Research on Accurate Extraction Algorithm for Fault Signal Characteristics of Mechanical Rolling Bearings

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Abstract. Traditional fault signal feature extraction algorithms such as auto-correlation analysis algorithm, morphological gradient algorithm and other algorithms have the disadvantage of low accuracy. Therefore, a fault signal feature extraction algorithm based on wavelet frequency shift algorithm and minimum entropy algorithm is designed. Based on the noise removal algorithm of mechanical equipment based on wavelet frequency shift design and the mechanical fault identification algorithm based on minimum entropy algorithm, the two algorithms are integrated to generate the feature extraction algorithm of mechanical rolling bearing fault signal. In this way, the feature of fault signal is extracted, and an example is given. The experimental results of simulation and application environment design show that, compared with the traditional design, Compared with the fault signal feature extraction algorithm, the proposed algorithm can improve the accuracy of the analysis results by about 4% when using the same data.

Keywords: Keywords mechanical rolling bearing · Fault signal · Extracting signal feature · Accuracy

1 Introduction

In industrial machinery and equipment, the parts of the equipment that are most subject to wear are mechanical rolling bearings. When the rolling bearings are damaged, they often cause mechanical equipment to malfunction, in this regard, the fault signal characteristic of the rolling bearing needs to be extracted, and the fault point of the rolling bearing is determined according to the extraction result so as to be repaired in time. The traditional fault signal feature extraction algorithm has low accuracy. Therefore, this paper uses wavelet frequency shift algorithm to calculate the noise removal of the equipment, and uses the minimum entropy algorithm to identify the mechanical fault, Based on these two algorithms, the fault signal feature extraction algorithm is designed. Experimental results show that the algorithm designed in this paper is more suitable for the extraction of fault signal characteristics of mechanical rolling bearings than traditional algorithms.

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2 Design Fault Signal Feature Extraction Algorithm

This paper designs fault signal feature extraction algorithm based on wavelet frequency shift denoising algorithm and minimum entropy mechanical fault recognition algorithm.

2.1 Remove Mechanical Equipment Noise

In the process of collecting and transmitting the fault signal of the mechanical rolling bearing, it will be interfered and influenced from the outside and inside of the mechanical equipment, resulting in the use of an accurate extraction algorithm to extract fault signal characteristics, affected by the internal and external noise of the mechanical rolling bearing, the accuracy of the calculation result is reduced. Therefore, before the feature extraction of the fault signal of the mechanical rolling bearing, the wavelet algorithm is used to perform the noise removal calculation on the original signal of the mechanical device [1, 2].

The wavelet noise removal algorithm is to decompose the original signal of the mechanical equipment, use the high-pass filter and low-pass filter to perform frequency filtering on the original signal in turn, group the filtered signals, and conduct sampling at a ratio of 2:1, wavelet noise removal calculations were performed on the selected samples. When the wavelet noise removal calculation is performed, the selected sample signal is first subjected to wavelet frequency shift, so as to avoid the phenomena of mixed high and low frequency signal superposition when performing wavelet calculation [3].

The basic equation for frequency shift calculation is:

$$F\left[x(t)^{e0t}\right] = X(m - m_0) \tag{1}$$

Multiplying the signal $x(t)$ of the mechanical device with e^{0t}, the frequency of the signal can be decreased and the value $f_0 = \mathrm{m}_0 \div 2\pi$ is decreased. Set the frequency of the original signal taken by the sample to be f_y. The frequency of the signal includes the frequencies of different sizes. The frequency of the largest value is denoted by $f_{\max}.f_{\max} = f_y \div 2$ In the noise removal calculation of mechanical equipment, the signal is sampled at each point. When the signal of the Jth layer is calculated by wavelet, the frequency of the sample signal is decreased to $f_y^J = 2 - {}^J f_y$ and at the Jth layer, the maximum value of the signal frequency does not exceed the value of $f_y^J \div 2 = 2^{-J-1} f_y$, so when the high frequency signal is subjected to wavelet decomposition calculation, make sure that the wavelet shift value is $2^{-J-1} f_y$. That is, when high-frequency signal decomposition is performed on mechanical equipment signals, the frequency shift of the signal at layer J is $x_{2n+1}^J(t)$ times $e^{i\pi 2 - J, f} yt$, and $\mathrm{t} = e^{i\pi t} = (-1)^t$, Then design a wavelet algorithm [3] to remove mechanical equipment noise, namely:

$$x_{2n}^{J+1}(t) = 1/2 \sum_m h(m - 2t) x_n^J(m) \tag{2}$$

$$x_{2n+1}^{J+1}(t) = 1/2(-1)^t \sum_m g(m-2t) x_n^J(m) \tag{3}$$

$$x_{\mathrm{m}}^J(t) = \sum_m h(t-2m) x_{2n}^{J+1}(\mathrm{m}) + \sum_m (-1)^t g(t-2m) x_{2n+1}^{J+1}(m) \tag{4}$$

In the above equation, $x_{\mathrm{n}}^J(m)$ represents the signal of the Jth layer; $x_{2n+1}^{J+1}(t)$ represents the high frequency shift signal of the Jth layer; $x_{2n}^{J+1}(t)$ represents the low frequency-shifted signal of layer J; $x_{\mathrm{m}}^J(t)$ represents the fault signal of layer J of the mechanical device sample; h, g are independent variable parameters.

2.2 Identify Mechanical Failure Entropy

In order to improve the fault signal feature extraction accuracy of mechanical rolling bearing, this paper will design the minimum entropy algorithm to automatically identify the fault signal of mechanical equipment. The minimum entropy algorithm refers to highlighting the sharp pulse of the calculated data through the calculated deconvolution results when identifying a mechanical device failure. In the actual calculation process, the number of spikes will not be excessive, the minimum entropy deconvolution calculation is performed on the basis of the spike pulses, and iterative calculations are performed until the maximum kurtosis value appears. In the calculation process, the greater the calculated kurtosis value, the greater the proportion of impact components in the signal of the mechanical equipment. That is, this signal is the fault signal sent by the equipment; conversely, when the calculated kurtosis value is smaller, the proportion of the impact component in the signal of the mechanical equipment is smaller, that is, this signal is not a fault signal sent by the equipment [4–6].

When the mechanical rolling bearing fails, the fault signal of the mechanical device is set as s(n), and the calculation equation of s(n) is:

$$s(n) = h(n) \times x(n) + e(n) \tag{5}$$

In this equation, s(n) represents the fault vibration signal sent by the mechanical equipment; h(n) represents the calculated transfer function of the equation; x(n) represents the impact sequence of the mechanical rolling bearing; e(n) represents fault noise of mechanical equipment [7, 8].

In the actual calculation process, the value of x(n) will gradually decrease with the influence of the internal and external noise of the machine. When the value is the same as s(n), the fault signal characteristics of the mechanical equipment will disappear and the entropy value will gradually increase. A filter L(n) is set by the calculated deconvolution result, the value of s(n) is input into the equation, and the feature of x(n) is restored [9]. The equation is:

$$x(n) = L(n) \times s(n) = \sum L(n) s(n-1) \tag{6}$$

By integrating Eqs. (3) and (4), a minimum entropy algorithm for identifying mechanical faults can be obtained, namely:

$$s(n) = h(n) \times \sum L(n)s(n-1) + e(n) \tag{7}$$

2.3 Implement Fault Signal Feature Extraction

The design mechanical equipment fault noise removal algorithm and 1.2 design mechanical fault identification minimum entropy algorithm are integrated to obtain the mechanical roller bearing fault signal feature extraction algorithm, namely:

$$x_{2n}^{J+1}(t) = 1/2 \sum_{m} h(m-2t)x_n^J(m) \tag{8}$$

$$x_{2\mathrm{n}+1}^{J+1}(t) = 1/2(-1)^t \sum_{m} g(m-2t)x_n^J(m) \tag{9}$$

$$x_{\mathrm{m}}^J(t) = \sum_{m} h(t-2m)x_{2n}^{J+1}(\mathrm{m}) + \sum_{m} (-1)^t g(t-2m)x_{2n+1}^{J+1}(m) \tag{10}$$

$$s(n) = h(n) \times \sum L(n)s(n-1) + e(n) \tag{11}$$

The detailed fault data of the mechanical rolling bearing is brought into the fault signal feature extraction algorithm equation. First, Eqs. (8), (9) and (10) are used to separate the internal and external noise of the mechanical equipment and the sound information related to the equipment fault, the signal sent by the mechanical equipment is transformed by wavelet frequency shift to get the signal related to the fault signal characteristic calculation and the signal similar to the fault signal; then the calculated signal data is brought into Eq. (11), the minimum entropy calculation identifies the detailed signals of these signals that can reflect the characteristics of the mechanical rolling bearing fault signal, and uses the indicators of the time domain signal to calculate the fault signal frequency of the detail signal, according to the frequency of the fault signal, the characteristics of the fault signal are inferred, and then the fault signal characteristics of the mechanical rolling bearing are extracted.

3 Experimental Analysis

3.1 Experimental Data

The bearing rolling mill bearing fault data was used as experimental data. During the experiment, manual electric sparking was used inside the bearing of the SKF6502-5RS mechanical rolling bearing, a 0.012 inch diameter mechanical failure ring was created on the outside of the bearing and on the rolling elements. The motor was then used to perform data measurements and vibration signal frequency measurements on this faulty rolling bearing. The vibration signal acquisition frequency is 15000 Hz and the signal acquisition point frequency is 13000 Hz. The pre-calculated theoretical mechanical rolling bearing internal fault signal frequency is 750 Hz, the bearing external fault signal frequency is 872 Hz, and the bearing roller body fault signal frequency is 731 Hz.

3.2 Experimental Results and Analysis

After adopting the fault signal feature extraction algorithm and the traditional algorithm that are designed in this paper, the calculated results are plotted as a bending moment envelope. See Figs. 1, 2, and 3 for details.

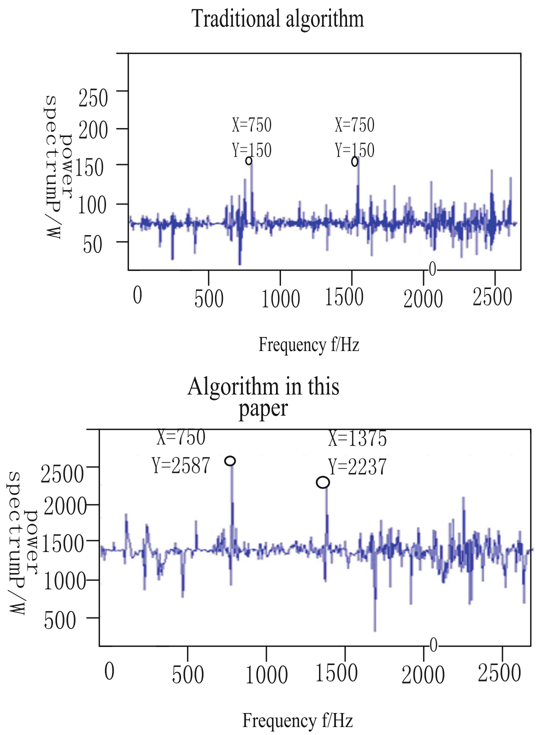

Fig. 1. Bearing internal fault envelope

As can be seen from Fig. 1, when calculating the characteristics of the bearing internal fault signal, the calculation results of the algorithm and the traditional algorithm designed in this paper are all the same as the frequency of the internal bearing fault signal of the theoretical bearing, which is 725 Hz. However, the power spectrum calculated by the algorithm at 725 Hz is obviously larger than that calculated by the traditional algorithm, and it is closer to the frequency of the theoretical internal fault frequency. The accuracy of the algorithm compared with the traditional algorithm is improved by about 4%.

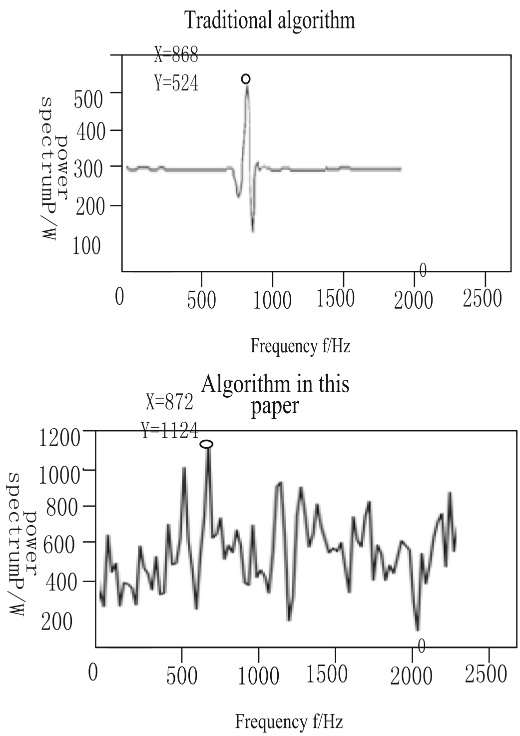

Fig. 2. External fault envelope of the bearing

It can be seen from Fig. 2 that when calculating the external fault signal characteristics of the bearing, the calculation results of the algorithm designed in this paper are the same as the frequency of the external fault signal of the theoretical bearing, both are 872 Hz, and the power spectrum is closer to the frequency of the theoretical external fault frequency. The accuracy of the calculation results of this algorithm is also improved by about 4% compared with the traditional algorithm.

As can be seen from Fig. 3, when calculating the characteristics of the bearing roller fault signal, the calculation results of the algorithm designed in this paper are more similar to the frequency values of the theoretical bearing roller body fault signal, compared with the calculation results of traditional algorithms. The calculation results of this algorithm are more accurate.

To sum up, when the fault signal characteristics of mechanical rolling bearing are accurately extracted, the algorithm designed in this paper is more accurate than the traditional algorithm, and the accuracy is improved by about 4%.

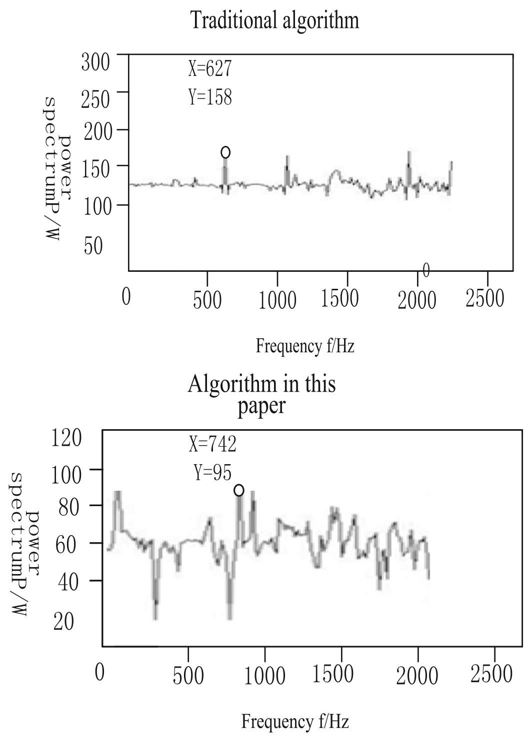

Fig. 3. Bearing roller fault envelope

4 Conclusion

This paper proposes a new fault signal feature extraction algorithm based on the wavelet frequency shift algorithm and the minimum entropy mechanical fault recognition algorithm, and improves the accuracy of the calculation results by removing noise and deconvolution calculations. The test data shows that the algorithm designed in this paper is about 4% more accurate than the traditional algorithm, and it has high effectiveness. It is hoped that the study in this paper can provide useful help for the accurate extraction of the fault signal characteristics of mechanical rolling bearings.

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