

Flight Technology Evaluation Based on Flight Parameters

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Abstract. Based on the flight safety, this paper develops a flight technology evaluation method based on the gradient boosting decision tree (GBDT) model by collecting and analyzing flight data. This method comprehensively considers flight parameters and provides a more accurate pilot flight technology assessment tool through the analysis of flight records. It is expected to improve the training plan and enhance the technical level of pilots to further improve the safety and sustainable development of air transportation. By introducing the deep learning network structure optimization evaluation method, the flight safety is further enhanced.

Keywords: Flight safety; flight technology assessment; gradient boosting decision tree; deep learning network.

1. Introduction

Flight safety is the cornerstone of the survival and development of the civil aviation transportation industry. With the rapid development of the global civil aviation industry, research on flight safety issues has become increasingly important. In order to improve the level of flight safety, we need to start from many aspects. By strengthening the collection and analysis of flight data, we study a flight technology evaluation method based on flight parameters to improve the pilot's flight technology.

Flight data include : speed, height, attitude, thrust setting and system status[1]. These data are critical to flight safety monitoring and analysis. The flight parameter detection data mainly comes from the Quick Access Recorder (QAR) on the aircraft, which records all kinds of key parameters generated by the aircraft during flight in real time[2].

Based on the GBDT (Gradient Boosting Decision Tree) model, this paper develops a flight technology evaluation method that comprehensively considers flight parameters. GBDT is a powerful machine learning algorithm, which has the advantages of processing high-dimensional data, strong robustness and anti-noise ability[3]. This method can evaluate various characteristic quantities related to the pilot's flight technical qualification, and obtain the flight technical evaluation scheme based on flight parameters. This program will provide airlines and regulators with more accurate pilots' pilot technology assessment tools to help them develop training programs, improve the technical level of pilots, and further enhance the safety and sustainable development of air transport.

At present, most of the research on pilots' operation behavior based on QAR data focuses on the evaluation of pilots' operation level and the exploration of operation behavior patterns[4]. For example, through the feature extraction, similarity measurement and cluster analysis of multivariate time series data of flight parameters, the flight operation mode is mined. The evaluation model of flight operation level based on flight quality monitoring standard. In order to improve the more efficient mining application of QAR data, we use deep learning network structure to optimize the flight technology evaluation method and further increase flight safety.

The evaluation method used in this paper can effectively process the high-dimensional features in the flight parameter detection data and accurately evaluate the pilot's flight technical level. At the same time, the GBDT model can find the key factors that affect the pilot's flight technical level, and help us understand which features are most important to the technical level by providing feature importance information.

2. Problem analysis and data preprocessing

2.1 Problem analysis

In the field of flight safety, accurate assessment of the pilot's flight technology level is crucial to ensure the safety and stability of air traffic. However, the traditional manual evaluation method has subjectivity and limitations, so a more objective and accurate evaluation method is needed[5]. The purpose of this study is to explore the application of machine learning methods in the evaluation of pilots' flight skill level, with special attention to machine learning methods based on GBDT model, as shown in figure 1, which is the model structure of GBDT algorithm.

Specifically, we comprehensively analyze each pilot's flight record by analyzing the given flight parameter measurement data. We will combine the flight parameters with the preset pilot flight technical qualifications to establish machine learning related models, such as GBDT gradient lifting decision tree model and BP neural network model.

In order to train and evaluate these models, we divide the data set into training set and test set. We feed these models repeatedly until the error between the output model results and the actual values is very small. Using this method, we can objectively evaluate the pilot's flight skill level based on machine learning models, and improve and improve the shortcomings of traditional methods. The introduction of this assessment method will significantly improve flight safety and make a substantial contribution to the safety and stability of air traffic[6].

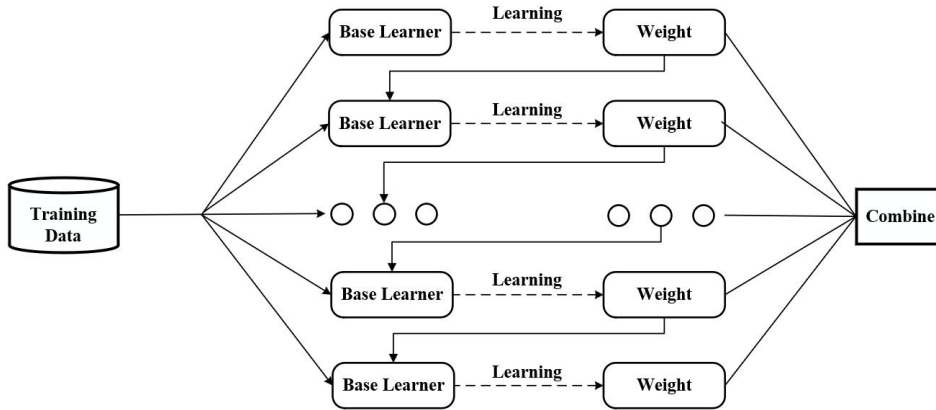


Fig. 1 Model structure of GBDT algorithm

2.2 Data preprocessing

Before evaluating the pilot's flight technical level, we conducted a comprehensive preprocessing of the flight parameter measurement data. The preprocessing process is designed to ensure the quality and consistency of the data, thereby improving the performance and accuracy of subsequent machine learning related models.

First, we perform a data cleaning step to remove possible outliers and noise. By using statistical analysis and domain knowledge, we can accurately identify and exclude data points that deviate from the normal range to ensure the reliability of the data. Secondly, we deal with possible missing values. Using appropriate methods, such as interpolation or deletion, we fill or delete missing data to maintain the integrity and consistency of the data set. This helps to avoid introducing bias or misleading results in subsequent training and evaluation processes. In addition, we normalized or standardized the data. By scaling the values of different features, such as minimum-maximum scaling or Z-score normalization, we eliminate the dimensional differences between different features and ensure that they are compared and analyzed at similar scales. Finally, we perform feature selection or dimensionality reduction. With the help of correlation analysis, information gain and other methods, we screen out the most relevant and representative features for pilots' flight

skill level assessment, so as to reduce the dimension of data and improve the training efficiency and prediction performance of subsequent models.

Through the above data preprocessing steps, we successfully processed the flight parameter measurement data and provided high-quality input for the subsequent machine learning related models. This provides a reliable basis for the evaluation of the pilot 's flight technology level.

2.3 Establish training set and test set

On the prepared flight parameter data set, we adopt a random sampling method, 70% of which are used as learning training samples, and the remaining 30% are used as verification samples[7]. This sampling method is designed to ensure the representativeness and generalization ability of the samples, so as to obtain reliable results in the process of model training and testing.

For learning training samples, we will use these data to construct and train machine learning related models. By simulating the training and testing process, we are able to evaluate the performance and accuracy of these models in the assessment of pilots ' flight skill levels. At the same time, in order to verify the stability and reliability of the model, we will use the remaining 30% validation samples to verify the trained model. By comparing and analyzing with the actual observations, we can evaluate the generalization ability and prediction accuracy of the model on new data.

Through the above steps, we can make full use of machine learning methods to train and verify based on the pre-processed flight parameter measurement data. This method is objective and accurate, and provides a reliable method and tool for the evaluation of pilot 's flight technology level.

3. Establishment of the model

3.1 GBDT gradient boosting decision tree for feature importance assessment

GBDT (Gradient Boosting Decision Tree) is a common ensemble learning algorithm based on decision tree[8]. The algorithm establishes a decision tree in each iteration, so that the residuals of the current model are reduced in the gradient direction[9] ; then the decision tree is linearly combined with the current model to obtain a new model, and a series of decision tree models are repeatedly trained until the number of decision trees reaches the specified value, so as to obtain the final strong learner and improve the performance of the model. Below we give the training formula :

$$F(x) = F_k(x) = \sum_{k=1}^K h_k(x; a_k) \quad (1)$$

where $h_k(x; a_k)$ represents the predicted output of the k th decision tree, K represents the number of decision trees, and a_k represents the parameters of the decision tree. After the basic parameter setting is completed, we use the softmax auxiliary activation function to calculate the category of flight parameters. The expression is as follows :

$$p_k(x) = \frac{\exp(F_k(x))}{\sum_{l=1}^K \exp(F_l(x))} \quad (2)$$

where $p_k(x)$ represents the class probability. In the classification task, since the sample output is a discrete value, the residual cannot be fitted from the output category, so the difference between the predicted probability value and the real probability value of the category is used as the residual. In this regard, we use the cross entropy loss function, the formula is as follows :

$$L(\{y_k, F_k(x)\}_{k=1}^K) = -\sum_{k=1}^K y_k \log p_k(x) \quad (3)$$

In the same way, we solve the negative gradient, that is, the residual :

$$y_{ik} = - \left[\frac{\partial L(\{y_{il}, F_l(x_i)\}_{l=1}^K)}{\partial F_k(x_i)} \right] \{F_{l, m-1}(x)\}_1^K = y_{ik} - p_{k, m-1}(x) \quad (4)$$

In order to further improve the performance of the model, we also need to calculate the estimator of the decision tree leaf nodes. This estimator determines the contribution of each leaf node to the prediction results.

$$\{r_{jkm}\} = \arg \min_{r_{jkm}} \sum_{i=1}^N \sum_{k=1}^K \phi \left(y_{ik}, F_{k, m-1}(x_i) + \sum_{j=1}^J \gamma_{jk} I(x_i \in R_{jm}) \right) \quad (5)$$

The indicator function is $I(x_i \in R_{jm})$, if $x_i \in R_{jm}$, then $I=1$; otherwise $I=0$. $\{r\}$ represents the estimator of the decision tree leaf nodes, and j represents the number of leaf nodes in the decision tree, that is, the depth of the decision tree. Finally, the approximate results are obtained by Newton-Raphson method :

$$r_{jkm} = \frac{K-1}{K} \frac{\sum_{x_i \in R_{jkm}} y_{ik}}{\sum_{x_i \in R_{jkm}} |y_{ik}| (1 - |y_{ik}|)} \quad (6)$$

As shown in figure 2, according to the flight parameter training data that has been preprocessed, the parameters of the GBDT gradient boosting decision tree model are set.

Algorithm 1: GBDT Algorithm

Data: Training dataset $\{(x_1, y_1), (x_2, y_2), \dots, (x_n, y_n)\}$, where x_i is the feature vector and y_i is the label

Result: GBDT model $F(x)$

Initialize model $F_0(x) = 0$;

for $m = 1$ **to** M **do**

Compute negative gradient $r_{im} = -\frac{\partial L(y_i, F(x_i))}{\partial F(x_i)}|_{F(x)=F_{m-1}(x)}$, where L is the loss function;

Fit a regression tree to approximate r_{im} , obtaining leaf regions R_{jm} and leaf values c_{jm} ;

Update model $F_m(x) = F_{m-1}(x) + \eta \sum_{j=1}^J c_{jm} I(x \in R_{jm})$, where η is the learning rate;

end

Fig. 2 GBDT model parameter setting

Through a large number of repeated selection of features, select the optimal division of attributes, find out the best division of each type of flight parameter data, and the order of different feature divisions, so that the 'purity' of nodes is getting higher and higher. Finally, a suitable GBDT is established to evaluate the importance of features.

3.2 Model accuracy test

After the iteration and parameter modification of the flight parameter training data of multiple wheelsets, we select a set of representative results, and the contribution rate of each flight parameter to the flight technology evaluation can be obtained. Through data screening and cleaning, some flight parameters that contribute more to flight technology assessment are finally obtained. As shown in Figure 3. After analyzing the contribution rate, we import the test set data into the pilot technical level obtained by machine learning classification in the model, and test its accuracy. The test results are shown in Figure 4. The test results show that the accuracy of the output results of the GBDT gradient boosting decision tree model is as high as 81.3 %, which is in line with the expected results and can be used as a reference for the flight technology evaluation scheme.

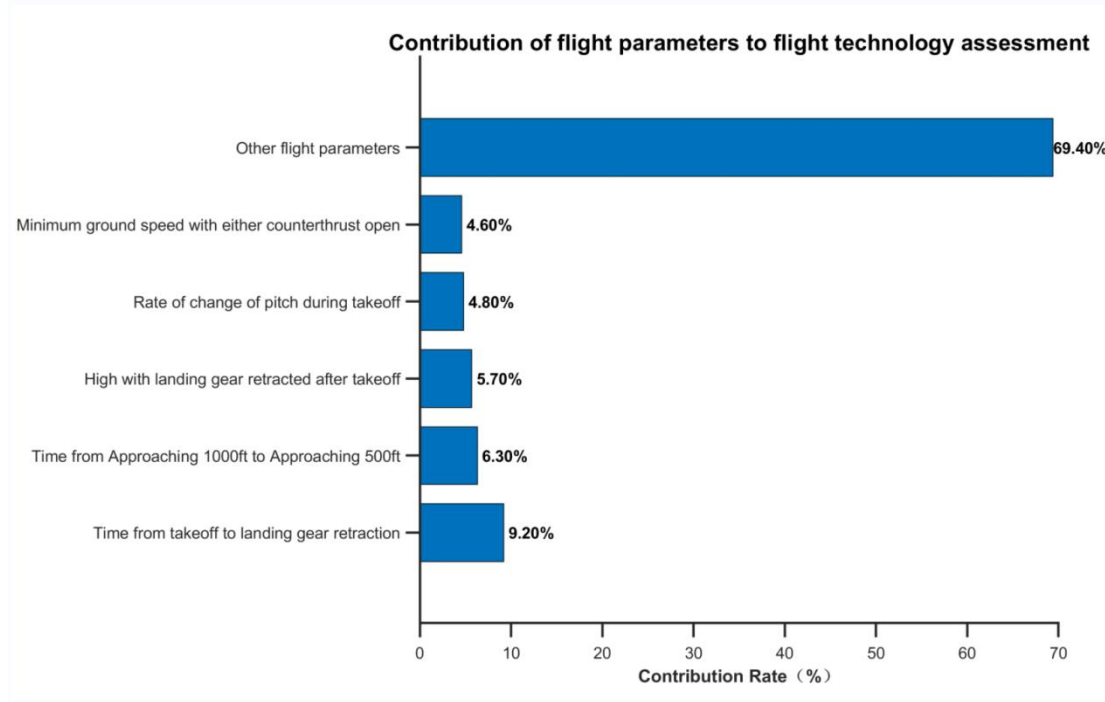


Fig. 3 Contribution rate of flight parameters to flight technology assessment

	Accuracy rate	Recall rate	Precision rate	F1
Training Set	1	1	1	1
Cross Validation Set	0.787	0.787	0.787	0.781
Test Set	0.813	0.813	0.808	0.808

Fig.4 Evaluation results of GBDT gradient boosting decision tree model

3.3 Comparison with BP neural network model

In addition to the previously mentioned GBDT model, we also tried a method based on back propagation (BP) neural network. This method uses the feedback error correction algorithm to further improve the evaluation accuracy of pilots ' flight technical qualifications[10]. We use the sorted training set as a sample of the input layer. Under the assumption that there is a deviation between the measured data and the actual pilot 's flight technical qualification, the information is fed back to the network through reverse propagation. In this way, we can adjust the weights of the output layer to reduce the square sum of network errors and meet acceptable standards. Through this process, we have obtained a set of optimal flight technology evaluation methods.

In the process of applying the BP neural network model, we need to construct a suitable neural network structure, as shown in Figure 5. In the input layer, we input the flight parameters as sample data and perform weighted calculations. The calculation results are passed to the hidden layer. Subsequently, in the second layer of neural network, we again weighted the data of the hidden layer, and finally obtained the output of the pilot 's flight technical qualification index.

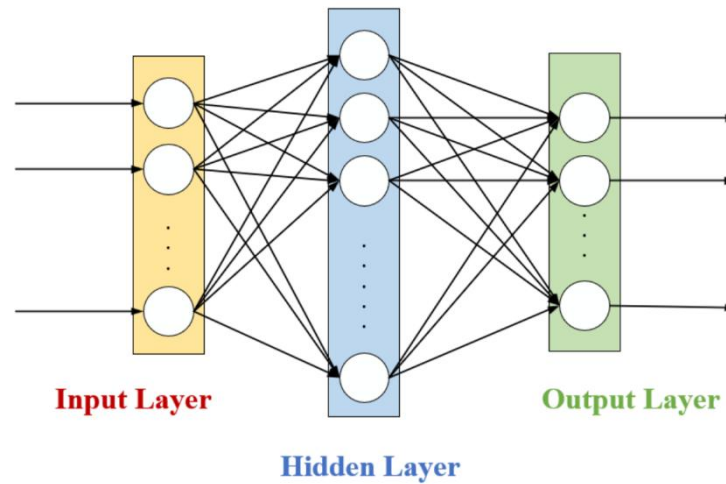


Fig.5 Structure diagram of BP neural network

In order to make the neural network model more in line with the actual value, the learning algorithm we use constantly adjusts the connection, weight and structure to improve the coincidence between the output of the network and the actual value. This iterative process continues until the required accuracy is achieved. After the training is completed, we use the data of the test set to input into the neural network to evaluate the accuracy and performance of the model.

By using the BP neural network model and conducting appropriate training and testing, we have obtained a set of reliable flight technology evaluation methods. This method can accurately evaluate the pilot 's flight technical qualifications and provide important reference and support for pilot training and flight safety.

4. Conclusion

By analyzing the flight parameter data, we developed a comprehensive flight technology evaluation method based on the GBDT (Gradient Boosting Decision Tree) model. The methodology aims to assess pilots ' flight skill levels and provide airlines and regulators with more accurate assessment tools to improve pilot training and flight safety.

In the experiment, we compared GBDT with BP neural network. The results show that GBDT has obvious advantages in flight technology evaluation.

However, if the flight parameter data is incomplete and erroneous, the generalization ability of the GBDT model will decrease slightly, which needs to be verified under different environments and conditions. In addition, we also need to consider the impact of human factors on the evaluation model in practical application.

Future research can further explore the improvement and application of GBDT to further improve the accuracy and efficiency of flight technology assessment. This study provides a reliable method for flight technology assessment and an important assessment tool for airlines and regulators. This method can improve the pilot 's training plan and improve flight safety, and continuously improve the safety and sustainable development of air transportation.

References

- [1] Olson, W. M. Aircraft performance flight testing. California: Air Force Flight Test Center, 2000.
- [2] Li, Lishuai. Anomaly detection in airline routine operations using flight data recorder data. Diss. Massachusetts Institute of Technology, 2013.
- [3] Y. Li, L. Zou, L. Jiang, and X. Zhou. Fault Diagnosis of Rotating Machinery Based on Combination of Deep Belief Network and One-dimensional Convolutional Neural Network. IEEE Access, 2019, 7: 165710–165723.

- [4] Li L, Hansman R J, Palacios R, et al. Anomaly detection via a Gaussian Mixture Model for flight operation and safety monitoring. *Transportation Research Part C: Emerging Technologies*, 2016, 64: 45-57.
- [5] Zhang H, Fritts J E, Goldman S A. Image segmentation evaluation: A survey of unsupervised methods. *computer vision and image understanding*, 2008, 110(2): 260-280.
- [6] Macchi L. A Resilience Engineering approach for the evaluation of performance variability: development and application of the Functional Resonance Analysis Method for air traffic management safety assessment. *École Nationale Supérieure des Mines de Paris*, 2010.
- [7] Han L, Yang G, Dai H, et al. Modeling maize above-ground biomass based on machine learning approaches using UAV remote-sensing data. *Plant methods*, 2019, 15(1): 1-19.
- [8] Guo R, Fu D, Sollazzo G. An ensemble learning model for asphalt pavement performance prediction based on gradient boosting decision tree. *International Journal of Pavement Engineering*, 2022, 23(10): 3633-3646.
- [9] Zhang B, Ren J, Cheng Y, et al. Health data driven on continuous blood pressure prediction based on gradient boosting decision tree algorithm. *IEEE Access*, 2019, 7: 32423-32433.
- [10] Wang L, Zhang J, Dong C, et al. A method of applying flight data to evaluate landing operation performance. *Ergonomics*, 2019, 62(2): 171-180.