Mechanical Systems and Signal Processing 48 (2014) 174–187

Contents lists available at ScienceDirect

Mechanical Systems and Signal Processing

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

A novel method for feature extraction using crossover characteristics of nonlinear data and its application to fault diagnosis of rotary machinery

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ARTICLE INFO

Article history:
Received 5 November 2013
Received in revised form
20 March 2014
Accepted 8 April 2014
Available online 26 April 2014

Keywords:
Detrended Fluctuation Analysis(DFA)
Nonlinear data
Crossover phenomena
Feature extraction
Rotary machinery

ABSTRACT

Defective rotary machinery typically exhibits a complex dynamical behavior, which is hard to analyze. Detrended Fluctuation Analysis (DFA) is a robust tool for uncovering long-range correlations hidden in nonstationary data. By DFA, an original series can be compressed into a fluctuation series, which can well preserve the dynamical characteristics of the original series. Lately, the fluctuation series has been separately analyzed by principal component analysis (PCA) and neural network (NN) for fault diagnosis of rotary machinery. However, the feature parameters extracted by PCA or NN normally lack clear physical meaning. In addition, the execution of PCA or NN usually consumes extra time. Interestingly, the scaling-law curve, by which the relation between the fluctuation function and the time scale can be illustrated graphically in a log–log plot, usually exhibits crossover properties. As a result, this study exploited the interesting crossover properties for fault diagnosis of rotary machinery and proposed a novel method for feature extraction of nonlinear data. The proposed method consists of three parts. Firstly, the vibration data from defective rotary machinery are analyzed by DFA and the resultant scaling-law curve is obtained. Secondly, the crossover points in the scaling-law curve are located and then employed to segment the entire scaling-law curve into several different scaling regions, in each of which a single Hurst exponent can be estimated. Thirdly, the whole or a part of the Hurst exponents are used as feature parameters for describing the conditions of defective rotary machinery. Next, the performance of the proposed method was measured using both real gearbox and rolling bearing vibration data with different fault types and severity. The results indicate that the proposed method can ease the problems mentioned previously and performs well in identifying fault types and severity of rotary machinery.

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http://dx.doi.org/10.1016/j.ymssp.2014.04.007
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1. Introduction

Rotary machinery, which covers a broad range of machines, always plays a crucial role in modern industry and hence requires considerable attention to its operation conditions. Rotary machinery commonly works in hostile environments and has really complex structures and mechanisms. When rotary machinery malfunctions, vibration data from it are usually associated with nonstationarity and nonlinearity. Consequently, the dynamical characteristics of complex rotary machinery are hidden deep in these nonstationary data and difficult to disclose [1]. Traditional techniques for data processing, such as Fourier transform and time series analysis, are unsuitable to process nonstationary and nonlinear data [2,3]. Recently, Bartelmus and Zimroz [4] have discovered an approximately linear relation between the amplitude of the signal and the load/instantaneous speed in a limited range of speeds and introduced a new diagnostic feature for condition monitoring of gearboxes in nonstationary operation conditions. Afterwards, Zimroz et al. [5] further confirms the above findings and also demonstrates the capabilities of load susceptibility characteristics (LSCh) for condition monitoring of a rolling bearing. However, the preceding two references do not refer to how the limited range of varying conditions, in which an approximately linear relation can be built, is determined. In past decades, some time-frequency analysis methods, including short time Fourier transform (STFT) [6], Wigner–Ville distribution(WVD) [7,8], wavelet transform(WT) [9–11], empirical mode decomposition(EMD) [2,12] and local mean decomposition(LMD) [13], have been formulated to probe nonstationary data and applied to feature extraction of defective rotary machinery. However, each of these methods leaves something to be desired and some even perform badly in analyzing nonstationary and nonlinear data [14–16]. Accordingly, there is a strong need to develop a novel method for feature extraction of nonstationary and nonlinear data.

Complex system theories seem to raise a possibility for solving the above problem. The theories argue that fluctuations of a time series are closely related to dynamical behavior of the complex system [17]. Specifically, long-range correlations of the time series have a close relation to the fractal structure of the complex system [18]. Presently, many methods have been addressed to detect long-range correlations of stationary time series [19–21]. Nevertheless, it is quite difficult for these methods to achieve satisfactory results for nonstationary data [22,23]. In the recent twenty years, a novel method named Detrended Fluctuation Analysis (DFA) has been put forward for uncovering long-range correlations in nonstationary data and quickly become popular due to its inherent superiority over some traditional methods [23,24]. Currently, DFA has been applied to data analysis in diverse research fields, e.g. heartbeat time series analysis [23,25], DNA sequence analysis [24], climate monitoring [26], bearing vibration data analysis [27], exhalation sequence analysis [28], natural language analysis [29], fetal cardiac data [30], human interaction activity [31] and intertrade durations [32]. Recently, DFA has been successfully employed as a tool for compressing an original series into a fluctuation series, which can well preserve the dynamical properties of the original series [33,34]. As a consequence, the scaling-law curve, by which the relation between the fluctuation function and the time scale can be shown graphically in a log–log plot, can embody the essence of the complex system. Since the fluctuation series derived by DFA has a far shorter length but remains the core of the original series, it is more convenient to use for characterizing the conditions of rotary machinery than the original series. In existing literatures [33,34], principal component analysis (PCA) and neural network (NN) have been separately utilized to analyze the fluctuation series for identifying different conditions of gearboxes and rolling bearings. However, the feature parameters extracted by PCA or NN normally lack clear physical meaning. In addition, the execution of PCA or NN ordinarily consumes extra time. Therefore, the problems mentioned previously can seemingly be avoided, if the dynamical characteristics of the fluctuation series can be disclosed without such algorithms as PCA or NN.

In fact, many dynamical systems, including gearboxes and rolling bearings, generally show complex scaling behavior and then their scaling-law curves usually exhibit interesting crossover characteristics [22,23,27,33–37]. This means that there are different long-range correlations in different time scales of the time series. Since the Hurst exponent, which is defined as the slope of the scaling-law curve, can be used to quantify the long-range correlations of the time series, there are different Hurst exponents in different scaling regions of the time series. Because these Hurst exponents have a close relation to the fractal structure of the time series and bear clear physical meaning, they are suitable as feature parameters for describing the conditions of the complex system. Indeed, Peng et al., [23] have utilized two Hurst exponents to detect departures of heart conditions from normality. Motivated by the previous work, this study exploited the crossover properties of nonlinear data for fault diagnosis of rotary machinery and proposed a novel method for feature extraction of rotary machinery. The proposed method comprises three parts. To begin with, DFA is used to investigate the vibration data from defective rotary machinery and the resulting scaling-law curve is derived. Then, the crossover points in the scaling-law curve are located and made use of dividing the whole scaling-law curve into several different scaling regions, in each of which a single Hurst exponent can be estimated. Finally, the whole or a part of the Hurst exponents is used as feature parameters for describing the conditions of defective rotary machinery. Afterwards, both real gearbox and rolling bearing vibration data with different fault types and severity were employed to assess the performance of the proposed method. The results show that the proposed method can clearly separate different fault types and severity of rotary machinery. Also, the proposed method can effectively overcome the problems occurring in the existing methods, since it extracts the feature parameters by exploiting the natural crossover properties of the scaling-law curve rather than by using such algorithms as PCA or NN.

This paper is organized as follows. In the following section, DFA is formulated, the physical meaning of the Hurst exponent is explained and a novel method for feature extraction of nonlinear data is proposed. In the third section, experimental data from defective gearbox and rolling bearing are used to check the effectiveness of the proposed method, a comparison is drawn between the proposed method and the PCA-based method and an in-depth discussion about the results is set up. Finally, a conclusion is given in the fourth section.