ARTICLE IN PRESS

ISA Transactions ∎ (∎∎∎∎) ∎∎∎–∎∎∎

Contents lists available at ScienceDirect

ISA Transactions

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

A novel procedure for diagnosing multiple faults in rotating machinery

Zhijian Wang [a], Zhennan Han [a,*], Fengshou Gu [a,b], James Xi Gu [c], Shaohui Ning [d]

[a] College of Mechanical Engineering, Taiyuan University of Technology, Taiyuan, Shanxi 030024, PR China
[b] School of Computing and Engineering, University of Huddersfield, Huddersfield HD1 3DH, UK
[c] Signal Processing and Algorithms Group, School of Engineering, Manchester Metropolitan University, All Saints Building, All Saints, Manchester M15 6BH, UK
[d] College of Mechanical Engineering, Taiyuan University of Science and Technology, Taiyuan, Shanxi 030024, PR China

ARTICLE INFO

Article history:
Received 8 August 2013
Received in revised form
11 September 2014
Accepted 16 September 2014
This paper was recommended for publication by Rickey Dubay

Keywords:
CMF
EEMD
CAF
Fault diagnosis

ABSTRACT

In analyzing signals from a wind turbine gearbox this paper suggests a new signal processing procedure named as CMF-EEMD method which is formed by applying conventional EEMD to a new type of combined mode function (CMF). This CMF consists of a low frequency CMF, denoted as C_L, and a high frequency CMF, denoted as C_h. Then it optimizes the amplitude of the added noise in decomposing C_h and C_L using EEMD. Finally, it calculates cyclic autocorrelation function (CAF) for every characteristic IMF from EEMD. The proposed procedure is applied to analyze the multi-faults of a wind turbine gearbox and the results confirm better performances in resolving different signal components by the proposed method than that from the cyclic autocorrelation function (CAF) of a direct EEMD analysis.

1. Introduction

Rotating machinery, as one of the most common types of mechanical equipment, plays an important role in industrial applications [1–3]. Modern rotating machinery such as wind turbine gearboxes has multi-gearing and multi-bearing. The dynamic responses of these components are complex and interfering with each other. It is usually difficult to diagnose their potential faults. Especially when multiple faults coexist, vibrations excited by several faults are combined with each other nonlinearly and non-stationary. This makes the observed vibration signals rather complex, which makes it difficult to identify each fault in using traditional methods. Therefore, a great deal vibration analysis methods have been studied in recent years for diagnosing multiple faults.

Among different methods, empirical mode decomposition (EMD) is of particular interest because of its highly adaptive nature in analyzing vibrations. EMD decomposes a signal into a series of intrinsic mode functions (IMFs) according to the signal characteristics, allowing the non-stationary and nonlinearity information of the signal to be revealed for more accurate characterization of signals, for example, gear fault diagnosis [4–6] and rolling bearing fault diagnosis [7–9]. However, EMD often cannot extract fault features accurately because of the problem of mode mixing [10]. To alleviate mode mixing, Wu and Huang developed ensemble empirical mode decomposition (EEMD) to improve EMD [11]. By adding noise to the original signal and calculating the means of IMFs repeatedly, the EEMD method can avoid the mode mixing problem in all cases. As such EEMD is more accurate and effective for diagnosing the faults of rotating machinery than EMD [12,13]. Proper selection of the added noise amplitude is very important, which directly affects EEMD decomposition results [14–16].

The filtering features of EMD are published by Flandrin and Rilling [17]. EMD is an adaptive band-pass filter bank, and the bandwidth of the IMFs is determined by the features of the signal itself rather than any other factors. Rather than using the individual IMF, in this paper, a CMF approach is introduced so that it combines the neighboring IMFs which contain high frequency components and IMFs which contain low frequency components to constitute two new IMFs C_h and C_L. EEMD is a self-adaptive analysis method and can decompose a complicated signal into a series of IMFs according to the signal local characteristics [13]. However, if the frequency components in the signal are too complex, it will affect the decomposition results [15]. Consequently, CMF is used as the pre-filter of EEMD to increase the accuracy and effectiveness of EEMD decomposition results.

In recent years, cyclic statistics have been used as a tool to exploit cyclostationarity in diagnostic practices. Cyclic autocorrelation function (CAF) can be applied to separate out the modulators effectively, especially for the weak modulators due to fault effects that cannot be detected by other conventional technologies, such as frequency

* Corresponding author. Tel:+86 15135155879.
E-mail address: wangzhijian1013@163.com (Z. Han).

http://dx.doi.org/10.1016/j.isatra.2014.09.006
0019-0578/© 2014 ISA. Published by Elsevier Ltd. All rights reserved.

domain and envelope detection. For example, the application of the cyclic autocorrelation was successfully used for rolling bearing diagnosis [18], the cyclic frequency is found by spectral correlation graph to diagnose the machine fault [19]. However, when multiple fault frequencies and modulation sources coexist the analysis of cyclic autocorrelation causes problems with aliasing at high frequencies or low frequencies. To avoid this problem, the cyclic autocorrelation function may be applied to different IMFs containing different frequency bands, thus the aliasing phenomenon can be effectively avoided.

In this paper, combining the advantages of EEMD and cyclic autocorrelation function leads to the proposal of an improved EEMD with CMF for multi-fault diagnosis in rotating machinery. CMF is used as the pre-filter to refine the vibration signal, and the improved EEMD and cyclic autocorrelation function is used to extract the multi-fault characteristics. This paper is organized as follows. The outlines of EEMD, CMF and cyclic autocorrelation are presented in Section 2. The proposed method for rotating machinery multi-fault diagnosis is discussed in Section 3. The experimental and practical validations are presented in Section 4. Finally, conclusions are given in Section 5.

2. Fundamentals of CMF, EEMD and CAF

2.1. Introduction of CMF

EMD decomposes a signal into a series of intrinsic mode functions (IMFs) [20,21] which are denoted as $C_1, C_2 \ldots, C_i$ covering respectively different frequency bands ranged from high to low correspondingly. Rather than examining individual IMF, a number of IMFs can be explored simultaneously to characterize signals in a natively wider band. This then induces the concept of combined mode function. For an obvious case, CMF can be obtained by combining the neighboring IMFs to obtain two combined IMF sets: C_h and C_L to represent high frequency components and low frequency components respectively. Obviously, CMF provides an adaptive filter band as they are just linear combinations of the IMFs which are obtained by adapting the signal contents. By combining the neighboring IMFs which contain high frequencies, we obtain the C_h as follow:

$$C_h = C_1 + C_2 + \ldots + C_m \tag{1}$$

where m is the maximal number of IMF containing high frequency components in EMD. By combining the neighboring IMFs which contain low frequency components, we obtain the CMF C_L as follow:

$$C_L = C_{1+m} + C_{2+m} + \ldots + C_i \tag{2}$$

where $m < i \le n$, n is the maximal number of IMF in EMD, i represents the maximum number associated with the original signal.

The selection of m depends on the signal content of underlying problem. For example, to separate two modulation processes, this paper selects the first two IMFs as the high frequency components to cover frequency contents of the carriers of the modulation between bearing elements and its supporting shaft, and the remaining IMFs as the low frequency components which are the shaft frequency or sidebands of the modulation signals. The flow chart in Fig. 1, details the selection process for CMFs.

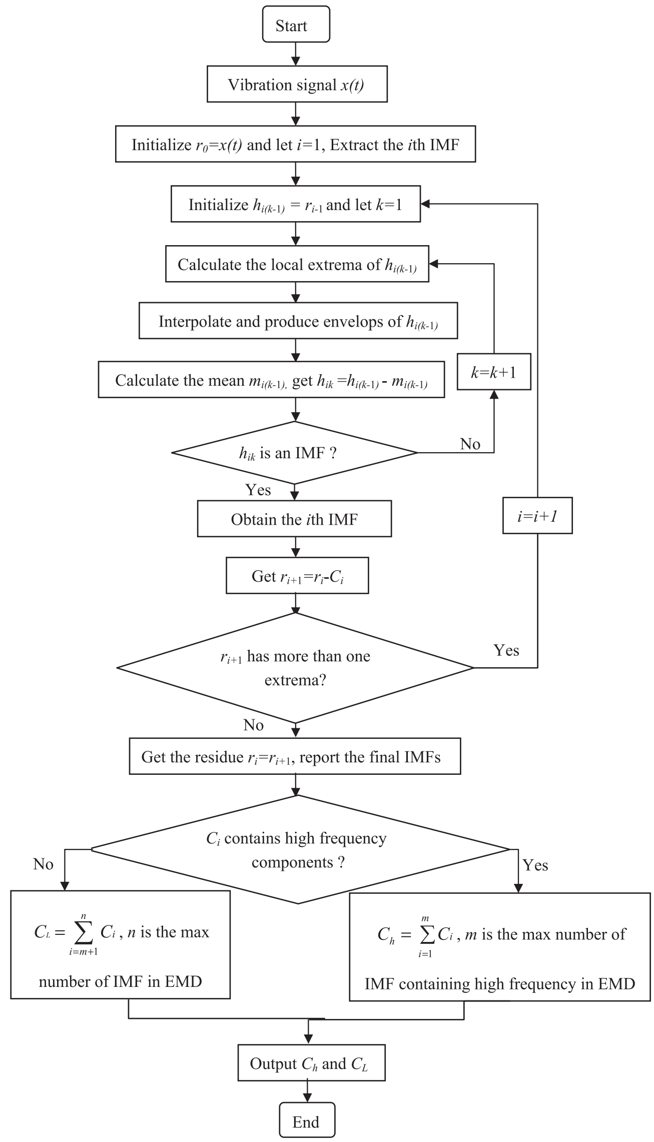

Fig. 1. The flow chart of the CMF.

2.2. EEMD

To solve the problem of mode mixing, EEMD is introduced based on the statistical properties of white noise [11]. The EEMD algorithm can be given as follows:

(1) Given $x(t)$ is an original signal, add a random white noise signal $n_j(t)$ to $x(t)$

$$x_j(t) = x(t) + n_j(t) \tag{3}$$

where $x_j(t)$ is the noise-added signal, $j = 1, 2, 3, \ldots, M$ and M is the number of trials.

(2) Decompose $x_j(t)$ into I (IMFs)$C_{i,j}$ $(i = 1, 2, 3\ldots, I)$ using EMD method described in Section 2.1.where $C_{i,j}$ denotes the ith IMF of the jth trial, and I is the number of IMFs.

(3) Repeat steps (1) and (2) with different white noise series each time until $j = M$.

(4) Calculate the ensemble means of corresponding IMFs of the decompositions as the final result

$$C_i = \left(\sum_{j=1}^{m} C_{i,j} \right) / M \tag{4}$$

(5) $C_i (i = 1, 2, 3\ldots, I)$ is the ensemble mean of corresponding IMF of the decompositions.

2.3. Cyclic autocorrelation

If $x(t)$ is a non-stationary signal with zero mean and its statistic parameters such as the mean and the correlation function change periodically or multi-periodically with time, the second order

Please cite this article as: Wang Z, et al. A novel procedure for diagnosing multiple faults in rotating machinery. ISA Transactions (2014), http://dx.doi.org/10.1016/j.isatra.2014.09.006