Fault diagnosis of wind turbine bearing based on CNN-XGBoost

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Abstract. When a wind turbine bearing fails, because the fault signal shows the characteristics of instability and non-linearity, it is difficult to extract the fault features artificially, resulting in a lower accuracy of the wind turbine bearing fault classification. In order to realize the automatic extraction of wind turbine bearing faults and improve the accuracy of fault classification, this paper proposes a wind turbine bearing fault identification method based on the combination of convolutional neural network and limit gradient lifting algorithm. First, convert the original bearing fault signal into a grayscale image. Then, the gray image is input to the convolutional neural network to automatically extract the feature of the fault. Finally, the limit gradient boosting algorithm optimized by the grid search algorithm is used as a classifier to classify the fault. The simulation results show that the method used in this paper can achieve a high rate of correctness of wind turbine bearing fault identification, indicating that this method is effective for wind turbine bearing fault diagnosis.

Keywords: Convolutional Neural Network; Grayscale Image; Limit Gradient Lifting; Grid Search; Fault Diagnosis.

1. Introduction

In the process of human industrial development, human demand for energy is obtained by burning traditional fossil fuels, such as coal, petroleum, and carbon. In the process of burning these fossil fuels, a large amount of CO$_2$ and harmful gases will be produced, which will cause the global climate to continue to warm. Global warming will cause a series of environmental problems, such as rising sea levels, acid rain, desertification, and reduction of biodiversity, which will bring huge challenges to human survival. Under such severe circumstances, the global energy structure must shift from traditional energy sources to new energy sources as soon as possible. As a clean and renewable energy source, wind energy has quickly entered the sight of mankind. Secondly, wind energy is also the fastest growing new energy source in the world, and it has been used in Europe for hundreds of years [1]. Therefore, based on many advantages, governments of various countries have increased their investment in wind energy research [2].

According to statistics released by the World Wind Energy Association at a press conference in April 2020, it can be seen that by the end of 2019, the total capacity of wind turbines worldwide has reached 6508GW.
Bearings are one of the important parts of a wind turbine, which are specifically distributed in important parts such as the main shaft, gear box, and yaw. When the wind turbine is working, the load it receives is constantly changing, which makes the bearings in different positions prone to various failures. According to statistics, bearing faults account for about 45% of all wind turbine faults [3].

2. Basic theory of fault identification

2.1. Introduction to the data set

Although the bearings at different positions inside the wind turbine are different in structure and technology, in terms of function, these bearings at different positions can be abstracted as rotating equipment, and their failure modes are roughly the same, and the failures presented by the failure The signals have a certain periodicity, so the fault diagnosis methods of different parts of the bearing also have a certain similarity [4]. In addition, since the temperature of the environment where the wind turbine works outdoors is uncontrollable, almost all the bearings used in the wind turbine are rolling bearings with a long life.

This paper uses bearing data from Case Western Reserve University for simulation analysis. This data set is widely used in the field of bearing fault diagnosis. As shown in Figure 1 from left to right, the experimental equipment includes motors, torque sensors, encoders, dynamometers, and dynamometers. The collected data comes from the vibration signal of the drive end, and the fault is artificially introduced through the electric spark technology. The tested bearing is a 6205-2RS JEM SKF deep groove ball bearing, the motor load is 1hp, the sampling frequency is 12KHz, and the spindle speed is 1772r/min. Taking into account that in actual work, the bearing will have different situations of failure, even in the same situation, there will be different degrees of wear. Therefore, the experimental data should describe the different failures of the bearing as fully as possible.

The data includes the state of the bearing under different working conditions, which are inner ring failure, outer ring failure, rolling element failure, and normal state. The outer ring failure uses the 6 o'clock direction centered on the 6 o'clock direction of the load zone. The data. The fault diameter indicates different degrees of wear of the bearing, including 0.18mm, 0.36mm, and 0.54mm.

![Figure 1. Experimental equipment diagram](image_url)

The data set contains a total of 10 operating conditions of the bearing under 10 different conditions. With 1024 data points as a sample, 1000 samples are taken for each operating condition using overlapping sampling, a total of 10000 samples, the training set and the test set are in accordance with 7:3 is divided, the specific situation of the data set is shown in Table 1.

**Table 1. Experimental data set**

| Sample number | Fault type         | Fault label | Fault diameter/mm | Sample label |
|---------------|--------------------|-------------|-------------------|--------------|
| 1             | normal status      | Normal      | 0                 | 00000000001  |
| 2             | Outer ring failure | IR007       | 0.18              | 0000000010   |
| 3             | OR014              | 0.36        | 0000001000        |
| 4             | OR021              | 0.54        | 0000010000        |
| 5             | Rolling element failure | OR007 | 0.18 | 0000010000 |
| 6             | OR014              | 0.36        | 0000100000        |
| 7             | OR021              | 0.54        | 0001000000        |
| 8             | Inner ring failure | B007        | 0.18              | 0010000000  |
| 9             | B014               | 0.36        | 0100000000        |
| 10            | B021               | 0.54        | 1000000000        |
2.2. Description of experimental equipment
This experiment is based on the Tensorflow framework developed by Google. The computer system is windows10 64-bit, the running memory is 8GB, the graphics card is NVIDIA GeForce GTX1050Ti, and the CPU model is Intel(R) Core(TM)i7-7700HQ@2.80GHz ×8, The software used is Pycharm.

2.3. Processing of experimental data
In recent years, convolutional neural networks have shined in various large-scale competitions, especially in image processing. The vibration signal of the bearing is one-dimensional, so it is necessary to convert the vibration signal of the bearing into the form of a picture. Here we will use a simple method to deal with it, the processing process is as follows.

First, randomly select the length of \( n \times n \) points from the continuous original time series signal to form a matrix \( Q(n,n) \). After normalizing the matrix \( Q \) using formula (1), a grayscale image with a pixel of \( P(n,n) \) is obtained.

\[
P(n,n) = \text{round} \left( \frac{Q - \min(Q)}{\max(Q) - \min(Q)} \times 255 \right);
\]

\[(n = 0,1,2 \cdots 255)\] (1)

Where round is the rounding function.

The following takes the outer ring with a fault diameter of 0.36mm as an example, and Figure 2 demonstrates the process of converting a one-dimensional time domain signal into a picture. In order to save space, other situations can be handled in this way.

![Figure 2. Data preprocessing process](image)

2.4. Construction of the fault model
In the fault diagnosis of machinery, the feature extraction of faults is particularly important for the accuracy of fault classification. Section 2.3 has transformed the original vibration signal of the bearing into the form of a picture, and the next work is to build a convolutional neural network.

As a feed forward neural network, convolutional neural network is particularly good at processing image type data. The structure of convolutional neural network is composed of input layer, convolution layer, pooling layer, fully connected layer, output layer and so on. The input layer is a picture data set transformed from one-dimensional time-domain vibration signals. The convolutional layer is the feature extraction layer of the neural network. Through different convolution kernels, the weight sharing mechanism is used to perform weighted summation with the pixels of the picture in turn, plus a bias, so that different feature maps can be obtained.

The main function of the pooling layer is to reduce the dimensionality of the feature map after the convolution operation, reduce the training parameters of the neural network, and further extract the features. The most commonly used is maximum pooling.

The function of the fully connected layer and the output layer is to flatten the features extracted by the pooling layer and then perform classification and output. The output layer generally uses the softmax layer.
The extreme gradient boosting algorithm is a tree-based Boosting algorithm [5]. XGBoost is widely used in classification problems. The algorithm uses the information of the second derivative of the loss function to reduce the amount of calculation and speed up the convergence of the calculation process.

The hybrid classification model designed in this paper consists of two parts. The first part is the convolutional neural network, and the second part is the XGBoost classifier. The last dense layer of the convolutional neural network is replaced by the classifier. When the model is compiled, the learning rate is set to 0.001, the number of iterations is set to 50, and the m optimization algorithm is used to optimize the cross-entropy loss function.

The specific parameters and structure diagram of the model are shown in Table 2 and Figure 3.

Table 2. Model parameter table

| Network layer       | parameter settings                  | Network layer input | Network layer output |
|---------------------|-------------------------------------|---------------------|----------------------|
| Convolution 1       | Nuclear size 3×3, Number of cores 16, Step size 1 | 32×32×1            | 32×32×16             |
| Convolution 2       | Filling method same, Activation function ReLU | 32×32×16           | 32×32×16             |
| Pooling 1           | Pooling window size 2×2, step size 2 | 32×32×16           | 16×16×16             |
| Convolution 3       | Core size 3×3, number of cores 32, step size 1 | 16×16×16           | 16×16×32             |
| Convolution 4       | Filling method same, Activation function ReLU | 16×16×32           | 16×16×32             |
| Pooling 2           | Pooling window size 2×2, step size 2 | 16×16×32           | 8×8×32               |
| Flatten             | —                                   | 8×8×32             | 2048                 |
| Fully connected 1   | Number of neural unit nodes 128, activation function ReLU | 2048               | 128                  |

Figure 3. Schematic diagram of the structure of the hybrid model

In the process of XGBoost classification, a grid search algorithm is used to select the hyperparameters in the XGBoost classifier. The maximum depth of the tree \( \text{max\_depth} \in [3,10] \), and the minimum weight of the child's observations \( \text{min\_child\_weight} \in [1,6] \). Cross-validation is also performed while optimizing, and the number of cross-validation is selected as 5.

3. Evaluation of the failure model

In order to evaluate the correct rate of model classification, this paper introduces three evaluation parameters, which are precision rate, recall rate, and F1-Score. The accuracy of the model is positively correlated with these parameters. Table 3 shows the changes of these three parameters during the classification process.
Table 3. CNN-XGBoost performance indicators

| Data label | Precision | Recall | F1-Score |
|------------|-----------|--------|----------|
| Normal     | 1.00      | 0.99   | 0.99     |
| IR007      | 0.99      | 1.00   | 0.99     |
| IR014      | 0.99      | 0.99   | 0.99     |
| IR021      | 1.00      | 1.00   | 1.00     |
| OR007      | 1.00      | 1.00   | 1.00     |
| OR014      | 0.99      | 1.00   | 0.99     |
| OR021      | 1.00      | 1.00   | 1.00     |
| B007       | 1.00      | 1.00   | 1.00     |
| B014       | 1.00      | 1.00   | 1.00     |
| B021       | 1.00      | 1.00   | 1.00     |
| Avg/total  | 0.997     | 0.998  | 0.996    |

In order to show the change of the model's classification accuracy of fault types more clearly, the model's training set and validation set accuracy and loss rate change curves are shown in Figure 4. From the change curve, we can see that the model's classification accuracy rate up to 99.8%, and there is no fitting situation. It can be seen that the model can effectively adaptively extract fault features and accurately classify fault types.

![Figure 4. CNN-XGBoost training set and validation set accuracy and loss rate change curve](image)

4. Conclusion

When a wind turbine bearing fails, because the fault signal shows the characteristics of instability and non-linearity, it is difficult to extract the fault features artificially, resulting in a low accuracy of the wind turbine bearing fault classification. This paper proposes a wind turbine bearing fault identification method based on the combination of CNN-XGBoost. Using CNN, features can be extracted directly from the original vibration signal of the bearing without manual intervention. Then, use XGBoost for classification. The simulation results show that the accuracy of the method used in this paper can reach 99.8% for the fault diagnosis of wind turbine bearings, which shows the effectiveness of this method for the fault diagnosis of wind turbine bearings.
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