Research on Gearbox Fault Diagnosis Based on DCNN and XGBoost

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Abstract. In order to solve the problem of complex fault diagnosis of gearbox, the DCNN (Deep Convolution Neural Network) was combined with the XGBoost (eXtreme Gradient Boosting) algorithm to establish the fault diagnosis model. Firstly, the DCNN Model was used to adaptively extract the feature matrix of the original vibration acceleration signal. Secondly, the XGBoost model was trained by the feature matrix, so the gearbox fault diagnosis model of DCNN-XGBoost was obtained. Finally, the visualization effect of the feature matrix obtained by DCNN is better than that of the artificial extraction feature matrix; and the diagnostic accuracy of DCNN-XGBoost model is better than DCNN model.

Introduction

The gearbox is a mechanical device\cite{1} which achieves the speed change effect by virtue of the mutual engagement between the large gear and the small gear. There is one gear on each of the two transmission shafts in the gearbox, and the angular speed of the gear is the same as that of the shaft; the linear speed of the two gears that bite each other is the same. Owing to the diameter of the two gears which on different shafts is different, so the angular speed and the rotation speed of the two shafts will be different. thus, the gearbox can achieve the effect of acceleration and deceleration. Because the vibration signal is easy to obtain, the method based on the vibration signal processing plays an important role in the fault diagnosis of the gearbox. However, the structure of the gearbox is complicated, and the complex vibration signal is composed of all kinds of vibration signals\cite{12-13}, which makes it more difficult to diagnose and identify the faults. Therefore, many scientists at home and abroad regard the fault diagnosis of gearboxes as their own research topics\cite{10-11}.

In this paper, XGBoost\cite{2-3} algorithm is introduced into the field of gearbox fault diagnosis. XGBoost algorithm is an efficient implementation of GBDT\cite{6} (gradient boosting decision tree) algorithm. Generally speaking, the implementation of GBDT is relatively slow, while XGBoost is characterized by fast calculation speed and good model performance. Because of DCNN\cite{4-5} has a good effect on extracting feature matrix of vibration signal, DCNN was combined with the XGBoost algorithm to establish the fault diagnosis model.

XGboost Algorithm

XGBoost algorithm was first proposed in 2014, which is very similar to the traditional gradient lifting tree. The definition of complexity of the tree in XGBoost is different from the traditional lifting tree. The tree is divided into structural part and leaf weight part.

\begin{equation}
\Omega (f) = \gamma T + \frac{1}{2} \lambda \sum_{i=1}^{T} w_i^2 .
\end{equation}

Among them: T is total number of leaf nodes; \( \gamma \) is the parameters that control the weight of the number of leaves; \( \omega_j \) is the weight of the j leaf; \( f_i \) is Model function of tree\cite{8-9}.

In order to solve the difficult problem of loss function, the second order Taylor expansion of the loss function was carried out.
\[ f(x + \Delta x) \approx f(x) + f'(x)\Delta x + \frac{1}{2} f''(x)\Delta x^2. \] (2)

**DCNN-XGBoost Model**

**Deep Convolution Neural Network Model**

The DCNN (Deep Convolutional Neural Network) consists of three parts: convolution layer, pooling layer and fully connected layer. One convolution kernel of convolution layer corresponds to one characteristic graph. As shown in Figure 1, the original data \((1\times32\times32)\) is convolutioned by two layers convolution kernels \((64\times3\times3)\), and then characteristic graphs \((64\times16\times16)\) are obtained after pooling layer \((64\times2\times2)\).

\[ V = \text{conv}^2(W, X, \text{"same"}) + b. \] (3)

Among them: \(W\) is the original matrix; \(X\) is the convolution kernel; \"same\" shows that the size of the matrix does not change after convolution operation.

After the convolution and pooling operation of several layers, the obtained feature graph is expanded according to the row, connected into vector, input into the fully connected network, and the final high-dimension features are classified and processed. The formula (4) is the formula for softmax to calculate the classification probability.

\[ y_i = \frac{e^{z_i}}{\sum_{j=1}^{n} e^{z_j}}. \] (4)

Among them: \(z\) is the high-dimension feature; \(n\) is the Number of categories; \(y\) is the probability that the sample belongs to a certain class.

**DCNN-XGBoost Model**

The feature matrix obtained by DCNN full connection layer is used as the input data of XGBoost algorithm. In general, the feature matrix extracted by DCNN is sparse matrix. XGBoost algorithm can automatically learn its classification direction, which not only saves resources, but also saves time. The construction architecture of the model is as shown in Figure 2. Firstly, the feature information of the original data is extracted by DCNN. If the correct rate calculated by softmax fluctuates in a predetermined range, the number of iterations is increased. Otherwise, the feature matrix is output and the DCNN model is saved, and the parameters are adjusted by the feature matrix through the grid. After adjusting the parameters of XGBoost model with the method of cross-verification, the XGBoost model is trained by feature matrix again, and finally the DCNN-XGBoost model is formed to identify the compound faults of gearbox.

![Figure 1. Deep convolution neural network model.](image-url)
Parameter Adjustment

In this paper, the XGBoost module in python is used to analyze the data. XGBoost algorithm is a multi-parameter model, and the adjustment of parameters determines the performance of the model to a great extent.

The adjustment process is shown in Figure 3. According to the correlation between these parameters, this paper sets the value of learning rate first, the value of the other parameters is the default for the system, adjusts the number of weak learning devices, then fixes the value of n_estimators and the value of learn_rate, adjusts the following parameters in the same way. Finally adjusts the value of learn_rate again, and obtains a set of optimization parameters.

Experimental Process and Results

Extraction Feature Matrix

The inner structure of the wind turbine gearbox is as shown in Figure 4. The planet wheel in the front box transmits power to the solar wheel, and then transmits to ① (the low speed shaft gear located in the back box) through the inner gear coupling, and then through the ② (transmission shaft) transmits to the ③ (high-speed shaft). The high speed shaft is connected with the generator through the flexible coupling, and then the no-load experiment is carried out by driving the gearbox of the wind turbine by the motor. The rated speed of the motor is 1650 r/min. At rated power, the vibration data of six states of gearbox are collected, such as normal, high speed shaft wear (in the left of Figure 5), high speed shaft wear and transmission shaft wear, high speed shaft broken tooth (in the middle of Figure 5), high speed shaft broken tooth and transmission shaft wear, transmission shaft wear (in the right of Figure 5) etc.

The vibration acceleration data obtained from the sensor horizontal at the high speed axis are divided into 120 groups with 1,024 points in each group. 100 groups are taken as training data and the remaining 20 groups are used as test data. Adding the tag column, the size of training matrix is 600×1025 and the size of test matrix is 120×1025.
Extract the artificial feature matrix, i.e. extract 14 time-domain indexes such as maximum value, minimum value, average value, standard deviation, peak value, kurtosis, margin and so on, and then extract the DCNN feature matrix of training matrix as shown in Figure. 1, divide the training matrix into two parts, one training DCNN network, one part of which tests DCNN network and output accuracy. When the test accuracy is within the predetermined range of iterations or 100%, the DCNN feature matrix of 600×257 is obtained.

Figure 6 is the trend diagram that the correct rate of DCNN test set varies with the number of iterations, and the highest accuracy rate of test data is 100%. Figure 7 is obtained by t-SNE dimension reduction visualization algorithm. The left picture of Figure 7 is the effect diagram of DCNN feature matrix dimension reduction, and the right picture of Figure 7 is the effect diagram of artificial feature matrix dimension reduction.

As a visualization tool for dimension reduction, t-SNE uses conditional probability to represent the similarity between high dimensional distribution point distance and low dimensional distribution point distance. Gaussian distribution corresponds to high dimension, t distribution corresponds to low dimension, achieves the effect of the same cluster aggregation and different cluster alienation. It can be seen from Figure 7 that DCNN feature matrix is superior to artificial feature matrix in distinguishing fault categories by feature matrix visualization.
Model Comparison

The fault categories are expressed as 0-normal; 1-high-speed shaft wear; 2-high-speed shaft wear and transmission shaft wear; 3-high-speed shaft broken teeth; 4-high-speed shaft broken teeth and transmission shaft wear; 5-transmission shaft wear.

Figure 8 is a confusion matrix for predicting the operation state and the actual operating state of the test matrix with the size of 120×1025 by the DCNN model, and the horizontal axis is the predicted state and the vertical axis is the real state. It can be seen from the confusion matrix that the feature representing the 0 state is identified as the 1 state and the 4 state, and the feature of the partial representative 3 state is identified as 2 and 5 states, and the 4 state and the 5 state are also misjudged.

The results obtained by using XGBoost algorithm instead of softmax are shown in Figure 9. The accuracy of other faults is significantly improved, the misjudgment of 4 state and 5 state is corrected, and the recognition ability of 0 state and 3 state is optimized.

Summary and Prospect

In this paper, a DCNN-XGBoost model is proposed to solve the problem of compound fault diagnosis of gearbox. Firstly, the feature matrix extracted by DCNN is compared with the artificial feature matrix, and it is proved that that DCNN feature matrix is superior to artificial feature matrix in distinguishing fault categories by feature matrix visualization. Secondly, the DCNN-XGBoost model is compared with the DCNN model by using the wind power gearbox experimental platform. The results show that the DCNN-XGBoost model has a good diagnostic effect. Therefore, the combination of DCNN and XGBoost has a high practical value in the field of compound fault diagnosis of gearbox.

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