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Fault Diagnosis of Wind Turbine Rolling Bearing Based on VMD-SG-ResNet

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Abstract: In view of the noise existing in the original vibration data, the VMD-SG noise reduction algorithm is proposed, and the fault diagnosis of wind turbine rolling bearing is realized by combining the two-dimensional gray image and ResNet. Firstly, VMD is used to decompose the original signal to get IMF components, and Savitzky-Golay filter is used to denoise the noisy components, and the denoised components and other components are reconstructed to get a pure signal.After the one-dimensional signal is converted into a two-dimensional image, a diagnosis model is built based on ResNet network. The experimental results show that the rolling bearing fault diagnosis based on the model has a high diagnosis accuracy.

Keywords: Olling bearing, Two-dimensional gray image, Fault diagnosis, ResNet network, VMD.

1. Introduction

Nowadays, with the rapid development of the world economy, non-renewable energy has been over-exploited by human beings, resulting in an urgent need for inventory. Wind energy, as a stable and clean renewable energy, is abundant in energy storage. Therefore, wind power generation has become an important choice for energy development in recent years. According to statistics, the installed capacity of the fan is increasing year by year, but due to the harsh environment of the fan, it is easy to cause fan failure, and the bearing, as the main part of the fan, also has a high failure rate, so fault diagnosis is of great significance for the safe and stable operation of the wind turbine and reducing the maintenance costs in the later period.

At present, there are three main methods for bearing fault diagnosis: model-based method, signal processing-based method and deep learning-based method. In practice, it is difficult to establish an accurate model due to noise disturbance, modeling error and other reasons, which makes the effect of fault diagnosis poor. Relatively speaking, the latter two methods are more popular with researchers at home and abroad. In reference [2], the bearing vibration acceleration signal is converted into frequency domain signal by using fast Fourier transform, and the signal characteristics are extracted by 1D-CNN to diagnose the fault. Reference [3] proposed an improved coarse-grained multi-scale scattered entropy, and then used variational modal decomposition to decompose the vibration data and selected the best IMF component according to the cross-correlation coefficient, and then used the improved method to extract the nonlinear characteristics of IMF component and used PNN for fault diagnosis. Reference [4] uses PSO to determine the optimal parameters of Morlet wavelet, and uses the improved kurtosis index based on iterative two-means combined with envelope demodulation to classify rolling bearing faults. Reference [5] uses principal component analysis to reduce the dimension of the original vibration data and extract the corresponding features, and finally uses the deep belief network to realize fault diagnosis. Reference [6] introduces a multi-attention module based on the one-dimensional convolutional neural network to improve the diagnosis accuracy by enhancing the fault-related features.

In the process of bearing vibration data acquisition, it is inevitable to be polluted by noise, which will cover up the original signal data and have a certain impact on the subsequent feature extraction and fault diagnosis. Reference [7] proposes a CEEMDAN and wavelet threshold joint denoising method, which first decomposes the vibration signal into IMF components through CEEMDAN, and uses the continuous mean square error to select the IMF components with more noise, and then uses wavelet threshold denoising to denoise these components. Finally, the denoised components are reconstructed to obtain the denoised signal. In reference [8], the vibration signal is decomposed into IMF components by using integrated empirical mode decomposition, and then the noise level of IMF components is analyzed by using grey relation, and the components with larger noise are selected by using grey model to eliminate the noise, and finally the components are reconstructed.

In this paper, we propose a deep learning model based on VMD denoising (VMD-SG-ResNet). Firstly, the bearing fault data is decomposed into several IMF components by variational mode decomposition (Variational mode decomposition, VMD), and the correlation coefficients between each IMF component and the original signal data are calculated, and the high noise IMF components with smaller correlation coefficients are selected. A Savitzky-Golay filter is used for carrying out smooth filtering and noise reduction on the signal, and then the component subjected to noise reduction and other components are reconstructed together to obtain the final signal data subjected to noise removal; This paper will also build the ResNet model. After the denoised data is converted into a two-dimensional gray map, it will be input into the model to improve the diagnostic accuracy by extracting deep-seated features. The effectiveness of the proposed method is verified by the fault diagnosis of different parts of the rolling bearing damage in West Reserve University.

2. Analysis of Diagnostic Methods

2.1. Principle of VMD decomposition

Variational modal decomposition is a new modal decomposition algorithm proposed by Konstanin et al. Compared with the EMD family of decomposition algorithms, such as EMD, EEMD, CEEMDAN, ICEEMDAN and so on, VMD does not need to add Gaussian noise before decomposition. Although CEEMDAN and other algorithms add white noise of positive and negative sequences to offset each other in the decomposition process, there is still a certain reconstruction error.

The variational mode decomposition is a signal decomposition and estimation method[8],, which determines the frequency center and bandwidth of each component by iteratively searching for the optimal solution of the variational model in the process of obtaining the decomposed components, so as to adaptively realize the frequency domain subdivision of the signal and the effective separation of each component[9]. Variational mode decomposition is an adaptive decomposition method, which can determine the number of IMF components to be decomposed according to the actual situation. The goal of VMD is to decompose the actual input timing signal into K discrete sub-signals, which have specific sparsity in reproducing the input signal[10].

The process of VMD decomposition is actually the process of finding the optimal solution of the variational problem, which can be realized by solving the construction of the corresponding variational problem. The constrained variational problem corresponding to the VMD decomposition is as follows:

$$\left\{ \begin{array}{l} \min_{\{u_k\},\{\omega_k\}} \{ \sum_k ||\partial_t[\left(\delta(t)+\frac{j}{\pi t}\right) * u_k(t)]e^{-j\omega_k t}||_2^2 \} \\ s.t. \ \sum_k u_k = f \end{array} \right. \tag{1}$$

Among,Is the decomposed IMF components,Represents the central frequency of each IMF component.

Each mode component can be obtained by solving the above formula..The expression formula of is:

$$\hat{u}_k^{n+1}(\omega) = \frac{\hat{f}(\omega) - \sum_{i \neq k} \hat{u}_i(\omega) + \frac{\hat{\lambda}(\omega)}{2}}{1 + 2\alpha(\omega - \omega_k)^2} \tag{2}$$

Among, Is a quadratic penalty parameter, Is the Lagrange multiplication operator. Center frequency The expression formula of is:

$$\omega_k^{n+1} = \frac{\int_0^\infty \omega |\hat{u}_k(\omega)|^2 d\omega}{\int_0^\infty |\hat{u}_k(\omega)|^2 d\omega} \tag{3}$$

The specific steps are as follows:

```
Algorithm    2: Complete optimization of VMD
Initialize ,,,n0
Repeat
    nn+1
    for k=1: K do
        Update   for all :

  :

End for
Dual ascent for all :

Until convergence:                    (7)
```

In formula (7), is the accuracy of discrimination.

2.2. Smoothing noise reduction by Savitzky-Golay filter

Savitzky-Golay filter was proposed by Savitzky and Golay many years ago, and soon after it was proposed, it has been widely used in data stream smoothing and denoising. This method can directly deal with the problem of data smoothing in the time domain, and it uses the least square method to fit the polynomial to get the denoised value.

2.3. ResNet Model

In this paper, the signal-picture conversion method proposed in reference [13] is used. In this method, segment data with the size of M is randomly obtained from the original signal and combined into an image of M * M, and the converted data is guaranteed to be an integer between 0 and 255 through formula (8).

$$P(m,n) = round\{\frac{L[(m-1) \times M + n] - \min(L)}{\max(L) - \min(L)} \times 255 \tag{8}$$

Among, In the two-dimensional gray scale map,All right, noThe value of the column; The letter M is that the size of the converted picture is M * M; L is the value of the time sequence signal after single sampling, and its length is M2; L (I) is the value of the ith data point in L; round (X) is a rounding function, which can round the data.

Since CNN came out, it has made great achievements in various fields. In the early stage, LeNet5 model was the most widely used model, but in the more complex image recognition field, the model is not effective due to the limitation of the number of layers. Since then, more excellent models have emerged, such as AlexNet[12], GoogLeNet, VGG, etc. These models use deep network framework to solve the above problems.

However, with the increase of the number of network layers, the structure of these models is becoming more and more complex, and the difficulty of training is also increasing, but the performance of the models is declining rapidly, resulting in the disappearance of gradients and other issues. In order to solve the above problems, He Kaiming, Zhang Xiangyu and others[11]proposed the ResNet network in 2015. The network is composed of multiple residual blocks, and its core is to introduce the identity mapping and directly skip one or more layers of networks, as shown in the following figure:

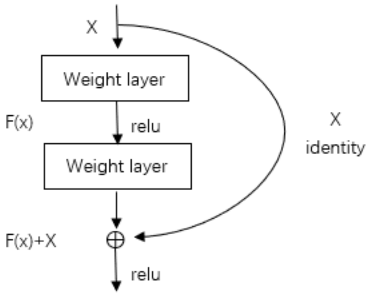

Figure 1. Residual module

Compared with the serial structure of the ordinary network, the residual module adds the jump mapping. In order to supplement the feature information lost in the convolution process, the residual module adds the input to the output directly. In the process of addition, it is necessary to ensure the calculation of the same dimension. If it is not satisfied, it is necessary to match the dimensions through some operations, such as increasing the dimension with zero-padding or using 1 * 1 convolution to increase the dimension. Deep residual network solves the degradation problem of deep network through residual learning, which makes the model training more stable and the model performance better.

3. Diagnostic Process

The main process of this study includes denoising preprocessing of data sets, signal-image conversion and model training and verification. The process is as follows:

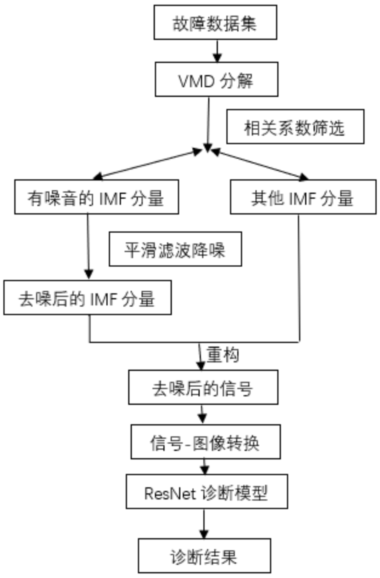

Figure 2. Diagnostic process

The VMD-SG-ResNet algorithm model firstly decomposes the vibration data of the rolling bearing by VMD, calculates the correlation coefficient between each IMF component and the original data, selects the data with small correlation coefficient as the noise data, and uses Savitzky-Golay filter to smooth filter and reduce noise. After that, the denoised components and other components are reconstructed to form denoised signal data, and then these data are converted into two-dimensional grayscale images, which are input into the ResNet model for training, and the model with optimal parameters is obtained through the training data set, and the test set data is input into the model for testing.

4. Experiment and Discussion

4.1. VMD-SG Noise Reduction

As an important part of wind turbine, the normal operation of rolling bearing is very important for wind turbine. In This paper, the vibration data of rolling bearing from the electrical engineering laboratory of Case Western Reserve University in the United States are used for experiments, and the fault types include rolling element (RE), inner ring (IR) and outer ring (OR). Each type of fault includes three different degrees of damage size: 0.01 mm, 0.36 mm and 0.54 mm. The above nine fault States and the normal state of the bearing together constitute the 10 health States of the experiment. Each health state has 500 samples, and each sample is obtained by collecting 4096 continuous data points with a frequency of 12 Kw. Then these samples are denoised by VMD-SG and converted into two-dimensional gray images and input into ResNet model for fault diagnosis.

Fig. 3 shows the waveform of the original vibration signal of the bearing outer ring with a damage of 0.18 mm (500 data points are selected for clear observation).

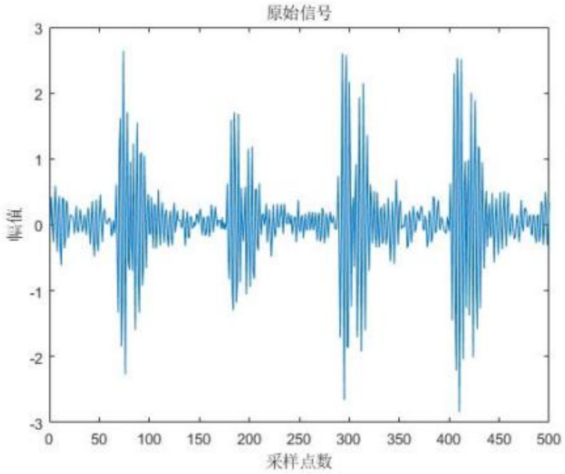

Figure 3. Waveform of Original Signal with Outer Ring Damage Size of 0.18

After VMD, the original vibration signal is decomposed into 10 IMF components. The characteristic parameters of VMD decomposition in this experiment are: penalty factor alpha = 2000, noise tolerance Tau = 0, number of decomposed modes K = 10, no DC component DC = 0, initialization center frequency is uniformly distributed, that is, init = 1, and convergence criterion tolerance tol = 1e-7. The decomposed waveforms of each IMF component are shown in Figure 4.

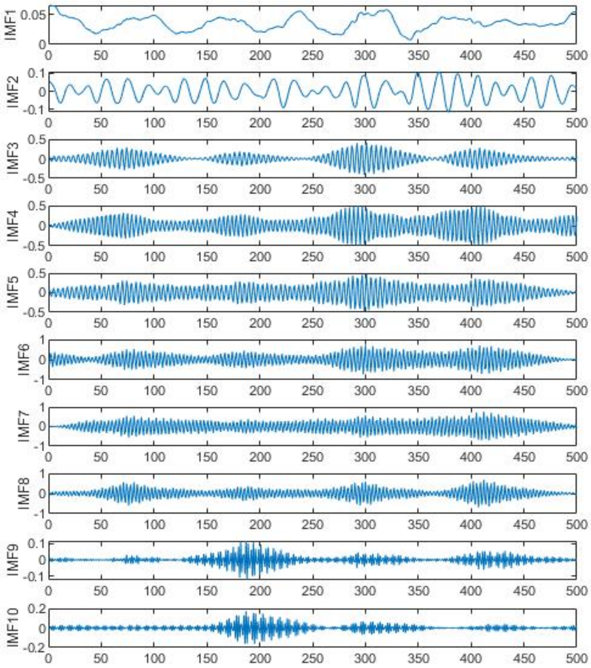

Figure 4. Waveform of IMF component

The correlation coefficient of each IMF component with the original vibration data is calculated using Equation (9The results are shown in Table 1.

In the formula, Represents each IMF component, and y represents the original vibration signal.

Table 1. Table of correlation coefficients of each IMF component

Modal components	IMF1	IMF2	IMF3	IMF4	IMF5
	0.0499	0.0847	0.2819	0.3872	0.3725
Modal components	IMF6	IMF7	IMF8	IMF9	IMF10
	0.5355	0.5754	0.4712	0.0797	0.0809

It can be seen from Table 1 that the correlation coefficients of each IMF component and the original signal are quite different. Among them, the correlation coefficients of IMF 3, IMF4, IMF5, IMF5, IMF6, IMF7 and IMF 8 are all greater than 0.2, which shows that they are the dominant IMF components. However, the coefficients of IMF 1, IMF 2, IMF 9 and IMF 10 are all less than 0.09, and it is preliminarily determined that these four IMF components contain more noise signals.

And performing Savitzky-Golay smoothing filtering on the IMF 1, the IMF 2, the IMF 9 and the IMF 10, and reconstructing the denoised four components and other IMF components to obtain a denoised signal. Fig. 5 is a waveform diagram of a vibration signal after noise reduction.

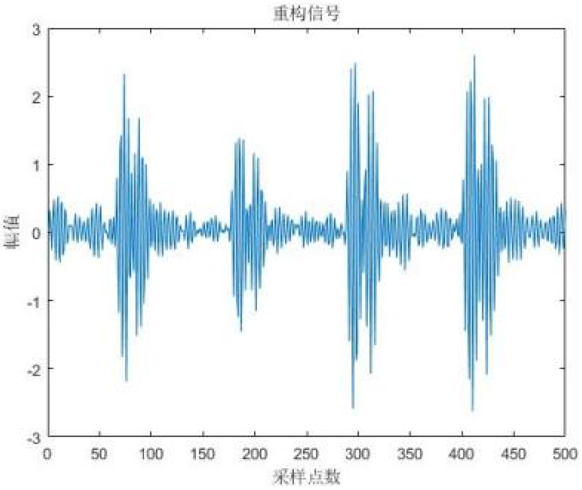

Figure 5. Vibration signal waveform after noise reduction

It can be seen from fig. 1 and fig. 3 that the pure signal after noise reduction and the original signal without processing have a high degree of coincidence in signal peak value and local waveform characteristics; In order to further verify the similarity between the signal after VMD-SD noise reduction and the original signal, the correlation coefficients of 10 types of two signals in the experiment are calculated, and the results are shown in Table 2.

Table 2. Table of correlation coefficients between various health States and original signals after noise reduction

Signal type	B0.18	B0.36	B0.54	I0.18	I0.36
	0.9793	0.9791	0.9884	0.9885	0.9708
Signal type	I0.54	normal	O0.18	O0.36	O0.54
	0.9584	0.9892	0.9894	0.9664	0.9777

It can be seen that the two kinds of data still have a high correlation after VMD-SG noise reduction.

4.2. Conversion to grayscale image

The vibration signal denoised by VMD-SG is converted into a two-dimensional grayscale image by using the method mentioned in the previous section. Each state contains 500 image samples with a size of 64 * 64. Finally, a data set with 5000 image samples is obtained. The grayscale images of various types are shown in Figure 6.

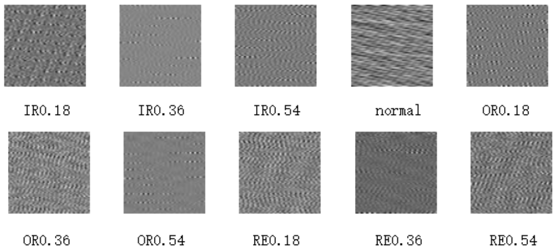

Figure 6. Gray-scale maps of health States in Figure 6 and 10

90% of the images were randomly selected as the training set, and the remaining 10% of the samples were used as the test set to verify the performance of the model, that is, 4500 images were used as the training set and 500 images as the test set.

Fig. 7 shows the confusion matrix drawn by the diagnostic model for 500 images in the test set. It can be seen that only one image is classified incorrectly, that is, the real label is IR0.18 and classified as RE0.18, and the rest are classified correctly, with an accuracy rate of 99.8%.

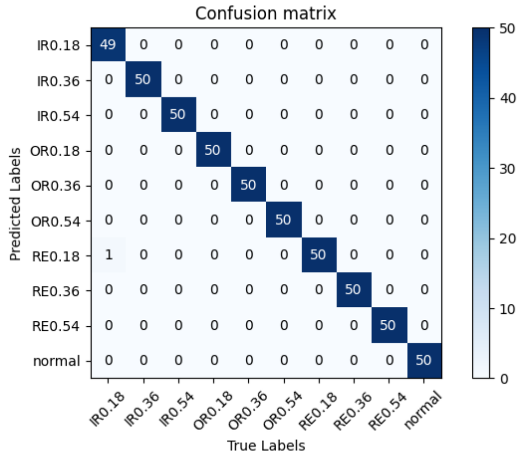

Figure 7. Model Confusion Matrix of VMD-SG-ResNet

In order to better observe the experimental results, 500 groups of test image data were input into ResNet and VMD-SG-AlexNet for comparative experiments. The diagnosis results are shown in Figure 8 and Figure 9.

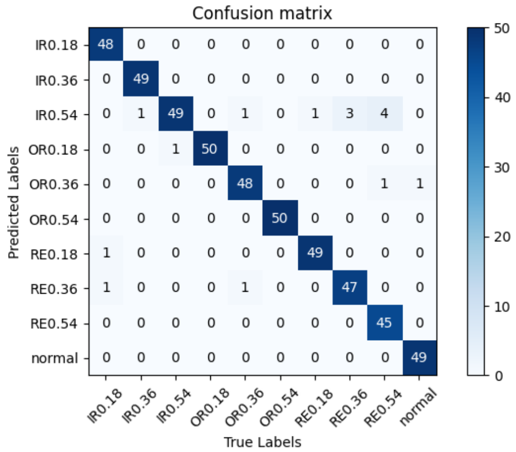

Figure 8. ResNet model confusion matrix

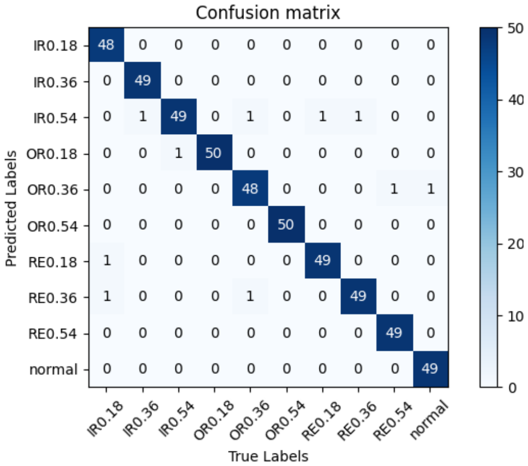

Figure 9. VMD-SG-AlexNet Model Confusion Matrix

It can be seen from Figure 8 that ResNet has 16 image diagnosis errors, and the rest are correct, with an accuracy rate of 96.8%. It can be seen from Figure 9 that 490 images of VMD-SG-AlexNet are correctly diagnosed, 10 images are incorrectly diagnosed, and the diagnostic accuracy rate reaches 98%.

Finally, the test results of the above three models are shown in Table 3. It is obvious that the rolling bearing diagnosis effect of VMD-SG-ResNet model is better than that of ResNet and VMD-SG-AlexNet, with an increase of 3% and 1.8% respectively.

Table 3. Diagnostic results of each model

Diagnostic method	Correct diagnosis/sheet	Error diagnosis/sheet	Accuracy/%
VMD-SG-ResNet	499	1	99.8
ResNet	484	16	96.8
VMD-SG-AlexNet	490	10	98

5. Conclusion

In this paper, a rolling bearing fault diagnosis method based on VMD-SG-ResNet is proposed. The original vibration data is decomposed and denoised by using variational modal decomposition and Savitzky-Golay filter. The denoising method not only eliminates the noise, but also effectively retains the feature information in the original signal, which lays the foundation for the subsequent fault diagnosis. The one-dimensional time series data is converted into a two-dimensional grayscale image, and the ResNet network is built to extract the two-dimensional features of the image independently, which further improves the diagnostic accuracy of the model. Through comparative experiments, the diagnosis accuracy and performance of the VMD-SG-ResNet model are further verified, and the effectiveness and feasibility of the proposed method in fault diagnosis are proved.

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