Mechanical Systems and Signal Processing ■ (■■■■) ■■■–■■■

Contents lists available at ScienceDirect

Mechanical Systems and Signal Processing

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

Multivariate empirical mode decomposition and its application to fault diagnosis of rolling bearing

Yong Lv [a], Rui Yuan [a,*], Gangbing Song [b]

[a] School of Mechanical Engineering, Wuhan University of Science and Technology, Wuhan 430081, China
[b] Smart Material and Structure Laboratory, Department of Mechanical Engineering, University of Houston, Houston, TX 77204, USA

ARTICLE INFO

Article history:
Received 1 April 2015
Received in revised form
22 February 2016
Accepted 17 March 2016

Keywords:
Multivariate EMD
Multiple sensors
Fault correlation factor
Rolling bearing

ABSTRACT

Rolling bearings are widely used in rotary machinery systems. The measured vibration signal of any part linked to rolling bearings contains fault information when failure occurs, differing only by energy levels. Bearing failure will cause the vibration of other components, and therefore the collected bearing vibration signals are mixed with vibration signal of other parts and noise. Using multiple sensors to collect signals at different locations on the machine to obtain multivariate signal can avoid the loss of local information. Subsequently using the multivariate empirical mode decomposition (multivariate EMD) to simultaneously analyze the multivariate signal is beneficial to extract fault information, especially for weak fault characteristics during the period of early failure. This paper proposes a novel method for fault feature extraction of rolling bearing based on multivariate EMD. The nonlocal means (NL-means) denoising method is used to preprocess the multivariate signal and the correlation analysis is employed to calculate fault correlation factors to select effective intrinsic mode functions (IMFs). Finally characteristic frequencies are extracted from the selected IMFs by spectrum analysis. The numerical simulations and applications to bearing monitoring verify the effectiveness of the proposed method and indicate that this novel method is promising in the field of signal decomposition and fault diagnosis.

1. Introduction

Rolling bearings are widely used in mechanical drive systems in manufacturing. The failure of a rolling bearing may lead to the failure of the mechanical system, thus resulting in the loss of production, even personal injury or death. Therefore it is of vital importance to monitor rolling bearings to detect early damage in manufacturing systems. As a load bearing component, a rolling bearing usually works with the input mechanism and loading devices, and its corresponding vibrations are always mixed with the vibratory responses of other components within the entire machine [1]. At the beginning phase of bearing failure, the vibration signal of the bearings is usually accompanied by various types of noise. At this phase, using multiple sensors [2] to collect the vibratory signal of the bearing and obtain the common frequency components through analysis is very beneficial to obtain accurate fault characteristic frequencies.

The analysis of vibration signal is vital for monitoring the operating condition of rolling bearings, and the accurate extraction of fault characteristic frequencies from vibration signal is particularly important [3]. In the process of monitoring

* Corresponding author.
E-mail address: 201403703005.@wust.edu.cn (R. Yuan).

http://dx.doi.org/10.1016/j.ymssp.2016.03.010
0888-3270/

Please cite this article as: Y. Lv, et al., Multivariate empirical mode decomposition and its application to fault diagnosis of rolling bearing, Mech. Syst. Signal Process. (2016), http://dx.doi.org/10.1016/j.ymssp.2016.03.010

rotating machinery, using signal processing methods to analyze and extract fault characteristic frequencies is becoming a common technique. Several signal processing methods, such as wavelet transform (WT) [4], independent component analysis (ICA) [5], and empirical mode decomposition (EMD) [6], are widely used in this field. In the wavelet transform, different wavelet basis functions need to be chosen to determine wavelet coefficients, thus allowing reconstruction of the signal [4]. While EMD is a kind of adaptive nonlinear and nonstationary data analysis method, compared to WT, there is no basis functions requirement in the extraction of complex mechanical vibration signal characteristic frequencies [7]. The EMD method decomposes the nonlinear and nonstationary signal into an approximating stationary time series representing the time scale of the signal, namely intrinsic mode function (IMF) [8], to describe the frequency components of the signal. The IMF is a kind of complete, adaptive, and basically orthogonal expression which is determined by the original signal rather than the preset basis functions. In the field of signal processing, EMD is widely used in the nonlinear and nonstationary signal processing [9], however most studies are primarily aimed at univariate signal. When dealing with multivariate signal [10] collected from multiple sensors, which are placed in different locations on the machine, EMD can only process multivariate signal individually in extracting fault frequency components from individual IMF groups of different lengths, thus causing the uncertainty problem of scale arrangement between different IMF groups. For example, the order and frequency components of one IMF group do not correspond to the same order and frequency components of other IMF groups [11]. The problem mentioned above leads to difficulty in the subsequent process of determining the effective IMFs [12], and the resulting multiple IMF groups cannot show the correlation information among relevant sensors. Therefore the existing EMD method has its limitations when using EMD method to process multivariate signal.

In 2007, Rilling et al. [13] proposed a bivariate EMD. In the bivariate EMD, the projection of bivariate signal in a number of directions is used to calculate the local mean of the bivariate signal. The direction vectors are unevenly distributed on a complex plane after the projection. Performing an interpolation on the maximum value of the projection, by using a complex spline function, gives the envelope curve. The local mean approximation can be acquired through calculating the mean values [14]. In 2010, Rehman and Mandic [15] improved the EMD algorithm to a trivariate EMD, which regards trivariate signal as a pure quaternion (hypercomplex number), with each component being a real numerical time series. Performing the interpolation on the maximum value of projection, by using a specific spline function after obtaining the signal projection in a number of directions in three-dimensional space, gives three dimensional pure quaternion envelope curves [16]. The application of spline interpolation conducting on specific components of pure quaternion represents the expansion of rich spline function. Finally, the average of quaternion envelop curves can be calculated to obtain the local mean of trivariate signal. In the following studies, Rehman [11] extended EMD to multivariate EMD by introducing the theory of multivariate EMD. It allows simultaneous processing of multivariate signal which are composed of signal collected by multiple sensors from different locations on the machine. The improvement has all the advantages of existing EMD in processing nonlinear and nonstationary signal and additionally can successfully solve the uncertainty of IMFs arrangement, which contain characteristic frequency components. Through multivariate EMD decomposition of multivariate signal, the same characteristic frequencies appear in the same order in different IMF groups, which facilitates the determination of the orders of effective IMFs so as to extract the characteristic frequencies [17]. In a few cases, when one of the sensors does not work or a set of collected data goes wrong, the multivariate EMD can decompose the multivariate signal to multiple IMF groups, and comparison of IMF groups can contribute to extraction of the fault characteristic frequencies. The relationships among different sensors [18] can be reflected from the same frequency components found among different IMF groups. In summary, the multivariate EMD is of great significance in the field of multivariate signal processing.

This paper proposes a novel approach to fault feature extraction of rolling bearings based on the multivariate EMD, using NL-Means denoising method to preprocess the multivariate signal. In addition, the approach utilizes correlation analysis to compute fault correlation factor (FCF) so as to select effective IMFs, and then extract characteristic frequencies by spectrum analysis. The organization of this paper is as follows: Section 2 introduces the basic principles and characteristics of multivariate EMD. Section 3 describes the theory of fault feature extraction based on multivariate EMD using the NL-Means denoising method. Section 4 presents the numerical simulations, including the mixing of three original signal, which contain frequency modulated signal, by using a random matrix, and adding noise to simulate the multivariate signal collected by three sensors placed in different locations on the machine; conducting simulation analysis on the signal and finally extracting the characteristic frequencies. Section 5 presents the applications to bearing monitoring with practical experimental signal collected by multiple sensors to verify the validity of the proposed approach described in this paper. The conclusions of the studies and necessary discussions are given in Section 6.

2. The theory of multivariate empirical mode decomposition

2.1. Multivariate EMD

Standard EMD [6] uses an interpolation method to calculate the mean value of the upper and lower envelop curve of univariate signal so as to obtain the local mean value. However, the value of the local maximum and the minimum cannot be directly defined, and the IMF concept defined by the vibration mode is not clear. In order to address these issues, multivariate EMD was developed by Rehman et al. in 2013. This method regards n-variate signal ($n \geq 2$) as N-dimensional time series and chooses the appropriate direction vectors in N-dimensional space. The N-variate signal are respectively projected

Please cite this article as: Y. Lv, et al., Multivariate empirical mode decomposition and its application to fault diagnosis of rolling bearing, Mech. Syst. Signal Process. (2016), http://dx.doi.org/10.1016/j.ymssp.2016.03.010