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Research Article

The diagnostic line: A novel criterion for condition monitoring of rotating machinery

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ABSTRACT

This study examined scaling properties of an increment series from rotating machinery. Moreover, two fluctuation parameters for the smallest and largest time scales of a scaling range served as a pair of fluctuation parameters to describe system conditions. Therefore, an interesting phenomenon is observed: the data points, each representing a pair of fluctuation parameters, for fault conditions almost form a straight line, while those for normal clearly depart from the straight line. To describe the phenomenon, a novel concept termed the diagnostic line was introduced. Subsequently, properties of the diagnostic line were carefully investigated theoretically and numerically. Consequently, a decisive role of noise in forming the diagnostic line was determined. Accordingly, this study develops a novel criterion for condition monitoring of rotating machinery.

1. Introduction

A wide range of machines is typically covered by rotating machinery, which always plays a central role in various industrial fields. Therefore, condition monitoring of rotating machinery is absolutely critical for ensuring equipment safety in operation. Rotating machinery has elaborate structures and frequently works under poor conditions. For this reason, vibration data from defective rotating machinery are usually noisy, nonstationary and nonlinear. Consequently, developed to process stationary and linear data, conventional approaches to data analysis are unsuitable for analyzing vibration data from defective rotating machinery [1]. In recent decades, some time–frequency analysis algorithms, such as short-time Fourier transform (STFT) [2], Wigner–Ville distribution (WVD) [3,4], wavelet transform(WT) [5,6] and empirical mode decomposition(EMD) [1], have been presented to explore nonstationary data and deliver a good performance under certain conditions. Unfortunately, each of these time–frequency methods leaves something to be desired and some even perform poorly in probing nonstationary and nonlinear data [7–9]. Ref. [10] proposed a EEMD-based method for locating fault sources of rotating machinery. The EEMD-based method can overcome some deficiencies existing in traditional methods mentioned previously. Nevertheless, the two key parameters in the EEMD method, i.e. the amplitude of added white noise and the ensemble number, are a bit hard to determine for lack of a strict guideline. Detrended Fluctuation Analysis (DFA) [11], a novel method for uncovering long-range correlations buried in nonstationary data, has been successfully used for compressing a long original series from defective rotating machinery into a short fluctuation series, which can well preserve dynamical characteristics of the original series [12,13]. Next, dynamical characteristics of the fluctuation series can be displayed graphically by a scaling-law curve in a log–log plot. Nevertheless, a complex shape of the scaling-law curve of the original series usually causes great difficulties in extracting characteristic parameters from the scaling-law curve. Recently, Refs. [14–16] have carefully examined scaling characteristics of an increment series, which is obtained by performing a difference operation on an original series. Consequently, it is found that the amplitude component of the increment series mainly contains nonlinear information of the original series and the sign component mainly does linear information [14–16]. Additionally, Refs. [14–16] have separately analyzed the original and the increment series of cardiac interbeat intervals for detecting heart diseases by DFA. Surprisingly, a comparison between these two sets of results indicates that the increment series seems more suitable to analyze for detecting heart diseases than the original series [14–16]. Motivated by the works mentioned above, this study examined scaling characteristics of the increment series from rotating

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machinery. As a result, this study demonstrated that the increment series, whose scaling range is typically characterized by a single scaling exponent, has weaker long-range correlations and shorter scaling ranges. Accordingly, with the capability for broadly describing geometric characteristics of a scaling-law curve of the increment series, two fluctuation parameters for the smallest and largest time scales of the scaling range of the increment series were used as a pair of fluctuation parameters to characterize conditions of rotating machinery. As a result, an interesting phenomenon can be observed: the data points, each of which represents a pair of fluctuation parameters, for fault conditions can nearly form a straight line, whereas those for normal conditions considerably deviate from the straight line. Moreover, the generality of the interesting phenomenon was examined by three independent experiments on gears and rolling bearings. To describe the interesting phenomenon, a novel concept termed the diagnostic line was introduced in this study. Also, this paper benchmarked the performance of the proposed method by comparing it with the EEMD method. Subsequently, the properties of the diagnostic line were carefully investigated theoretically and numerically. As a consequence, a decisive role of noise in the formation of the diagnostic line was determined. Furthermore, a confidence interval at the 95% confidence level was estimated for the diagnostic line. Consequently, this study seems to develop a novel criterion for condition monitoring of rotating machinery.

This paper was organized as follows. The second section formulated the DFA algorithm and illustrated the relations between fluctuations of an original series and its increment series. In the third section, the increment series from rotating machinery were examined by DFA, the novel concept termed the diagnostic line was introduced, the properties of the diagnostic line were carefully investigated theoretically and numerically and a discussion is set up. Furthermore, a comparison between the proposed method and the EEMD method was drawn in the third section. Finally, the fourth section gave a conclusion.

2. Scaling characteristics of increment series

2.1. A description of DFA

The DFA process of a nonstationary and nonlinear series x_i $(i=1,\ldots,N)$ is briefly described below [11]:

(1) Construct a cumulative series $X(i)$,

$$X(i)=\sum_{j=1}^{i}\left(x_j-\overline{x}\right)$$
$$\overline{x}=\frac{1}{N}\sum_{i=1}^{N}x_i \tag{1}$$

(2) Separate the series $X(i)$ into K nonoverlapping segments with the same length s. Since the length N is seldom aliquoted by the length s, a minor part of data at the end of the series $X(i)$ will be left unused. To fully exploit the potential of the data, the same operation will be conducted again from the opposite direction. Accordingly, there are $2K$ data segments derived in the above process.

(3) Adopt the least-square algorithm to fit the polynomial trend for each of the $2K$ data segments. Therefore, the variance can be written as

$$F^2(\nu,s)=\frac{1}{s}\sum_{i=1}^{s}\left\{X[(\nu-1)s+i]-x_\nu(i)\right\}^2 \tag{2}$$

for the νth segment, $\nu=1,\ldots,K$, and

$$F^2(\nu,s)=\frac{1}{s}\sum_{i=1}^{s}\left\{X[N-(\nu-K)s+i]-x_\nu(i)\right\}^2 \tag{3}$$

for the νth segment, $\nu=K+1,\ldots,2K$. Here, the symbol $x_\nu(i)$ denotes the fitting polynomial trend in the νth segment. Also, the polynomial trend of order m is customarily named DFA*m*. By making a comparison between these results from different orders of DFA, the type of the polynomial trend in the time series is capable of being determined [17].

(4) Calculate the mean-square-deviation fluctuation function $F(s)$ for all the $2K$ segments

$$F(s)=\left\{\frac{1}{2K}\sum_{\nu=1}^{2K}F^2(\nu,s)\right\}^{1/2} \tag{4}$$

(5) Alter the time scale s, repeat the previous four steps and acquire the fluctuation function $F(s)$. If there exist long-range correlations in the series x_i, the relations between $F(s)$ and s can be shown by the following power law:

$$F(s)\sim s^{\alpha} \tag{5}$$

If Eq. (5) is satisfied in a range of time series, the range is called a scaling range. Here, the parameter α is called the scaling exponent.

2.2. Relations between fluctuations of an original series and its increment series

For a series $x_i(i=1,\ldots,N)$, its increment series Δx is defined as [15,16]

$$\Delta x_i=x_{i+1}-x_i,\ i=1,\ldots,N-1 \tag{6}$$

Next, the relations between fluctuations of the original series and its increment series can be built by the partition function and the two-point correlation function. The partition function $Z_q(l)$ of the series $x_i(i=1,\ldots,N)$ is defined as [16]

$$Z_q(l)=\left\langle\left|x_{i+l}-x_i\right|^q\right\rangle \tag{7}$$

Here, the symbol $\langle\cdot\rangle$ means to calculate the expectation of the time series and the symbol q represents the moment index. If the series x_i is long-range correlated, the partition function $Z_q(l)$ will follow a power law

$$Z_q(l)\sim l^{2H(q)} \tag{8}$$

where $H(q)$ is called the generalized Hurst exponent. If $H(q)$ is independent of q, the series x_i is monofractal. Otherwise, the series x_i is multifractal.

Afterwards, the two-point correlation function of the increment series Δx is defined as [16]

$$C(l)=\left\langle\Delta x_i\Delta x_{i+l}\right\rangle \tag{9}$$

For a stationary Gaussian series with long-range correlations, the two-point correlation function $C(l)$ satisfies the following equation [16]:

$$C(l)\sim l^{-\gamma}\quad(0<\gamma<1) \tag{10}$$

When $q=2$, the following relations can be established [16,18,19]:

$$Z_2(l)\sim\left\langle x_ix_{i+l}\right\rangle\sim l^{2-\gamma}=l^{2H(2)}=l^{2\alpha} \tag{11}$$

Here, the parameter α equals to $H(2)$ and $Z_2(l)$ symbolizes the partition function of the series x_i for $q=2$. According to Eq. (11), the fluctuations of the increment series have a close relation to those of the original series. For this reason, the increment series