International Journal of Scientific Engineering and Research (IJSER)
ISSN (Online): 2347-3878
Impact Factor (2024): 7.741

Fault Signal Separation Method for Rolling Bearing of Wind Turbine Based on Multi-Channel DCNN

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Abstract: ***The operating conditions of rolling bearings of wind turbines are variable and complex, so it is of great significance to accurately analyze the type of bearing failure, damage degree and fault location for improving the safety of wind turbines. In this study, a method of fault signal separation for rolling bearing of wind turbine based on multi-channel DCNN is proposed, and a kurtosis and envelope spectrum comparison method is proposed to evaluate the blind source signal separation effect. Firstly, the bearing signal was analyzed by Short Time Fourier Transform (STFT) to generate a Binary Time-Frequency Mask (BTFM) that can characterize the bearing fault. Secondly, the multi-channel DCNN signal separation model is established, and the time spectrum and binary time-frequency mask are used as training samples to train the model. Then, the mixed bearing time spectrum is used as the input of the model to obtain the binary mask of each fault. Finally, multiplying the mixed time-frequency spectrum by the corresponding fault time-frequency mask can obtain the time-domain signal that contains various faults in the mixed signal. Experimental results on vibration data set of Case Western Reserve University show that the proposed method can effectively separate bearing fault signals and obtain accurate information such as fault type, damage degree and fault location. This method can realize automatic bearing fault feature learning and fault signals and the separation of mixed signal, to improve the safety of the wind turbine.***

Keywords: Wind turbine, rolling bearing, fault characteristic analysis, multi-channel DCNN, blind source signal separation, binary time-frequency mask.

1. Introduction

With the increasingly serious problems such as global environmental pollution and non-renewable primary energy, wind power generation, relying on its mature technology and high-quality wind energy resources, has been strongly supported by investors and governments around the world, especially in the past decade, the development of China's wind power industry has achieved explosive growth [1]. Rolling bearings are crucial precision parts in rotating machinery equipment, responsible for supporting and transmitting power, but also the most easily damaged parts. According to statistics, about 30% of mechanical failures are caused by rolling bearings [2-4]. For wind farms, timely and accurate fault analysis has very high engineering application value, which can not only reduce the economic loss caused by faults, but also avoid personal safety accidents, which is of great significance for the safe and stable operation of wind turbines.

Blind source signal separation refers to the process of extracting and restoring various original signals that cannot be directly observed from mixed signals, which can be divided into Independent Component Analysis (ICA), Sparse Component Analysis (SCA), Non-negative Matrix Factorization (NMF) and Bounded Component Analysis (BCA) based on signal independence, sparsity, non-negative and geometric characteristics [5].ICA is the core technology in the field of blind source separation, which is mainly applied to multi-channel separation problems, but its prerequisite is that the source signals are independent from each other [6,7]. The sparsity of the signal means that the possibility of two or more source signals appearing at the same frequency is low, that is, most of the energy at any frequency belongs to a single source. SCA converts the problem of signal separation into the problem of data classification, and takes the sparsity of signals as a prerequisite to realize the blind source separation of signals [8]. NMF is a matrix decomposition method proposed by Lee and Seung et al. [9], which can ensure that all components after decomposition are non-negative. Since second-order statistics, fourth-order statistics or higher-order spectra are needed to construct a mixed matrix, the computational complexity is relatively high. BCA uses the geometric characteristics of the source signal character set and the convex set principle to establish the cost function, which has superior separation performance under the premise of short data blocks and high signal-to-noise ratio. Its disadvantage is that it is greatly affected by noise and has poor anti-noise ability [10].

The bearing vibration signal collected by the sensor contains not only the fault characteristic signal, but also a large number of noise signals generated by the running vibration of the bearing. Therefore, the original vibration signal must be extracted before the bearing fault analysis. Traditional methods of feature extraction are mainly divided into three categories: time domain, frequency domain and time-frequency domain [11]. Time domain signal is a way to describe the amplitude of vibration signal with time. The commonly used time domain statistical parameters include peak value, kurtosis and root mean square. The frequency domain method is to convert the time domain signal into spectrum, and then analyze the frequency of the vibration signal. The frequency domain feature extraction methods generally include envelope spectrum analysis, cepstrum analysis and high order spectrum analysis. Feature extraction methods based on time-frequency analysis include STFT, wavelet transform and Hilbert transform, etc. [12,13].

The operating conditions of wind turbines are very complex, and wind turbines often operate in extremely harsh environments, which make the vibration signal collected by bearing condition monitoring contain a large number of noise signals, and the fault signal and noise signal will be modulated between each other. At this time, the bearing fault signal cannot meet the common blind source separation method required by the independence, sparsity and other preconditions. The neural network model can analyze the fault characteristics of any frequency points, and realize an end-to-end fault signal separation model of rolling bearing. On this basis, this study proposes a multi-channel DCNN model, uses the STFT and BTFM to construct a matrix that can characterize the bearing fault characteristics, and separates the possible fault signals of the bearing from the collected mixed signals in order to find faults and eliminate hidden dangers in time. Finally, the bearing vibration case data, combined with the frequency domain analysis method of vibration signals, and the peak value and envelope spectrum comparison method were used to evaluate the blind source signal separation results and verify the effectiveness and feasibility of the proposed method. The overall scheme of the model is presented in Figure 1.

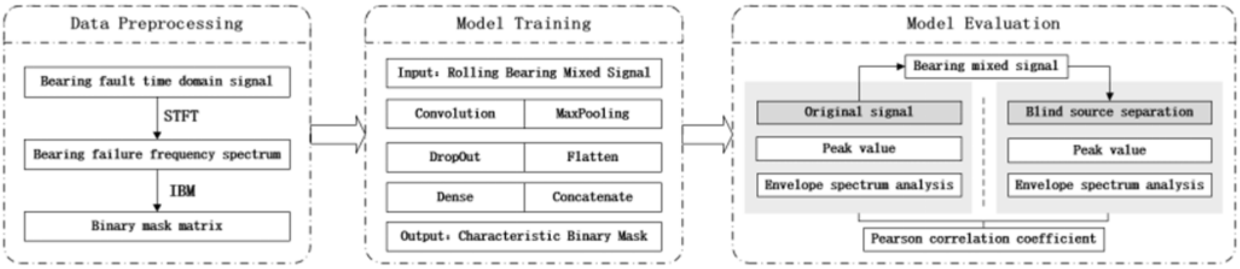

Figure 1: The overall scheme of the model

2. Materials and Methods

2.1Fault characteristics of rolling bearings

Bearing is one of the most important components in mechanical equipment, and its main role is to reduce rotary friction and reduce the noise of machine operation. Roller bearings are a kind of rolling bearings, usually composed of an inner and outer ring, a rolling body (ball or roller) and a cage. The inner ring rotates with the rotating axis, the outer ring remains static, and the rolling body rotates between the inner and outer rings, which can greatly reduce the contact area between the mechanical parts, thereby reducing friction and wear. This structure and principle make bearings widely used in automotive, machinery, aerospace and other fields, and play a very important role in improving the reliability, life and safety of mechanical systems [14,15]. The bearing structure is shown in Figure 2.

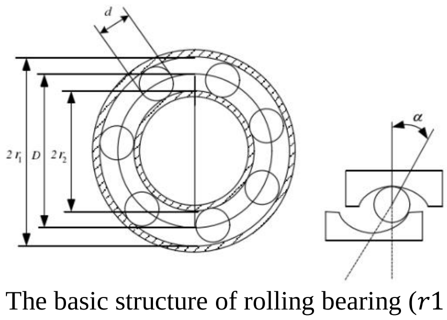

Figure 2: The basic structure of rolling bearing ($r1$ *is the radius of the outer raceway;* $r2$ *inner ring raceway radius;D is the diameter of the bearing pitch circle;d is the diameter of the rolling element;* α*is the contact Angle*)

From the point of view of diagnosis, only the characteristic information of bearing fault can be extracted to the actual analysis, and the energy of the vibration signal is very small when the bearing is in the normal state. When analyzing the bearing fault spectrum, it is found that the characteristic frequency of bearing fault has certain periodicity and obvious peak value in the harmonic component. For a single defect fault type, the formula for calculating the fault characteristic frequency of the rolling element, inner ring and outer ring is as follows:

$$f_b = \frac{D}{2d}|f_a - f_r|\left(1 - \frac{d^2}{D^2}\cos^2\alpha\right) \quad (1)$$

$$f_i = \frac{Z}{2}|f_a - f_r|\left(1 - \frac{d}{D}\cos\alpha\right) \quad (2)$$

$$f_0 = \frac{Z}{2}|f_r - f_a|\left(1 + \frac{d}{D}\cos\alpha\right) \quad (3)$$

When local damage occurs at a fixed point on a rolling bearing component, f_b, f_i and f_0 refer to the characteristic frequency of the impact of the single damage point on the bearing component, respectively, and are therefore also known as the fault characteristic frequency of the rolling element, inner ring and outer ring [16].

2.2 Bearing signal analysis based on STFT and BTFM

Signal is the carrier of information, is the physical expression of information, can be regarded as a function of time, or a function of frequency. By Fourier transform the time domain signal, you can check the frequency transformation of the signal. The signal of rolling bearing of wind turbine is non-stationary and contains a lot of noise, which brings great difficulty to bearing fault analysis and diagnosis. STFT is a time-frequency analysis method for non-stationary signals, which can convert time domain signals into characteristic time spectrum including time domain and frequency domain. Binary time-frequency mask was first used for single-channel signal separation, which can separate multiple source signals from aliasing signals and analyze sparse signals in the time-frequency domain [17,18]. Firstly, the STFT is applied to the bearing fault signal to obtain the two-dimensional time spectrum of bearing fault characteristics. Then the binary mask is used to calculate the mask of each type of fault feature, and the hybrid fault signal of the bearing is multiplied with the mask of the corresponding fault to obtain the separation spectrum of the fault. Then the inverse STFT is performed on the frequency spectrum to obtain the time domain signal after the separation of the fault. Figure 3 shows the fault signal separation framework, which includes four types of signals: rolling element fault, inner ring fault, outer ring fault and normal state.

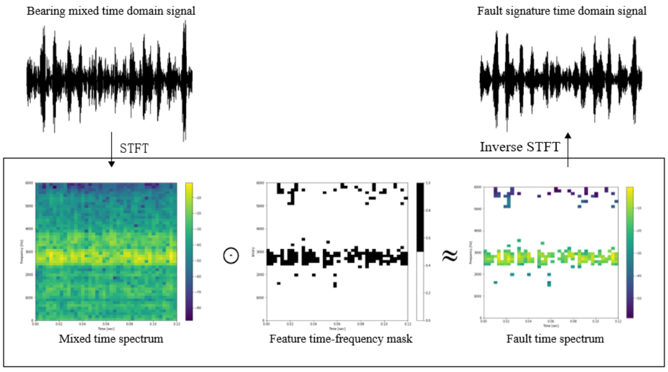

Figure 3: The fault signal separation framework

2.2.1 Short-time Fourier Transform (STFT)

Fourier transform is a method used to analyze synthetic signals. The time-domain signal is represented as the integral form of a complex exponential function, the original function is $f(t)$, and the image function is $F(\omega)$. The calculation formula is as follows [19] :

$$F(\omega) = \int_{-\infty}^{+\infty} f(t)\, e^{-iwt}\, dt \quad (4)$$

The inverse transformation of the continuous Fourier transform is shown in the following formula:

$$f(t) = \frac{1}{2\pi} \int_{-\infty}^{+\infty} F(\omega)\, e^{-iwt}\, dt \quad (5)$$

The STFT can only show that there is a certain frequency feature in the signal, but it cannot accurately express the time localization information of the relevant frequency feature. The rolling bearing signal is generally non-stationary and time-varying, which is reflected in that it is sometimes prominent in the time domain and sometimes in the frequency domain [20]. STFT can combine the advantages of time domain analysis and frequency domain analysis to make a comprehensive analysis of the fault signal, among which the time domain diagram and time spectrum of the outer ring fault are shown in Figure 4.

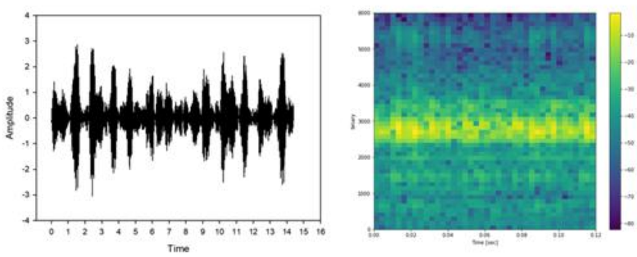

Figure 4: The time domain diagram and time spectrum of outer ring fault

The basic idea is to multiply the window function with the original signal and translate it continuously after Fourier transform. The calculation formula of STFT is as follows:

$$G_f(\omega, u) = \int_{-\infty}^{+\infty} f(t)\, g(t-u) e^{-iwt}\, dt (6)$$

where $f(t)$ is the original signal; $g(t-u)$ is the window function; $G_f(\omega, u)$ is the result of STFT and the value of real-time frequency energy density [21].

2.2.2 Binary time-frequency mask technique(BTFM)

The binary mask is used to extract the abnormal signal from the mixed signal which is different from the characteristic signal. According to the energy difference of the feature signal at different frequency points, it uses linear mapping method to compare the target signal with the interference signal and separate the feature value in the target signal [22,23]. In this study the bearing fault signals are divided into four categories. Firstly, the ideal ratio mask (IRM) is calculated. When one of the fault states is the target signal, the other three types of fault signals are interferences. The value range of this matrix is [0,1]. Formulas (8) and (9) are then used to find the BTFM of each type of fault. The bearing time spectrum and BTFM results are shown in Figure 5.

$$IRM = \frac{S_{target}^2}{S_{target}^2 + S_{interf\ 1}^2 + S_{interf\ 2}^2 + S_{interf\ 3}^2} (7)$$

$$BRFM = \begin{cases} 1, IRM \geq 0.5 \\ 0, IRM < 0.5 \end{cases} (8)$$

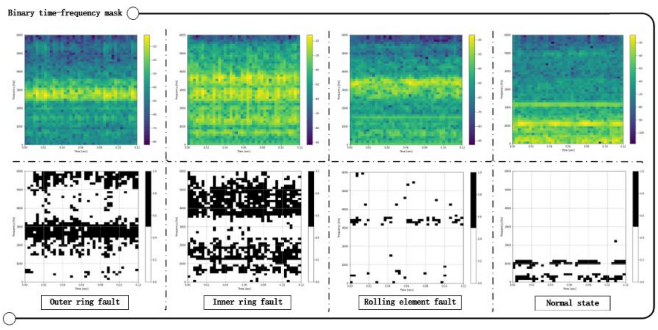

Figure 5: The bearing fault time spectrum and binary time frequency mask

2.2.2 Deep convolutional neural networks (DCNN)

Convolutional neural network is a kind of neural network with deep hierarchical structure and automatic feature extraction through convolutional pooling calculation. In the training process, backpropagation algorithm is adopted to constantly adjust parameters and optimize the network structure, and an approximate result is obtained [24]. The basic structure of the convolutional neural network includes input layer, convolutional layer, pooling layer, fully connected layer and output layer. The basic structure of the convolutional neural network in this paper is shown in Figure5.

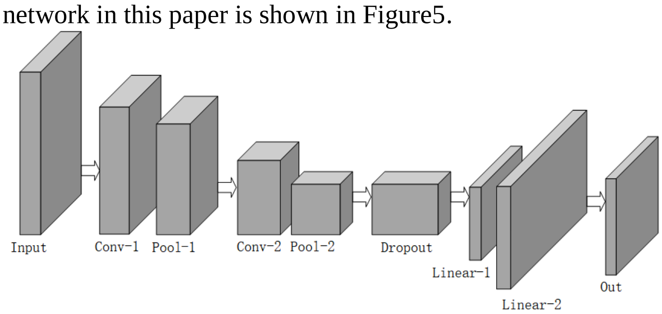

Figure 6: Basic structure of convolutional neural network

In the convolution layer, multiple convolution check input sets are convolved and a series of feature graphs are obtained by activation function. Each feature graph can share weights, and different convolution layers require different convolution kernels. The mathematical formula for the convolution process is as follows [25]:

$$a_{i,j} = f\left(\sum_0^2 \sum_0^2 w_{m,n} x_{i+m,j+n} + w_b\right) (9)$$

Where $w_{m,n}$ and $x_{i+m,j+n}$ are the weights corresponding to the convolution kernel and a local region, and w_b is the offset value of the convolution kernel.

The pooling layer is connected behind the convolutional layer to reduce the dimension of the feature graph. It can aggregate the features of different locations in the local areainto one feature, so as to output the feature graph without redundant information. Common pooling layer methods include maximum pooling layer, average pooling layer and random pooling layer. In the process of pooling, there are no learning parameters, so there is no need for backpropagation and gradient calculation [26].

In convolutional neural networks, the fully connected layer classifies feature fragments and is usually applied to the last one or two layers of the network to classify and integrate the features after convolution and pooling, and map them to the sample label space. The fully connected layer retains and integrates all the features in the image, regardless of the position relationship, each neural network will be connected with the neurons of the previous layer, so the number of parameters and calculation is huge. In the convolutional neural network model, only 2-3 layers of the fully connected layer are usually set [27].

3. Experimental

3.1Experimental environment

The software environment used for the example is Ubuntun16.04, Python3.7, Keras2.0.0, Tensorflow1.1.0. The hardware environment is two Intel Xeon E5-2680v4@2.4GHz processors, 128GB of RAM, and two Nvidia GTX-3060.

3.2 Experimental data set

In this study, the vibration data set of Bearing Failure Laboratory, Electrical Engineering Laboratory, Case Western Reserve University, USA, is used to verify the validity and practicability of the signal separation method.

The laboratory has a 2 HP electric motor, a torque sensor, a power measuring instrument, and an advanced electrical control system. Through EDM technology, we place multiple fault points on the bearing under test, and simulate the severity of the fault according to the damage diameter of each fault point. The fault diameters are 0.007, 0.014, 0.021, 0.028 and 0.040 inches, respectively. In this study, we selected SKF deep groove ball bearings to detect the first three fault diameters, and used the same model of NTN deep groove ball bearings as test bearings for the remaining two fault diameters. The fault types include inner ring fault, rolling element fault and outer ring fault, and the damage point of the outer ring fault is set at 3 o 'clock, 6 o 'clock and 12 o 'clock of the clock. The bearing is driven to rotate under the rotation of the motor with different power, and the speed is 1797, 1772/1750 and 1730 revolutions per minute, and the different speed indicates the different operating conditions. Acceleration sensors were used to collect vibration signals. The acceleration sensor is installed at the 12 o 'clock position of the drive end and the fan end of the motor housing through the magnetic base. At the same time, the vibration acceleration signal of bearing fault is collected. The vibration signal is collected by a 16-channel data logger with a sampling frequency of 12kHz. Because the characteristic frequency of the bearing's outer ring fault is the same at different positions, the vibration signal at 3 o 'clock of the above outer ring fault is selected as the vibration data of the bearing's outer ring fault in this study.

Bearing failure frequency can be calculated from formula (1) to formula (3). Bearing failure characteristic frequency is shown in Table 1 and bearing specification parameters are shown in Table 2.

Table 1: Driving end bearing specification (unit: mm)

Inner ring diameter	Outer ring diameter	Thickness	Rolling diameter	Pitch diameter
25	52	15	7.94	39.04

Table 2: Failure frequency (unit: Hz)

Inner ring fault	Outer ring fault	Rolling element fault
162.18	107.36	141.16

(Rotation frequency: 1797r/min)

3.3 Data preprocessing

In this study the fault types of rolling bearings are initially set to include four types: outer ring fault, inner ring fault, rolling element fault and normal state. In order to simulate the complex operating conditions and operating environment of wind turbines, the data of test bearings under different working conditions and samples under different damage degrees are mixed together. The process of data preprocessing is shown in Figure 7.

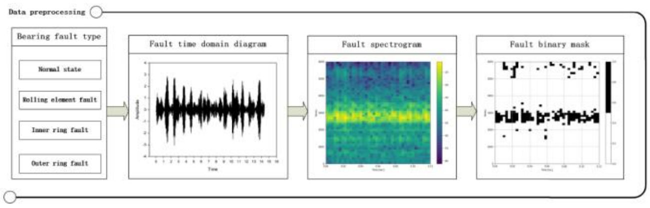

Figure 7: Data preprocessing process

The time domain signal of the bearing shows the amplitude variation of the bearing vibration with time during operation, and the corresponding two-dimensional time spectrum STFT (t,f) is obtained by short-time Fourier transform. Using Hamming window function, the length of Fourier transform is 100 points, the number of overlapping samples in each segment is 64, the sampling frequency is 12kHz, and the time spectrum of bearing vibration signal is calculated. The horizontal axis is time t, and the vertical axis is frequency f. The binary time-frequency masks of four types of bearing fault types are calculated by formula (8) and formula (9) to form the input data set of the model.

3.4 Sample characterization data

Bearing time domain signal is a kind of time series signal, embedded in the signal time dependence, in a given time range, each moment of the spectrum signal has a certain correlation. Therefore, when setting the model of the neural network, it should be taken into account that setting this time interval needs to be able to capture the characteristic signal of the bearing fault, so that the neural network model can learn the fault characteristics. The sampling frequency of data is 12kHz,the window size of STFT is 100, and the number of overlapping samples is 64, so a single STFT frame is about (~5.33ms≈64/12000), and 25 STFT frames in the target context are about 133.3ms. The sample data representation structure of multiple fault types is shown in Figure 8.

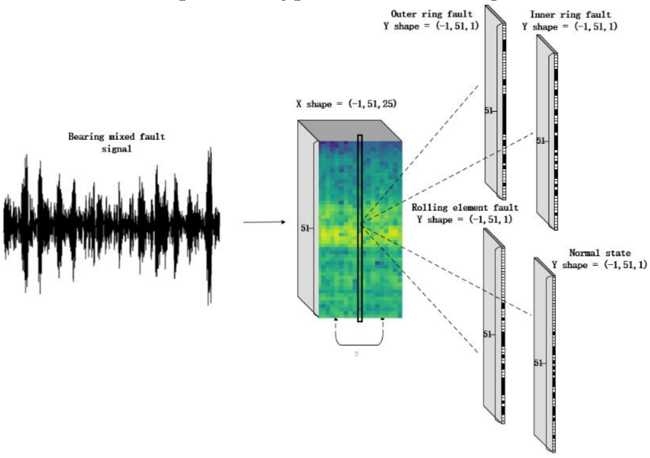

Figure 8: Data representation structure for multiple faults

3.5 Multi-channel DCNN model construction

The selection of parameters such as the size and number of convolutional nuclei, the size and number of pooled layers, and the number of neurons in the fully connected layers in the convolutional neural network affect the separation results of the model [28]. Based on LetNet-5, this paper modified its network parameters to find a multi-channel DCNN model suitable for signal separation, in which the single-channel model contains 4 convolutional layers, 4 maximum pooling layers and 2 fully connected layers. Both the convolution kernel size and the pool window size of the maximum pool layer are 3. The single-channel model structure is shown in Figure 9.

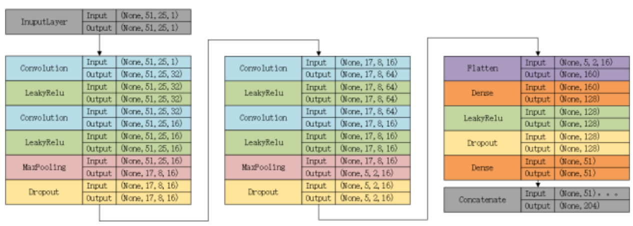

Figure 9: Single-channel DCNN model structure

The binary time-frequency mask is obtained by preprocessing the original data set of bearing signal, and the binary time-frequency mask is fed into the neural network model. The input of the model is (None,51,25,1), and the output of 51×25×32 is obtained by feature extraction of 32 3×3 convolution kernels. The 51×25×32 feature vectors are transformed into 16 51×25 outputs by convolution operation of 16 3×3 convolution kernels in the second layer. The maximum pooling layer is used to compress the feature map and remove the redundant information to get a 17×8×16 output. The activation layer adopts the nonlinear function LeakyRelu to activate each layer and increase the model expression ability.

Then, each point of the feature map is processed accordingly to get a 17×8×16 output feature map. Next, this feature map goes through 64 3×3 convolutions and 16 3×3 convolutions, along with a Max pooling layer to produce a 5×2×16 output. The output is then one-dimensional through the Flatten layer, with an output of 160. Finally, the fault values of single-class faults are output through two fully connected layers.

Bearing fault signals are divided into four categories, so it is necessary to build four convolutional neural network branches to extract the energy distribution of corresponding faults in the time spectrum respectively. The overall results of the model are shown in Figure 10.

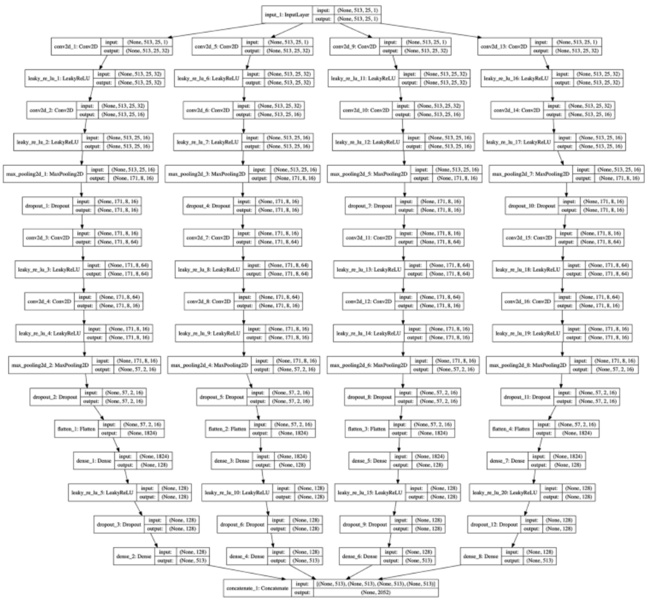

Figure 10: Multi-channel DCNN model structure

At the end of the model, the Dense layers of the four channels are joined together through the Concatenate layer. The output of the model is (None, 204), and each fault type corresponds to 51 values, respectively corresponding to the bearing's outer ring fault, inner ring fault, rolling element fault and normal state. The output structure of the model is shown in Figure 11.

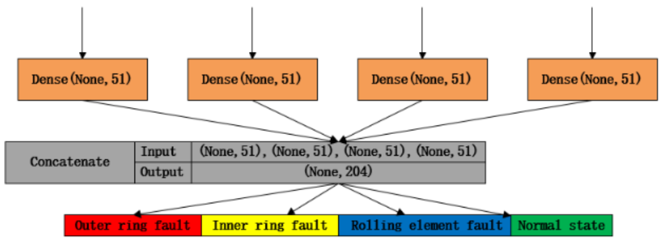

Figure 11: Model output structure

The minibatch number of the network is 128, the initial knowledge learning rate is 0.01, the learning rate reduction factor is 0.1, the learning rate adjustment cycle is 50, the data is scrambled before each round of training or verification, and the maximum number of rounds is 200.

3.6 Evaluation parameter

The evaluation indexes of the model can quantify the error characteristics of the model, and different evaluation indexes can analyze the model from different dimensions. The neural network model mainly evaluates the ability of multi-channel neural network to characterize the nonlinear relationship of training data based on the error between the real value and the predicted value of the model output, and adopts Root Mean Square Error (RMSE), Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE) to evaluate the model [29]. Secondly, bearing signal separation must be returned to the time domain and frequency domain signals used in bearing fault diagnosis. Therefore, a contra-analysis method of kurtosis and envelope spectrum is proposed to evaluate the model from the time domain and frequency domain perspectives.

3.6.1 Evaluation of neural network model

The RMSE, MAE and MAPE of the three model evaluation indexes are calculated as follows:

$$\gamma_{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N} (y_i - \hat{y}_i)^2} \quad (10)$$

$$\gamma_{MAE} = \frac{1}{N}\sum_{i=1}^{N}|\hat{y}_i - y_i| \quad (11)$$

$$\gamma_{MAPE} = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{\hat{y}_i - y_i}{y_i}\right| \quad (12)$$

Where: N is the total number of predicted data; $\hat{y}_i$ is the predicted value for the i th data.

3.6.2 Evaluation of signal separation results

Peak state refers to the tail measurement of the probability distribution of random variables, which can be used to study the singular value of the bearing class changing after the occurrence of anomalies [30]. The calculation formula is the difference between the fourth order distraction moment and the variance of the random variable. The calculation formula is as follows:

$$Kurt(X) = E\left[\left(\frac{X-\mu}{\sigma}\right)^4\right] = \frac{E[(X-\mu)^4]}{(E[(X-\mu)^2])^2} \quad (13)$$

The envelope demodulation method can amplify the high frequency natural vibration generated by the fault impact, and extract the fault characteristics of the rolling bearing through envelope detection and spectrum analysis. Due to the low frequency signal as a base band signal amplitude modulation, and the high frequency vibration amplitude is not equal, change, and therefore in the envelope spectrum can get to the fault characteristic frequency as the base wave frequency of harmonic signals.

For a given time-domain signal $x(t)$, the Hilbert transformation is as follows:

$$H[x(t)] = \frac{1}{\pi}\int_{-\infty}^{+\infty}\frac{x(\tau)}{t-\tau}d\tau \quad (14)$$

The analytic expression of construction is as follows:

$$z(t) = x(\tau) + jH[x(t)] \quad (15)$$

The envelope spectrum of the signal is as follows:

$$|z(t)| = \sqrt{x^2(t) + H^2[x(t)]} \quad (16)$$

Where, $|z(t)|$ is the envelope of signal $x(t)$, and the envelope spectrum of the envelope signal can be obtained by spectral analysis of $|z(t)|$ [31].

4. Experimental and Discussion

4.1 Neural network model results

In order to verify the effectiveness and accuracy of the proposed multi-channel DCNN based fault signal separation of wind turbine rolling bearings, taking wind turbine rolling bearings as test objects, the comprehensive loss value of four states during the training process of this method changes with the number of iterations, as shown in Figure 12.

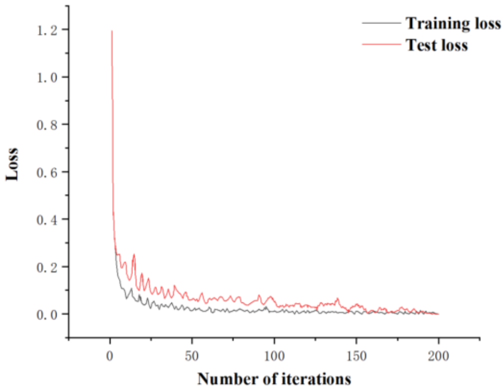

Figure 12: Loss curve of the proposed method on the dataset

The research results show that after 200 iterations of the data set, the final training loss is close to 0, which fully proves that the model in this study can successfully realize the fault analysis of rolling bearings.

In order to verify the superiority of the proposed method, Convolutional Neural Network (CNN), Long Short-Term Memory Network (LSTM) and Deep Residual Network Method based on Short Time Fourier Transform (STFT-DRNN) were respectively used to conduct feature extraction comparative experiments on bearing faults from four dimensions of training RMSE, MAE, MAPE and training time. The comparison results of each network model are shown in Table 3 (Error value and training time are taken as the training average of the four states).

Table 3: Comparison of experimental results

Method	$\gamma_{RMSE}/(m \bullet s^{-1})$	$\gamma_{MAE}/(m \bullet s^{-1})$	$\gamma_{MAE}/\%$
CNN	3.621	2.499	33.712
LSTM	3.358	2.401	33.581
STFT+DRNN	3.159	2.393	31.647
Ours	2.796	2.037	25.614

As can be seen from the above table, based on the open database of Western Reserve University (CWRU), the multi-channel sample constructed by the method proposed in this study is used for fault type diagnosis. After 200 iterations, The root mean square error, mean absolute error and mean absolute percentage error of the dataset reached $2.796(m \bullet \min^{-1})$, $2.037(m \bullet \min^{-1})$ and 25.614%, respectively. The three error indexes are significantly lower than the errors of the traditional methods of CNN, LSTM and STFT+DRNN, which fully verifies that our proposed model has good generalization ability and can effectively extract the feature distribution of bearing fault signals.

4.2 Signal separation result

In Table 2, according to the specifications of the rolling bearing, it is calculated that the fault characteristic frequency of the outer ring of the bearing is 107.36Hz, and that of the inner ring is 162.18Hz. The envelope spectrum is more sensitive to the bearing fault impact, which can eliminate unnecessary interference and highlight the bearing fault impact frequency, so the envelope spectrum analysis is more common in the bearing fault diagnosis. As shown in Figure 13, the envelope spectrum analysis of signals shows that the frequencies of 161.695, 323.391 and 485.096 are very similar to the integer multiple of the characteristic frequency of the inner circle fault 162.18. Therefore, the fault signal can be judged as the inner circle fault, whether it is the original signal or the fault signal after separation. Envelope spectrum analysis can diagnose the fault type of the signal. The analysis of the outer ring fault envelope spectrum is shown in Figure 14. It can also be seen that the characteristic frequency 107.36 overlaps with its harmonic signal, which shows the effectiveness of the signal separation method we used.

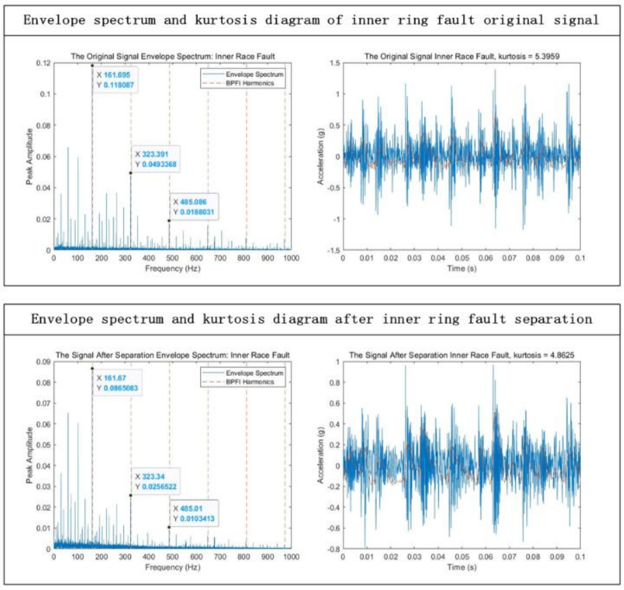

Figure 13: Inner ring fault signal analysis

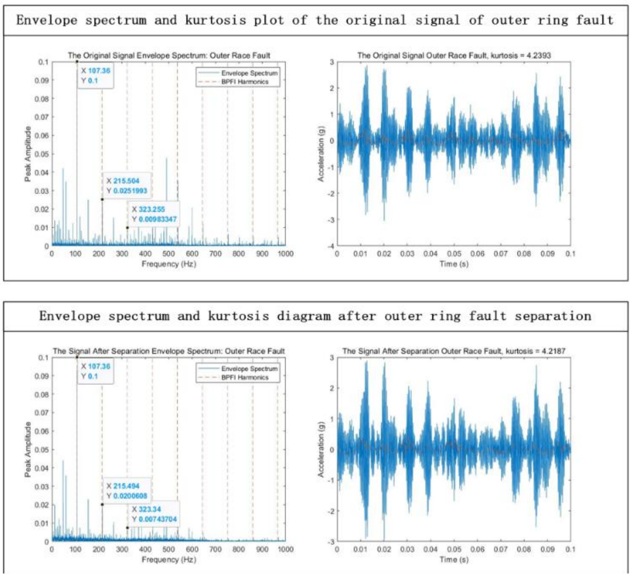

Figure 14: Outer ring fault signal analysis

The kurtosis value is used to evaluate the outlier value of the time-domain signal and reflect the cusp of the peak. In the signal separation results in Figure 13 and Figure 14, the original signal kurtosis value of the outer ring is 4.2393, and the signal kurtosis value after separation is 4.2187, the difference between the two is only 0.0206. The direction of the original signal and the separated signal is basically the same, which shows the reliability and authenticity of the proposed signal separation method.

5. Conclusion

Based on STFT, BTFM and multi-channel DCNN, a fault signal separation method for rolling bearing of wind turbine based on multi-channel DCNN is proposed in this paper. This method makes STFT of bearing time domain signals, draws reference from the outstanding performance of DCNN in the field of image classification, builds multiple neural network branches combined with multi-channel, fully extracts the feature distribution of bearing fault signals, and finally separates all kinds of fault signals in bearing mixed signals. It can be seen from the actual bearing data that the algorithm can still separate high-precision bearing fault signals from strong noise and non-stationary signals.

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