Chapter 40
Multi-Scale Fault Frequency Extraction Method Based on EEMD for Slewing Bearing Fault Diagnosis

Jie Yang, Jie Chen, Rongjing Hong and Hua Wang

Abstract In view of the large low-speed slewing bearing, the vibration signals are always very weak and overwhelmed by other strong noise, which makes fault feature extraction from the signals very difficult. In order to solve this problem, a denoising method based on multi-scale principal component analysis (MSPCA) and the ensemble empirical mode decomposition (EEMD) is proposed with a new intrinsic mode functions (IMFs) selection strategy. After that, the vibration signal is reconstructed by the selected IMFs. Finally, a method of multi-scale fault frequency extraction of slewing bearing based on EEMD is applied to denoise the vibration signals. The application of this method is demonstrated with laboratory accelerated slewing bearing life test data. Results show that EEMD-MSPCA is more effective in multi-scale fault frequency extraction of low-speed slewing bearing.

Keywords Slewing bearing · Ensemble empirical mode decomposition (EEMD) · Principal component analysis (PCA) · Denoising · Fault diagnosis

40.1 Introduction

Slewing bearing is widely used in wind turbines, engineering machineries, coal mine machineries, marine platform, military equipment, and other large rotating machinery. As the key component of large rotating machinery. when it has failure, it will cause great economic loss and sometimes may endanger the security of the operator. Therefore, strengthen slewing bearing diagnostic technique of research work has significant to prevent potential failures of the slewing bearing.

In recent years, some scholars have done some research on the fault diagnosis of slewing bearing. Liu et al. [1] put forward a brief review about the fault diagnosis of slewing bearing based on vibration signal, temperature signal, friction torque signal, acoustic emission, and stress wave. Wahyu et al. [2] used the adaptive multi-scale decomposition characteristics of the ensemble empirical mode decomposition

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(EEMD) for analyzing the vibration signals collected from lab slewing bearing subject to an accelerated life test and the real-case data from a sheet metal company. Matej et al. [3] presented a new method in terms of fault diagnosis of slewing bearing based on EEMD and principal component analysis (PCA), and its validity is shown by a simulation fault slewing bearing experiment. After that, Matej et al. [4] considered the nonlinear characteristics of slewing bearing vibration and then improved the combined method of a previous publication in PCA parts with kernel PCA. Recently, Wahyu [5] presented a novel application of circular domain features such as circular mean, circular variance, circular kurtosis, and circular skewness calculation-based condition monitoring method for low-speed slewing bearing.

Through the research on the slewing bearing fault diagnosis above, some problems have been found, that is most of slewing bearing failure was artificially simulated and the effectiveness of the presented method was proved by simulation experiments; therefore, we performed a slewing bearing accelerated life test to obtain vibration signal of slewing bearing from its normal condition to fault and then to final failure. This study is concerned with finding a reliable method for low-speed slewing bearing nature defects fault diagnosis.

40.2 Basic Theory of PCA and EEMD

PCA is a feature extraction method which transforms a high-dimensional into a lower-dimensional subspace which contains most of the original data information. This prepares the ground for multi-scale principal component analysis (MSPCA) denoising which is explained in Sect. 3. For example, one matrix X can be decomposed into a score matrix T and a loading matrix P using PCA, its calculating formula is as follows:

$$X = TP^T + E = \sum_{m=1}^{k} t_j p_j^T + E \quad (k < m),$$ (40.1)

where $T_{n \times k} = [t_1, t_2, \ldots, t_k]$, $P_{m \times k} = [p_1, p_2, \ldots, p_k]$, E is the residual matrix and k is the number of selected principal components.

When a PCA model is built and a new data sample x is to be tested for fault detection, its calculating formula is as follows:

$$x = \hat{x} + \bar{x} = PP^T x + (I - PP^T) x,$$ (40.2)

where $\hat{x} = PP^T x$ is the projection on the principal component subspace, and $\bar{x} = (I - PP^T) x$ is the projection on the residual subspace.

In this chapter, we use Squared prediction error (SPE) statistic to detect the fault sample. For a new scale measurement sample $X \in R^{n \times m}$, the SPE statistic is respectively computed as follows:

$$SPE = \left\| \bar{x} \right\|^2 = \left\| (I - PP^T) x \right\|^2.$$ (40.3)

For the fault detection purpose, we can compare the value of the SPE statistic with the corresponding threshold limit SPE_{lim}. The fault detection logic is if $SPE \leq SPE_{lim}$ it is fault-free, otherwise faulty [6, 7].

In the fault diagnosis of machinery, the method of empirical mode decomposition (EMD) has developed more extensive researches and applications in recent years [8, 9]. For the limitation of this thesis, the algorithm of EMD is not specifically discussed; however, the nonlinear components in nonstationary signals may result in a mode-mixing effect using the EMD method. Therefore, the EEMD algorithm was developed from the original EMD method by Wu and Huang [9], which added white noise into EMD procedures to restrain the mode-mixing effect. The EEMD decomposition algorithm can be shortly given as follows. First, initialize the number of ensemble M and the amplitude of the added white noise β. After that, follow the steps given below:

a. Add a white noise series with magnitude β to the original signal $x(t)$ to generate a new signal $y_m(t)$.

$$y_m(t) = x(t) + \beta n_m(t), \tag{40.4}$$

where ym(t) represents the noise-added signal of the mth trial, and nm(t) indicates the mth added white noise series.

b. Decompose the signal $y_m(t)$ into k intrinsic mode functions (IMFs) $C_{i,m}$ ($i = 1, 2, …, k$) using the EMD method. $C_{i,m}$ represents the ith IMF of the mth decomposition, and k is the number of IMFs.
c. If $m < M$, then go to step (a) with $m = m + 1$. Repeat steps (a) and (b) M times with a different white noise series each time to obtain an ensemble of IMFs.
d. Calculate the overall ensemble mean of the corresponding IMFs of the decomposition as the final result:

$$C_i(t) = \frac{1}{M} \sum_{m=1}^{M} c_{i,m}(t) \quad (i = 1, 2, …, k, m = 1, 2, … M). \tag{40.5}$$

40.3 Multi-Scale Denoising Method Based on EEMD and PCA

The proposed multi-scale denoising method has been improved by the wavelet multi-scale decomposition algorithm [6]. The EEMD technique was used instead of wavelet analysis (WT) because the wavelet transform is a nonadaptive decomposition algorithm, which has the shortcoming that its analysis results depend on the choice of the wavelet base function. However, the full data-driven EEMD does not suffer from this limitation due to its adaptive empirical nature. Figure 40.1 shows the multi-scale denoising and fault frequency extraction mode.
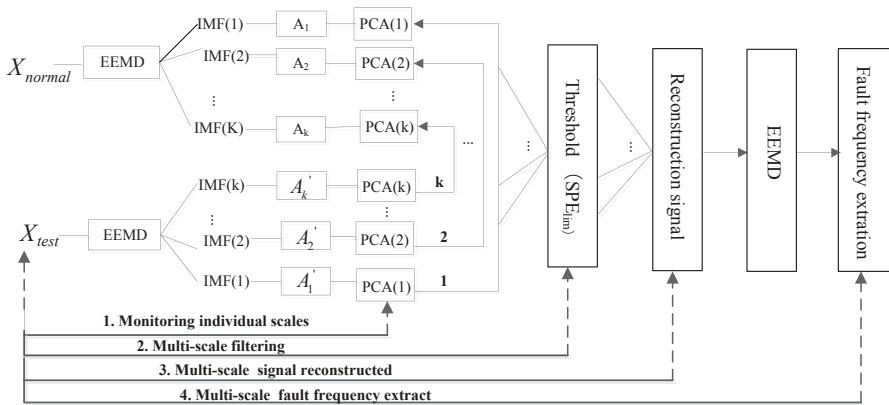
Fig. 40.1 EEMD multi-scale fault frequency extraction mode

The proposed method of multi-scale denoising technique requires two steps. In the first step, the normal vibration signal is decomposed by EEMD into k different timescale IMFs, then a normal MSPCA mode is constructed by these single IMFs, and the normal statistical limits SPElim of each timescale PCA model are calculated. In the second step, the newly measured vibration signal is also decomposed into k IMFs using the EEMD method; then the newly decomposed IMFs component is projected onto the corresponding normal PCA models constructed in the first step. Lastly, according to the statistical limits SPElim it is determined whether each timescale mode follows normal operation or not, and the certain timescale (IMFs) which has the failure existed to reconstruct the signal is selected.

40.4 Analysis of Real-Case Slewing Bearing Vibration Signal

In order to further verify the efficiency and performance of the proposed method for the real-case slewing bearing vibration signal denoising and fault diagnosis, the proposed method was applied to the slewing bearing accelerated life experimental data and the results, analysis, and description are presented below.

40.4.1 Slewing Bearing Experiment Bench

The experiment bench is an independent design and developed by our team to simulate the actual operation conditions of large-size bearing which can be used in a variety of applications experiment. Figure 40.2 shows the slewing bearing test bench which can bear axial load, radial load, and overturning torque. In this experiment, the test bench operated in one direction of rotation at a speed of 4 rpm. In
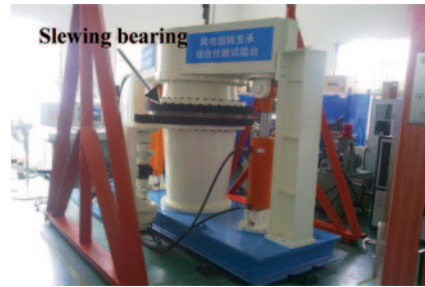
Fig. 40.2 Slewing bearing test bench

Table 40.1 Slewing bearing fault frequencies

Defect mode	Fault frequencies/Hz
Outer ring (BPFO)	3.18
Inner ring (BPFI)	3.28
Rolling element (BSF)	2.21
Cage train	0.49

this slewing bearing accelerated life test, four accelerometer sensors were placed on the slewing bearing at 90° to each other. The slewing bearing fault frequencies are shown in Table 40.1.

40.4.2   Analysis of Experimental Data

In order to ensure the extracted vibration data, which provides sufficient fault information, we must extract enough vibration data to analyze it. Referring to the fault frequencies presented in Table 40.1, the lowest frequency was 0.49 Hz. After simple calculation, 0.49 Hz is 2 s, we should extract at least 2-s-vibration data that can ensure to represent all fault frequencies; therefore, in this chapter, we extract 3-s-vibration data which are enough to represent all fault information and reduce the EEMD algorithm computation time.

The slewing bearing accelerated life test began on May 16, 2013. In order to accelerate the slewing bearing defect, the slewing bearing was continuously running with full load. After continuous operation of slewing bearing for 12 days (up to May 28), we were aware that failure could occur in slewing bearing on the basis that vibration and noise increase. Therefore, according to the EEMD multi-scale failure frequency extracted mode, two vibration data groups were analyzed: the vibration signal at midnight on May 16 as the normal sample (Fig. 40.3) and the vibration signal at midnight on May 28 as the fault sample (Fig. 40.4). Nevertheless, when we used the EEMD multi-scale fault frequency extraction mode, two parameters should be determined in EEMD method in order to obtain an optimum decompo-
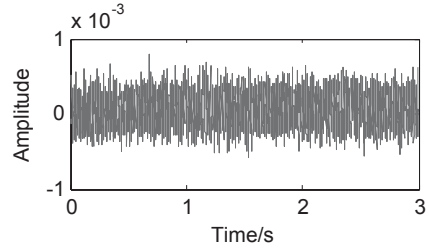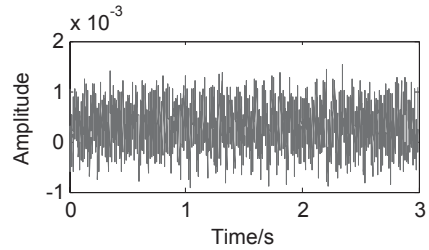
Fig. 40.3 Vibration
signal on May 16

Fig. 40.4 Vibration
signal on May 28

sition result. In this chapter, the white noise magnitude β of 0.02 is used and en-
semble number E of 100 is selected. The vibration signal on May 28 after filtering
is shown in Fig. 40.5 on the basis of the steps described in Sect. 3.1. Then, the fault
frequencies of the filtering signal were extracted by EEMD as shown in Table 40.2.
According to the results in Table 40.2, the frequencies 2.33 Hz and 3 Hz are close
to the corresponding characteristic defect frequency of the rolling element and outer
ring (BPFO) in Table 40.1, so we infer that the fault occurs in the rolling element
and the outer ring. Finally, slewing bearing was removed to inspect each compo-
nent, and it was found that some rolling elements have been damaged, and there
appeared a little bit of corrosion in the outer ring. The damaged rolling element and
outer ring were shown in Figs. 40.8 and 40.9. Therefore, the fault diagnosis method
proposed in this chapter was applied to the slewing bearing accelerated life experi-
ment, and the results verify its validity and feasibility (Figs. 40.6 and 40.7).

40.5   Conclusion

Based on EEMD and principal component analysis, this chapter proposes a method
in combination of the multi-scale denoising and the multi-scale fault frequency ex-
traction of slewing bearing fault diagnosis. In the presented method, the method of
multi-scale denoising with EEMD is performed to preprocess slewing bearing vi-
bration signals. Through the slewing bearing accelerated life experiment, vibration
signal analysis results demonstrate that the proposed method can reliably recognize
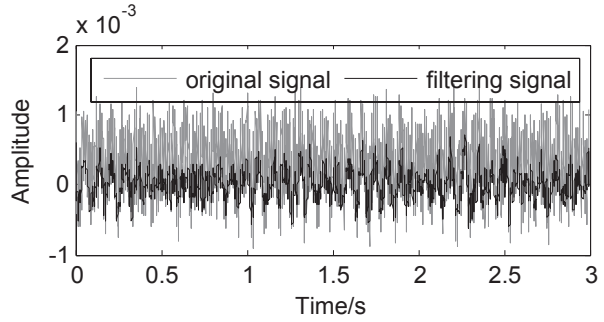the faults.

Fig. 40.5 Result of multi-scale denoising

Table 40.2 EEMD multi-scale fault frequency extraction results (May 28)

IMF	Frequency/Hz	IMF	Frequency/Hz
1	759.7	7	5.333
2	240.7	8	3
3	145.3	9	2.333
4	68	10	1.667
5	26.67	11	0.667
6	14	12	0.333

IMF intrinsic mode function

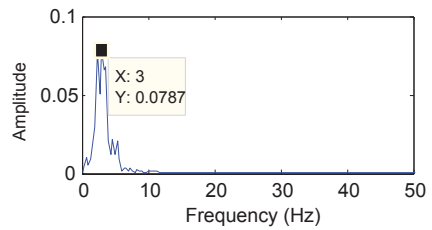**Fig. 40.6** Outer ring fault frequency

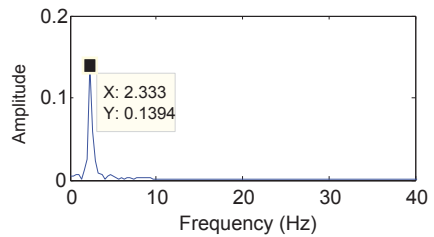**Fig. 40.7** Rolling element fault frequency

Fig. 40.8 Outer race failure

Fig. 40.9 Rolling element failure

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