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An investigation of rolling bearing early diagnosis based on high-frequency characteristics and self-adaptive wavelet de-noising

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A B S T R A C T

Rolling bearings are necessary parts in rotary machines. However, the problem of early fault diagnosis for rolling bearings is difficult to solve due to its low signal-to-noise ratio and non-linear and non-stationary signal. Based on a detailed investigation of rolling bearing vibration signals, this paper proposes a method for determining whether a fault occurs by comparing the high-frequency band power. If a fault occurs, we first de-noise the vibration signals using wavelet de-noising and then extract the fault characteristics in both the time domain and the time-frequency domain to avoid the limitations of using only one domain. Finally, the fault location is identified using the grey correlation method. According to the method application results, the recognition accuracy using the method proposed in this paper is satisfactory, proving that the method has superior performance.

1. Introduction

As significant components in rotating machinery, rolling bearings play an important role in the safe operation of machines. According to statistics, approximately 30 per cent of mechanical failures in rotating machinery are due to the failure of rolling bearings. Therefore, in recent years, early fault diagnosis of bearings has become a popular research topic for rolling bearings [1]. Yin Shen et al. [2] gave a useful review of the data-driven approaches for fault detection and diagnosis field and many applications of data-driven approaches for fault detection such as fuzzy positivistic C-means clustering method; they also proposed an improved partial least squares method [3,4].

In the past several decades, vibration signal, acoustic radiation, temperature and other parameters have been used in diagnosing bearing damage, with the vibration signal being the most widely used [5]. The vibration signal of a damaged bearing is nonlinear and non-stationary, making processing and analysing the signal very difficult. Based on analysis and comparison among bearing vibration signals in different working states, the amplitudes of the high frequency bands of normal bearing signals are relatively stable; after being damaged, typical impact load vibration characteristics appear in the high frequency bands, that is, damage arouses structural responses in the high frequency bands of the vibration signals. Therefore, bearing damage can be determined via high frequency signal analysis.

In high-frequency signal bands, discrimination of signals among different working states is vague, and in the signal acquisition stage, the noise will inevitably be mixed, affecting the classification accuracy of rolling bearings. The wavelet de-noising technique is an effective method for removing noise from signals [6]. The number of decomposition levels must be determined for wavelet de-noising. The method most commonly used is to decompose the noisy signal by a pre-set decomposition level according to user experience. However, a fixed suitable number of decomposition levels is not always available for different signals and different signal-to-noise ratios. When the decomposition levels are excessive, useful signal information is lost, decreasing the signal-to-noise ratio and substantially increasing the computing time; when the decomposition levels are too small, the signal-to-noise ratio cannot be sufficiently improved. Huai-yu Tang et al. [7] proposed an adaptive wavelet to determine the decomposition levels algorithm based on the white noise test method. However, these methods assume that the wavelet high frequency coefficients of the signal are subject to a normal distribution, so that the *F* distribution could be used to test the probability. In this paper, we propose an improved self-adaptive selection method to select wavelet decomposition levels that could be appropriate for other types of bearing vibration signals.

The time domain and time-frequency domain methods are both used very extensively in the analysis and processing of fault

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feature data. After Norden E. Huang et al. proposed empirical mode decomposition (EMD) in 1998, the development and application of local mean decomposition (LMD), local characteristic scale decomposition (LCD) and intrinsic time scale decomposition (ITD) allowed new approaches for signal time-frequency analysis [8]. Ben Ali et al. [9] used artificial neural network (ANN) and EMD to detect bearing vibration signals. Zhang Xiaoyuan et al. [10] used ensemble empirical mode decomposition (EEMD) to extract the permutation entropy and used the support vector machine (SVM) to analyse the decision. Liu Hongmei et al. [11] used LCD to extract the characteristic energy operator and then extracted a multiracial detrended fluctuation for analysis; however, the number of samples selected in this paper was small. Intrinsic time scale decomposition, which is a new time-frequency analysis method, was introduced by Frei et al. [12] in 2007. ITD can decompose a signal into several proper rotation (PR) components and accurately extract instantaneous characteristics of signals; in addition, ITD has a high decomposition efficiency, so it can process large amounts of data in real time. Yang Yu et al. [13] studied bearing fault diagnosis by combining ITD and variable predictive model based class discrimination (VPMCD). Guo Zixu et al. [14] used the ITD method for online monitoring of time-varying vibration. Based on the study and comparison of the above methods, both non-dimensional time domain characteristics and time-frequency domain characteristics extracted by the ITD were used to diagnose faults in this paper.

To analyse characteristic data, the artificial neural network (ANN) [15], support vector machine (SVM) [16,17] and VPMCD [18] are all commonly used. Although these methods have enabled many achievements in the fault diagnosis field [19–21], some limitations are still difficult to avoid: 1) the ANN is restricted by excessive fitting and long computation time; 2) SVM requires an excessive number of samples, as this method cannot easily select the best parameters for a large number of optional parameters [22]; and 3) the model selection of the VPMCD is complicated [23]. Because the rolling bearing fault signal is difficult to obtain, the nonlinear and non-stationary characteristics require identification and calculation of signal data in small samples and a complex environment. Grey relational analysis is an important part of grey system theory, which was proposed by Chinese scholar Deng Julong. Grey system theory is particularly useful for analysing incomplete, inaccurate information and uncertain systems, making it appropriate for analysing rolling bearing fault signals [24]. The subjects investigated by grey system theory are the “small samples”, which are “partial information known and partial information unknown” and uncertain systems with “poor information”. Compared to ANN and SVM, grey relational analysis can be computed more quickly and select the parameters more easily. In the pattern recognition field, grey relational analysis has been widely used. Sarıkaya et al. [25] used Taguchi-based grey relational analysis to analyse multi-response optimisation of the minimum quantity lubrication parameters; Gang Xu et al. [26] comprehensively evaluated coal-fired power plants using grey relational analysis as the data processing method. Because the problem of bearing fault diagnosis is quite similar to pattern recognition, we used grey relational analysis to process the data in this paper.

Focusing on the problem of damage identification for rolling bearings, this paper compared the high-frequency bands to identify the bearing failure first, followed by identifying the specific faulty parts. The improved adaptive wavelet de-noising method was used to de-noise the signal. We extracted both non-dimensional time domain characteristics and time-frequency domain characteristics to identify the bearing fault location using grey relational analysis. Finally, we verified the validity of the proposed method through a case study. The results of the application showed that we could distinguish between normal bearings and faulty ones using high-frequency characteristic analysis and that the early fault diagnosis method based on the time domain and time-frequency domain analysis combined with grey correlation analysis in this paper is feasible and effective.

2. Bearing fault diagnosis based on the power of the high-frequency bands

When we apply an impact load on machinery or equipment, triggering the high-frequency vibration response in the mechanical or equipment structure is very easy. The high-frequency vibration response of the structure is caused by a periodic impact load when a bearing is damaged. In the normal working state, the high-frequency region amplitude is relatively stable. When the high-frequency vibration signal power appears to increase abnormally, we can determine that the impact load is appearing, indicating that damage has occurred. Therefore, we can identify whether the bearing failure occurred by comparing the power of the high-frequency bands in the bearing vibration signal.

The power spectral density function reflects the distribution of signal energy in different frequency bands. The energy value in the selected frequency band can be obtained by integrating the spectral density function in the power spectrum. After the power spectral density function is obtained, the energy value in the ith frequency band can be calculated using Eq. (1).

$$F_i = \int_{f_{i1}}^{f_{i2}} S(f)df \ (i = 1, 2, \ldots, m) \tag{1}$$

where f is frequency, f_{i1} and f_{i2} are boundaries of each frequency band and $S(f)$ is the power spectral density function.

To analyse the signal characteristics in different acquisition times, the power can be transformed into the mean power in the frequency band using Eq. (2).

$$P_i = \frac{F_i}{t} \tag{2}$$

where t is the signal acquisition time.

The power P_i reflects the energy contained within the ith frequency band. In the high-frequency band, the signal amplitude aroused by bearing damage is higher, and the differences between the normal state and fault state are obvious. By comparing the vibration signal power in the high-frequency bands, the existence of bearing damage can be distinguished.

3. Improved self-adaptive optimal wavelet decomposition level method

In the signal acquisition stage, the signal is inevitably mixed with noise, which affects the classification accuracy of bearing fault identification. Wavelet threshold de-noising is an effective method for removing the noise from the test signal; the number of wavelet decomposition levels is one of the key problems in determining the performance of a wavelet threshold de-noising algorithm. The decomposition level is generally selected according to the signal characteristics and experience; however, the decomposition level can only be a fixed value, and ensuring that the algorithm achieves the best noise reduction effect can be difficult based on subjective experience. Therefore, selecting the number of wavelet decomposition levels is very important. To solve this problem, Huai-yu Tang et al. [7] proposed an adaptive wavelet algorithm to determine decomposition levels based on the white noise test method; however, these methods assumed that the wavelet high frequency coefficients of the signal are subject to a normal distribution, so that the F distribution could be used to test