this paper belongs to machine learning method. From a

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theoretical analysis, as long as there is a certain amount of behavior data of target objects with different styles, this method can carry out more detailed classification and style prediction.

However, this study has not yet incorporated the predicted speed into the optimization goal, and the time factor can be incorporated into the loss function for a unified design in the future. It is expected to achieve a shorter time to complete the high confidence of the combat style forecast.

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Published by: The Mattingley Publishing Co., Inc.

July - August 2020
ISSN: 0193-4120 Page No. 4407 - 4416

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