Journal of Sound and Vibration 333 (2014) 3321–3331

Contents lists available at ScienceDirect

Journal of Sound and Vibration

journal homepage: www.elsevier.com/locate/jsvi

Fault identification of rotor-bearing system based on ensemble empirical mode decomposition and self-zero space projection analysis

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ARTICLE INFO

Article history:
Received 26 May 2013
Received in revised form
6 March 2014
Accepted 10 March 2014
Handling Editor: L.G. Tham
Available online 29 March 2014

ABSTRACT

Accurately identifying faults in rotor-bearing systems by analyzing vibration signals, which are nonlinear and nonstationary, is challenging. To address this issue, a new approach based on ensemble empirical mode decomposition (EEMD) and self-zero space projection analysis is proposed in this paper. This method seeks to identify faults appearing in a rotor-bearing system using simple algebraic calculations and projection analyses. First, EEMD is applied to decompose the collected vibration signals into a set of intrinsic mode functions (IMFs) for features. Second, these extracted features under various mechanical health conditions are used to design a self-zero space matrix according to space projection analysis. Finally, the so-called projection indicators are calculated to identify the rotor-bearing system's faults with simple decision logic. Experiments are implemented to test the reliability and effectiveness of the proposed approach. The results show that this approach can accurately identify faults in rotor-bearing systems.

1. Introduction

Rotor-bearing systems are important components of rotating machinery. Faults either in rotors or in bearings may cause deterioration of the equipment performance and may even lead to fatal machine breakdown, personal casualties and economic loss [1,2]. Thus, accurate and reliable identification of the rotor-bearing system's faults is needed. Vibration analysis based health assessment technologies of machine equipment have been extensively researched during the past few decades because vibration signals usually carry abundant information regarding mechanical health conditions [3,4].

To date, the signal processing tools that have been applied to diagnose mechanical faults can be categorized into three types: time domain analysis, frequency domain analysis and time–frequency domain analysis. Time domain analysis is the simplest; it diagnoses faults mainly by analyzing statistical indicators, such as kurtosis, crest factor and root mean square, directly extracted from the time series of the vibration signals [5,6]. Frequency domain methods usually diagnose mechanical faults by observing the fault characteristic frequencies hidden in the vibration signals. Liu et al. [7] combined fast Fourier transform (FFT) with an amplitude recovery method to diagnose induction motor faults. Although FFT is the simplest frequency domain analysis method, its frequency resolution is low when there is a small number of sampling points. To diagnose the faults in rotating machinery, Shi et al. [8] introduced a general interpolated FFT that is highly accurate for small data sets. Interpolated discrete Fourier transform (IpDFT), which can identify multiple characteristic

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http://dx.doi.org/10.1016/j.jsv.2014.03.014
0022-460X/

components with high accuracy and resolution, was applied to diagnose bearing faults in [9]. However, Fourier transform assumes that the obtained signals are stationary and linear, and they may be unsuitable for processing nonstationary and transient signals [10]. In addition, time domain analysis and frequency domain analysis can extract only part of the useful information from vibration signals because they lose information in each of the other domains. Therefore, time–frequency analysis technologies have been introduced for fault diagnosis. In [11], the spectral kurtosis based on short-time Fourier transform (STFT) was investigated to diagnosis the faults of rotating machinery. Although STFT can analyze signals both in the time and frequency domains, its time and frequency resolutions are fixed because of the fixed-width windowing function [12]. The Wigner–Ville distribution (WVD) can analyze the nonstationary signal in the time–frequency domain and has been applied to diagnose mechanical faults [13], but its time–frequency components include interference terms. In [14], the discrete wavelet transform (DWT), using Daubichies-5 wavelet with five levels, was used to process the collected acoustic signals to diagnose gearbox faults at an identification efficiency of 90 percent. In [15], the continuous wavelet transform (CWT) with an appropriate base wavelet selected by the energy to Shannon entropy ratio was introduced to extract statistical features from the vibration signals for bearing fault diagnosis, in which classification accuracy was improved with autocorrelation. Li et al. [16] proposed a fault diagnosis method based on wavelet packet transform (WPT) and relevance vector machine (RVM), in which the Fisher criterion was used to find the optimal decomposition level and select the global optimal features. However, these wavelet-based methods cannot self-adaptively decompose a signal in the time–frequency domain, and their shortcomings have been analyzed in [17,18].

Empirical mode decomposition (EMD), a self-adaptive time–frequency analysis method, can reveal the overlap in both the time and frequency components, but other standard filtering techniques or traditional Fourier methods cannot [18,19]. Cheng et al. [20] used EMD to extract amplitude-modulated information from the vibration signals of rotor systems for local rub-impact fault diagnosis. In [21], EMD was combined with statistical characteristic calculations and a distance evaluation technique to extract features from nonstationary signals for high-accuracy gear fault diagnosis. Yang et al. [22] suggested a novel fault diagnosis method for bearings using EMD to obtain energy entropy from nonstationary vibration signals. However, the mode-mixing problem occurs when EMD is used to analyze the signals. To solve this issue, EEMD was proposed by Wu and Huang [23]. Guo et al. [24] proposed an EEMD-based signal compression method for bearing fault diagnosis and demonstrated that the approach provided a higher compression ratio and was highly efficient. Zhang et al. [25] used EEMD to decompose bearing vibration signals, and the effective features were successfully extracted from the obtained IMFs using an autoregressive model and kernel principal component analysis for bearing fault diagnosis. In [26], EEMD was applied to analyze nonlinear and nonstationary ambient data to accurately identify structural modes. These applications have demonstrated the effectiveness of EEMD in complex signal processing.

Other technologies should be introduced to construct an intelligent and automatic fault identification system, which cannot be done by only signal processing tools. Therefore, artificial neural networks [14], support vector machine (SVM) [27], RVM [16], fuzzy inference [28], clustering analysis [29] and Bayesian networks [30] have been combined with signal processing methods for fault identification. However, most of these methods need to design a complicated model, which includes selecting the appropriate parameters or costing time for training the model, before they can diagnose faults. In [31], the so-called zero-space vectors were utilized to obtain residual signals for fault severity assessment according to space projection analysis and algebraic calculations. Li et al. [32] proposed a sensitive feature decoupling technology for bearing fault diagnosis using a simple algebraic computation and decision logic. Although both methods can assess faults without any computational load to train the model, a drawback is that the number of features must be larger than that of the processing health conditions.

Here, a new approach based on EEMD and a self-zero space projection model (SSPM) is proposed to identify faults in a rotor-bearing system, as shown in Fig. 1. Vibration signals emitted by the faulty parts of a rotor-bearing system are nonlinear and nonstationary, and traditional signal processing tools may be unsuitable to process them. Hence, EEMD is first applied to decompose the vibration signals collected from the rotor-bearing system under different health conditions into a set of IMFs to obtain statistical features. Then, to identify faults, the SSPM is designed using these obtained features to calculate the so-called projection indicators and condition identification indicators with some simple decision rules. Compared to the method employed in [32], the proposed method can effectively identify the health conditions of a rotor-bearing system without selecting any sensitive features. Moreover, the number of features for designing the SSPM is not required to be larger than that of the processing health conditions. Experiments are developed on a simulator to test the reliability and effectiveness of the proposed approach, and the results show that EEMD–SSPM can identify the faults of rotor-bearing systems with very high accuracy.

The remainder of this paper is structured as follows. The fundamental of EEMD is introduced in Section 2. Section 3 mainly describes the proposed SSPM, including the design of the self-zero space vectors, definition of the projection indicators, computation of the condition identification indicators and thresholds. In Section 4, the experimental setup, results and discussion of the experiments are collated. Finally, the conclusions of this study are discussed in Section 5.

2. Ensemble empirical mode decomposition

2.1. EMD

EMD is a time–frequency signal processing method that can self-adaptively decompose a complicated signal into a set of IMFs, which are nearly orthogonal functions. In addition, each IMF represents a simple oscillation mode with a physical meaning. The EEMD algorithm of signal $x(t)$ is described as follows [18,33]: