Time-Frequency Analysis of Vibration Signal Distribution of Rotating Machinery Based on Machine Learning and EMD Decomposition

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Abstract. The conventional time-frequency analysis method of the vibration signal distribution of rotating machinery has a low correlation coefficient between the time-frequency features and the vibration signal, which leads to a low accuracy in identifying fault types of rotating machinery. For this reason, this paper proposes a time-frequency analysis method for the vibration signal distribution of rotating machinery based on machine learning and EMD decomposition. After collecting the vibration signal of the rotating machinery, it is decomposed by EMD, the collected signal is decomposed into a set of steady-state and linear data series, and the decomposed signal is filtered and denoised. Then set the time window to extract the local time domain feature components of the vibration signal, and then use the artificial neural network to identify the fault type of the rotating machinery. Experimental results show that this method improves the correlation coefficient between time-frequency characteristics and vibration signals, and improves the accuracy of identifying fault types in rotating machinery.

Keywords: Rotating machinery · EMD decomposition · Machine learning · Time-frequency characteristics

1 Introduction

Mechanical rotation will appear stationary or non-stationary characteristics of two cases, these two cases have a certain periodicity. But in the process of rotating machinery movement will appear vibration. Mechanical vibration contains the vibration of various frequency components from low to high frequency, and the vibration of rotating machinery is the same.

In order to better analyze the working efficiency and quality of machinery, it is necessary to study the vibration signal caused by machinery in work, and extract useful information from the vibration signal.

In the process of collecting mechanical vibration signal, the time domain signal should be analyzed emphatically. Time-frequency signals can reflect the time variation

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characteristics and frequency variation signals simultaneously, which provides useful information for vibration signal analysis. Therefore, it is of great significance to study the time-frequency analysis method of vibration signal distribution of rotating machinery for analyzing the running state of equipment and distinguishing characteristic signals from non-characteristic signals.

Reference [1] uses the Fourier transform analysis method to analyze and describe the above signal frequency changes, but the method cannot reflect the mechanical vibration signal in real time. Reference [2] decomposes the signal into sine or cosine functions, showing the characteristics of frequency change with time, but this method cannot show the characteristics of frequency change with time.

In view of the problems existing in traditional methods, this research proposes a time-frequency analysis method for the vibration signal distribution of rotating machinery based on machine learning and EMD decomposition. EMD has good time-frequency aggregation, which can distinguish time resolution from frequency resolution, avoiding the occurrence of linear time-frequency constraints. Machine learning can convert one-dimensional time-domain signals into two-dimensional The time-frequency plane improves the information processing effect of non-stationary signals. The experimental results also prove that this study gives full play to the technical advantages of machine learning and EMD decomposition, and improves the extraction effect of time-domain characteristics of vibration signals, so that the average accuracy of the analysis results of time-frequency distribution of vibration signals of rotating machinery by this method reaches 98.1%.

2 Method Design

2.1 Collect Vibration Signals of Rotating Machinery

Design a data collector to collect vibration signals of rotating machinery. The host device, slave device, power amplifier, power dynamic real-time simulation device, and electronic transformer are selected to form a vibration signal collector. Among them, the power dynamic real-time simulation device performs real-time closed-loop simulation of rotating machinery. The selected simulation equipment is a portable RTDS real-time digital simulator, which has a power component library, and refers to the on-site conditions of the rotating machinery to set the power component parameters to correctly simulate various fault states that occur during the operation of the rotating machinery. The host device is respectively connected with the simulation device and multiple slave devices, and its communication module is configured with an optical fiber interface and an 8-bit modular interface, and transmits the simulation data of the simulation device to the slave device through the optical fiber connection. The slave device is also equipped with optical fiber interface and 8-bit modular interface, which is connected to the port of signal analysis and processing, and the analog data switch information sent by the host is input to the terminal, and the D/A conversion card is set to transmit through the internal D/A module. The number of analog quantities is 12, which converts the analog data into a standard 5V voltage analog signal, which is input to the power amplifier [3]. The optimized D/A module conversion circuit is shown in Fig. 1.

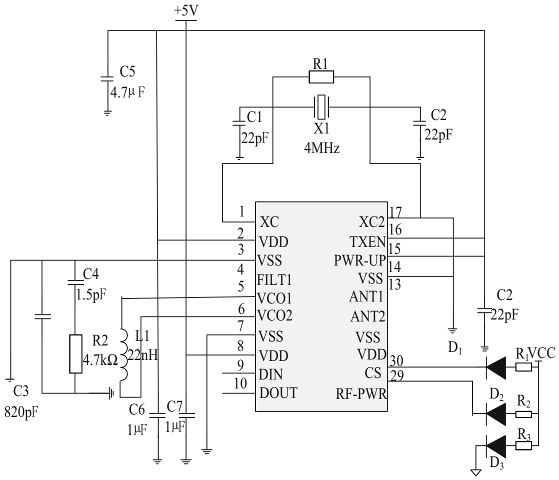

Fig. 1. D/A conversion circuit of rotating machinery vibration simulation data

The analog signal of the slave device is amplified by the power amplifier to meet the current and voltage of the signal collection, and the analog signal is received through the external synchronous clock interface to synchronously obtain the vibration signal of the rotating machine. Finally, the high-current generator is used as the current source, and the high-voltage generator generates the rated voltage. The rated current is passed through the optical fiber to obtain the current signal digital quantity, which is input to the electronic transformer calibrator to detect the output rotating machinery vibration signal and output in real time. The analog signal, including whether the waveform is synchronized, whether the polarity and transformation ratio are consistent, completes the verification of the vibration signal of the rotating machinery. For the communication module of the system host device, a communication network is built, and the line sampling signal is transmitted to the time-frequency analysis terminal. The switch information selects fiber optic Ethernet and GOOSE network, and configures the switch according to the interval. The components of the Ethernet switch are shown in Fig. 2.

The Ethernet switch adopts dual power supply, provides 1 Gbps rate optical fiber Ethernet interface, control recovery time < 5 ms, group ring any port, guarantees zero packet loss of the switch under strong electromagnetic interference, and transmits rotating machinery vibration signals [4]. At this point, the collection of vibration signals of rotating machinery is completed.

2.2 EMD Decomposes Vibration Signals of Rotating Machinery

Through EMD decomposition, the non-stationary and non-linear rotating machinery vibration signal is decomposed into a set of steady-state and linear data series, namely the eigenmode function. EMD obtains the intrinsic vibration mode through the characteristic time scale, and then decomposes the time series data from the intrinsic vibration mode, and decomposes a multi-component signal into multiple eigenmode functions. Each eigenmode function is transformed by Hilbert. The Hilbert spectrum is calculated, and

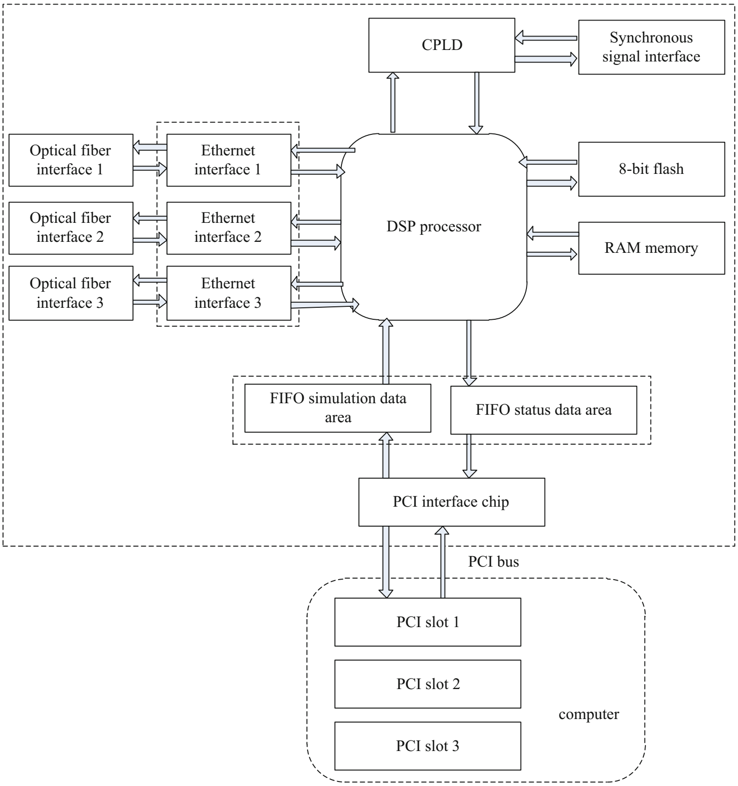

Fig. 2. Rotating machinery vibration signal communication switch

its structure is determined according to the scale characteristics of the original signal itself. In addition, the eigenmode function must meet the following two conditions: For a column of data, the number of extreme points and zero-crossing points must be equal or at most a little different; At any point, the envelope composed of local maximum points and the envelope composed of local minimum points have an average value of zero [5]. Suppose the time series data of the vibration signal of the rotating machinery is x(t), find all the maximum and minimum points of x(t), and use the cubic spline function to fit them to the upper and lower envelopes of the original data series. The average value of the upper and lower envelopes is the average envelope m_1. Subtract m_1 from the original data sequence to obtain a new data sequence h_1 with the low frequency removed, namely:

$$h_1 = x(t) - m_1 \tag{1}$$

Under normal circumstances, h_1 is not necessarily a stationary data series, so the above process needs to be repeated for it [6]. If the average envelope of h_1 is m_{11}, the data sequence h_{11} after removing the envelope representing the low-frequency components, namely:

$$h_{11} = h_1 - m_{11} \tag{2}$$

Repeat the above process to make the obtained average envelope tend to zero, so that the first eigenmode function component c_1 is obtained, which represents the highest frequency component in the signal data sequence. Subtract c_1 from x(t) to obtain a new data sequence r_1 with the high frequency components removed, and perform EDM decomposition on r_1 to obtain the second eigenmode function component c_2, and repeat until the last data sequence r_n can no longer be decomposed. At this time, r_n represents the trend and mean value of the data sequence x(t) [7]. The above process can be expressed as:

$$\begin{aligned} r_1 &= x(t) - c_1 \\ r_2 &= r_1 - c_2 \\ &\vdots \\ r_n &= r_{n-1} - c_n \end{aligned} \tag{3}$$

Among them, r_{n-1} is n − 1 the th vibration signal data sequence, and c_n is the n th eigenmode function component. From the above formula:

$$x(t) = \sum_{i=1}^{n} c_i + r_n \quad i = (1, 2, \cdots, n) \tag{4}$$

The original data sequence can be expressed as the sum of the eigenmode function component and a residual term, and a steady-state linear data sequence set containing the vibration information of the rotating machine can be obtained. So far, the EMD decomposition of the vibration signal of the rotating machine is completed.

2.3 Filter Processing Vibration Signal of Rotating Machinery

The wavelet packet denoising method is used to filter the vibration signals of rotating machinery. From the energy point of view, the wavelet packet noise reduction algorithm is adopted, a scale function is introduced, and each scale signal is intercepted through the filter bank, and the wavelet system generated by the expansion of the scale function is obtained. The calculation formula of wavelet function ϕ is:

$$\varphi = \left(a_j - 2c_j\right)D \tag{5}$$

Among them, D is the impulse response of the orthogonal mirror filter, a_j is the scale coefficient of the j-th layer of the scaling function, and c_j is the wavelet coefficient of the j-th layer. Select wavelet function ϕ, wavelet decomposes noise-containing rotating machinery vibration signal, assigns signal characteristics to wavelet decomposition coefficients of different scales, and compresses the signal to obtain wavelet packets. According to the order of energy, arrange the wavelet packets, select the first A wavelet packets with larger energy, and reconstruct the vibration signal of the rotating machinery [8]. To reduce the error between the reconstructed signal and the original signal, the calculation formula is:

$$C = \min\left\{\frac{1}{A}\sum_{\lambda=1}^{A}\left[d(\lambda) - g(\lambda)\right]^2\right\} \tag{6}$$

Among them, C is the error minimization objective function, and $\mathrm{d}(\lambda)$ and $\mathrm{g}(\gamma)$ are the reconstructed signal and the original signal of the λ-th wavelet packet, respectively. On this basis, the wavelet packet basis which can form a set of orthogonal basis is extracted and decomposed. After decomposition, a sequence of information function is given, and then the bottom-to-top search method is adopted to find the optimal wavelet packet base that can express the signal characteristics. The specific search process is shown in Fig. 3.

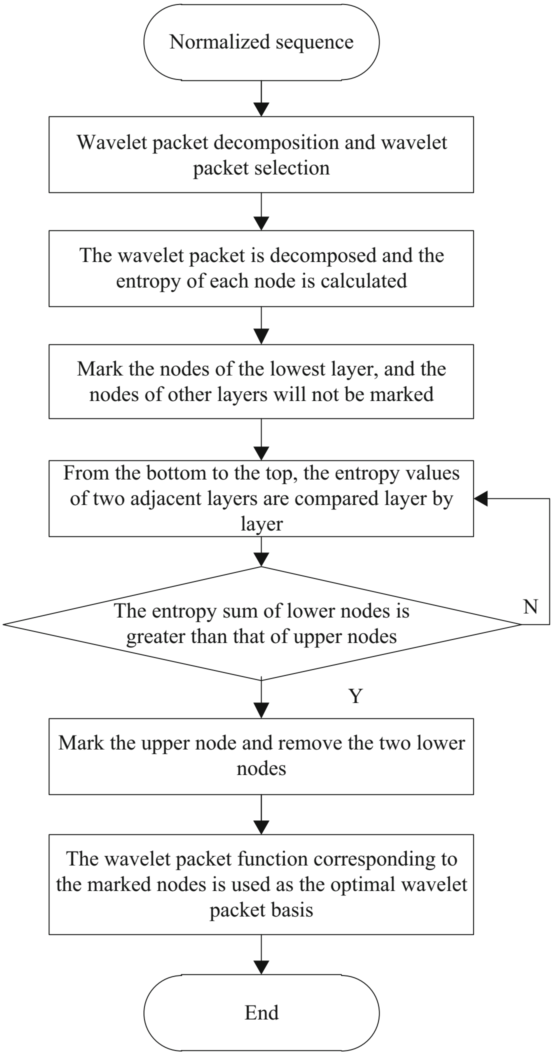

Fig. 3. The optimal wavelet packet base search process

Threshold quantizes the optimal wavelet packet basis decomposition coefficient, and obtains the oscillation signal containing the vibration information of the rotating machine after the noise is eliminated. So far, the filtering of the vibration signal of the rotating machinery is completed.

2.4 Extract Local Time Domain Feature Components of Vibration Signal

For the rotating machinery vibration signal after decomposition and denoising, a time-frequency period window is set to extract the signal video feature components. First calculate the time series data in the cyclic stationary process:

$$\mathrm{x(t)} = \mathrm{x(t} + T) \tag{7}$$

Among them, T is the signal period. Take the local smoothing window function and apply it to the time series data, then the instantaneous correlation function $J\mathrm{(t)}$ of $\mathrm{x(t)}$ is:

$$J\mathrm{(t)} = \mathrm{x}\left(\mathrm{t} + \frac{\xi}{2}\right)\mathrm{x}^*\left(\mathrm{t} - \frac{\xi}{2}\right) \tag{8}$$

Among them, ξ is the instantaneous correlation coefficient, and $*$ is the conjugate [9]. According to the product of the free correlation function and the periodic function, in the stationary process of the period T, the instantaneous correlation function $J\mathrm{(t)}$ of $\mathrm{x(t)}$ is also the instantaneous correlation function of the time domain t. Expand the instantaneous correlation function to obtain the Fourier series, and determine the frequency of the vibration signal. The period and the function $J\mathrm{(t)}$ have a strong autocorrelation. Taking $\frac{1}{T}$ as the fundamental frequency and taking the frequency value to an integer multiple, its value represents the cyclic frequency. The cycle frequency number represents the energy of the cycle frequency. After the machine fails, the cycle frequency number is used as an important diagnostic basis.

Clarify the time-frequency domain on the Fourier series curve. When using each of the time-frequency domains, groupings of discrete components of cyclic frequency are formed. Different components have different sensitivity to faults. The more sensitive discrete components of cyclic frequency are useful in diagnosing faults. Time has a very good relationship characteristic. During the diagnosis process of rotating machinery, it is not necessary to know the entire distribution of the signal in the time and frequency domain, only to check it. For the discrete components of the insensitive cycle frequency number, the Fourier series is expanded under a single cycle, and with the help of the time-frequency domain local windowing method, the Fourier series and the signal frequency have a harmonic relationship, that is, there is a quadrature in the $[0, 2T]$ interval. The relationship, using the orthogonality in the harmonic function interval, calculates the window function of the vibration signal distribution in the time domain and the frequency domain, finds the harmonic frequency that can be used for detection, after a series of simplification and integration, the detection The time-frequency distribution at the characteristic frequency component extracts the local time-frequency characteristic component of the vibration signal, and obtains the important information of the local time-domain characteristic component. So far, the extraction of the local time-domain feature components of the vibration signal is completed.

2.5 Analyze the Failure of Rotating Machinery Based on Machine Learning

The extracted local time domain features of the vibration signal are input into the artificial neural network of machine learning to diagnose the failure mode of rotating machinery.

Firstly, by means of graphs, real-time tracking of the changes in the fault parameters of the rotating machinery to obtain fault samples, using the artificial intelligence algorithm of the neural network to number and classify the rotating machinery faults, and then through the data collector to collect the vibration signals of the running state of the rotating machinery, Take the characteristic components of the vibration signal at each time and frequency as the characteristic quantity of the fault of the rotating machinery, so as to obtain the characteristic information described by the value of the vibration signal, and obtain the learning sample input by the neural network. A single hidden layer neural network is selected, and the local time-domain characteristics of the extracted vibration signal and the fault diagnosis mode of rotating machinery are respectively used as the input and output of the network [10]. Determine the neural network structure, initialize the number of nodes in each layer, obtain the output values of the hidden layer and the output layer, adjust the connection weights of the input layer to the hidden layer, and the output threshold of the hidden layer and output layer, calculate the actual output value and the training sample The deviation. The specific neural network structure is shown in Fig. 4.

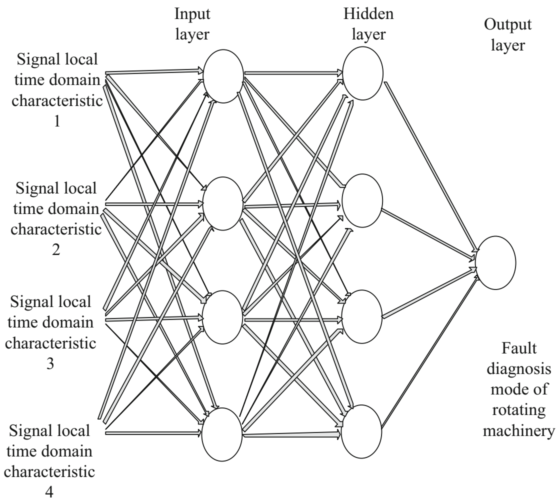

Fig. 4. Neural network structure of rotating machinery fault diagnosis

As shown in Fig. 4, when the network error converges to the minimum, the corresponding hidden layer node number is 4, and the rotating machinery fault diagnosis mode is used as an output node of the neural network. Calculate the input U_{t} of neuron τ in the middle layer of the network, the formula is:

$$U_\tau = \sum_{y=1}^{R} Z_{y\tau} P_y - \alpha_\tau \quad \tau = 1, 2, \ldots, Q \tag{9}$$

Among them, P_y is the fault feature vector input by the input layer neuron y, α_τ is the output threshold value of the middle layer neuron τ to each unit, and R and Q are the number of input layer and middle layer neurons. Use the transfer function to calculate the output of each unit in the middle layer and the response of each unit in the output layer, randomly select the next learning sample to input into the network, and repeat the above process until the neural network iteration error is less than the preset value [11]. Use the linear function to activate the input layer and output layer of the neural network, and then use the Sigmoid function to activate the hidden layer, and normalize the data before input to make the data at the same level, eliminate the influence of dimensions, and avoid the Sigmoid function the saturation area of the training data [12]. Update the number of training multiple times, reduce the error between the output value and the training sample, realize the neural network training of the device fault characteristics, compare the output value with the test sample, output the diagnosis result of the rotating machine, identify the fault diagnosis mode of the rotating machine, and It is applied to the rotating machinery tested. So far, the fault recognition of rotating machinery based on machine learning has been completed.

3 Experiment and Analysis

The time-frequency analysis method of the vibration signal distribution of rotating machinery designed in this paper based on machine learning and EMD decomposition is compared with two sets of traditional time-frequency analysis methods of the vibration signal distribution of rotating machinery. Use three sets of methods to perform time-frequency analysis on rotating machinery vibration signals to diagnose rotating machinery faults.

3.1 Experiment Preparation

The test data is collected from a single-stage gearbox failure test bench, and the failure type of the failed gear is tooth surface spalling. The number of gear teeth on the input shaft of the gearbox is 20, the number of gear teeth on the output shaft is 21, the sampling frequency is 20000 Hz, and the number of spectrum analysis points is 409600. The speed of the input shaft is 1000 r/min, the speed of the output shaft is 952.2 r/min, and the speed of the input shaft is 16. 67 Hz, and its meshing frequency is 333.3 Hz. The operating parameters of rotating machinery are shown in Table 1.

Table 1. Rotating machinery operating parameter settings

Parameter	Numerical value	Parameter	Numerical value
Number of reactive power compensation equipment put into operation	1 station	Active power correlation coefficient	865 units
Reactive power correlation coefficient	0.47	Active power distribution ratio	0.62
Reactive power distribution ratio	3.28	Power Factor	4.22
total capacity	11850 kVA	Compensation point reactive power compensation capacity	0.55–0.85
Rated voltage of compensation device	10 kV	Rated power	800 kVA
Reactive power compensation efficiency	96%	Load factor	2500 kW
Short-circuit capacity	450 MV.A	Distance between compensation point and center	80%

The time-domain waveform and frequency spectrum of the gear fault vibration signal are shown in Fig. 5.

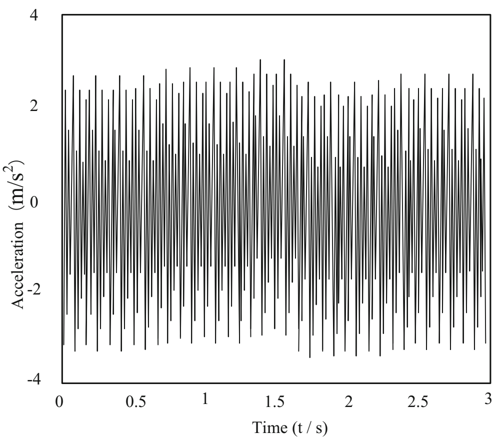

Fig. 5. Time-domain waveform diagram of gear failure

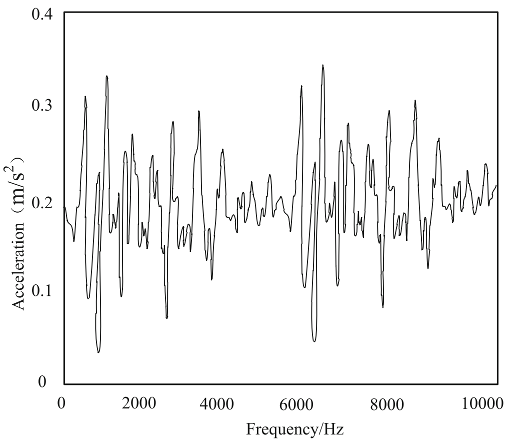

Fig. 6. Frequency spectrum of gear failure

It can be seen from Fig. 5 and Fig. 6 that the time-domain waveform of the time-domain waveform diagram is more complicated, and the frequency components of the spectrogram are also more complicated, it is difficult to distinguish the specific characteristics of the signal, and it is difficult to distinguish useful information.

3.2 Experimental Result

The First Set of Experimental Results

Record the three methods to extract the local time-domain features of the vibration signal, and the experimental comparison results are shown in Fig. 7.

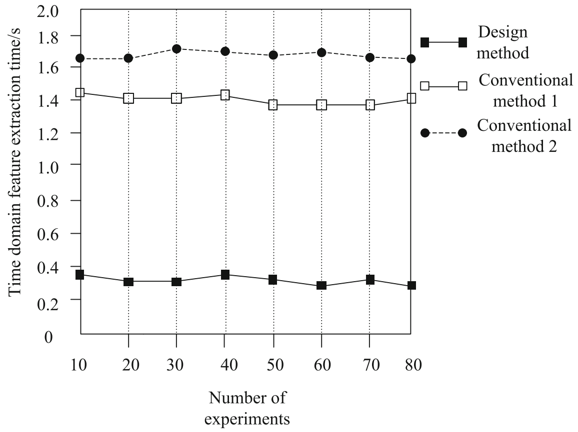

Fig. 7. Comparison results of time domain feature extraction time

It can be seen from Fig. 7 that the average extraction time of the signal time domain features of the method in this paper is 0.37 s, and the average extraction time of conventional method 1 and conventional method 2 are 1.42 s and 1.67 s respectively. Compared with the two conventional methods, the average extraction time of this method is Respectively reduced by 1.05 s and 1.30 s.

The Second Set of Experimental Results

On the basis of the first set of experiments, the vibration signal collection period was changed to test the time-domain characteristics of the signals extracted by the three sets of methods and the degree of similarity to the vibration signals of rotating machinery. The cross-correlation coefficient is used to measure the effect of signal extraction in the time domain. The larger the correlation coefficient, the more similar the extracted time domain features and the vibration signal. The experimental comparison results are shown in Table 2.

Table 2. Comparison of correlation coefficients of extracted signal time domain features

Signal acquisition period/s	Method correlation coefficient	Conventional Method 1 Correlation Coefficient	Conventional Method 2 Correlation Coefficient
0.02	0.792	0.734	0.701
0.04	0.801	0.746	0.708
0.06	0.813	0.752	0.714
0.08	0.838	0.771	0.723
0.1	0.849	0.782	0.735
0.12	0.851	0.789	0.741
0.14	0.872	0.794	0.749
0.16	0.889	0.805	0.758
0.18	0.891	0.816	0.763
0.2	0.905	0.837	0.771

As shown in Table 2, the correlation coefficient of the method in this paper is always higher than the two conventional methods, with an average correlation coefficient of 0.850. The average correlation coefficients of conventional method 1 and conventional method 2 are 0.783 and 0.736, respectively. It can be seen that the correlation coefficients of the method in this paper are increased by 0.067 and 0.112 respectively.

The Third Set of Experimental Results

After the three sets of methods extract the time-domain characteristics of the vibration signal, identify the fault diagnosis type of the rotating machinery, and calculate the fault diagnosis accuracy rate. The results are shown in Table 3.

Table 3. Results of the third group of experiments (%)

Signal acquisition cycle/s	A group recognition accuracy rate	B group recognition accuracy rate	C group recognition accuracy rate
0.02	98.7	90.4	86.4
0.04	97.7	91.6	87.9
0.06	98.1	89.9	85.3
0.08	97.5	90.6	86.5
0.1	97.4	91.9	87.5
0.12	96.9	92.4	87.6
0.14	100	90.7	86.9
0.16	99.2	89.7	86.3
0.18	97.1	90.1	86.1
0.2	98.2	92.8	88.5

As shown in Table 3, for the tooth surface peeling failure of rotating machinery, the average recognition accuracy of this method is 98.1%, and the recognition accuracy of conventional method 1 and conventional method 2 are 91.0% and 86.9%, respectively. It can be seen that this method recognizes The accuracy rate has been increased by 7.1% and 11.2% respectively.

In summary, the method in this paper shortens the time-domain feature extraction time of the vibration signal compared with the conventional method, and the extracted time-domain feature is more similar to the vibration signal, which improves the recognition accuracy of the fault type of the rotating machinery.

4 Conclusion

This study gives full play to the technical advantages of machine learning and EMD decomposition, improves the extraction effect of time-domain characteristics of vibration signals, and improves the fault identification accuracy of rotating machinery, making the average accuracy of the analysis results of time-frequency distribution of vibration signals of rotating machinery by the method in this paper reach 98.1%. However, there are still some shortcomings in this study. Therefore, in the future research, it will be considered to introduce the improved BITD algorithm to further improve the extraction efficiency of time domain features.

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