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Spectrum auto-correlation analysis and its application to fault diagnosis of rolling element bearings

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ABSTRACT

Bearing failure is one of the most common reasons of machine breakdowns and accidents. Therefore, the fault diagnosis of rolling element bearings is of great significance to the safe and efficient operation of machines owing to its fault indication and accident prevention capability in engineering applications. Based on the orthogonal projection theory, a novel method is proposed to extract the fault characteristic frequency for the incipient fault diagnosis of rolling element bearings in this paper. With the capability of exposing the oscillation frequency of the signal energy, the proposed method is a generalized form of the squared envelope analysis and named as spectral auto-correlation analysis (SACA). Meanwhile, the SACA is a simplified form of the cyclostationary analysis as well and can be iteratively carried out in applications. Simulations and experiments are used to evaluate the efficiency of the proposed method. Comparing the results of SACA, the traditional envelope analysis and the squared envelope analysis, it is found that the result of SACA is more legible due to the more prominent harmonic amplitudes of the fault characteristic frequency and that the SACA with the proper iteration will further enhance the fault features.

1. Introduction

Rolling element bearings are widely used in rotating machines and bearing failure is one of the most causes of the machine breakdowns and accidents. Therefore, the performance of rolling element bearings is closely related to the safe and efficient operation of the apparatus and the condition monitoring technique is of great significance in engineering applications. Moreover, since the occurrence of the fault will induce a rapid degradation of the bearing performance, the corresponding fault diagnosis has attracted much attention in condition monitoring programs and the vibration based diagnostic technique has been universally investigated due to the non-invasive nature and the high reactivity to incipient faults.

Generally, the vibration based diagnostic technique aims at obtaining some descriptors to reveal the condition of rolling element bearings. For example, the root mean square, variance, kurtosis, etc., are widely used to evaluate the performance of rolling element bearings. However, compared with these statistical scalars, the fault characteristic frequency is a more pertinent fault index, which can directly expose the occurrence and location of the bearing fault. Many feature extraction methods are developed to obtain the corresponding fault characteristic frequency over the past several decades.

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As the most known method for the fault diagnosis of rolling element bearings, the envelope analysis (EA) is able to highlight the fault characteristic frequency on the spectrum of the signal envelope [1–3]. Nevertheless, the traditional EA cannot meet the diagnostic requirements of the incipient fault, whose fault feature is very weak and often seriously contaminated by the noise. In order to enhance the feature extraction ability of EA, many signal processing techniques, such as wavelet analysis [4–7], empirical mode decomposition (EMD) [3,8,9] or ensemble empirical mode decomposition (EEMD) [10], are introduced and many indicators, such as kurtogram [11,12] and protrugram [13] are proposed. However, the investigation by Ho and Randall [14] indicated that it was preferable to analyze the squared envelope rather than only the envelope of the vibration signal, since the signal to noise ratio (SNR) was supposed to be bigger than unity at the occurring moment of the fault impulse and could be increased after the squaring operation. Furthermore, the squared envelope analysis (SEA) may avoid the masking effect which is caused by the extraneous components introduced by the rectification operation in the EA.

Besides the EA, the cyclostationary analysis was also introduced to extract the fault characteristic frequency of rolling element bearings in the last decade. The cyclostationarity of the bearing vibration, induced by the fault, was implicitly admitted in Ref. [15] and was first formally demonstrated in Ref. [16]. Many cyclic statistical indicators [17–19], such as cyclic spectral density (CSD) and cyclic coherence, were introduced to reveal the fault features on the plane of frequency (f) and cyclic frequency (α). Meanwhile, inspired by the amplitude modulation characteristic of the vibration induced by the fault, Urbanek et al. [20] proposed a new two dimensional descriptor called modulation intensity density (MID) to represent the vibration signal on the plane of modulation frequency and carrier frequency to expose the fault features. Since the bearing fault is only represented by the modulation or cyclic frequency, the Integrated Cyclic Coherence (ICC) [19] and integrated MID [20] were proposed by scrutinizing the whole cyclic or modulation frequency domain while shrinking the f or carrier frequency domain in the result of cyclic coherence or MID. Unfortunately, the ICC or integrated MID, both of which need to evaluate the corresponding matrix descriptor before condensing the information by integration, do not solve the computation impediment, which is too onerous in the industrial applications where *real-time* processing is required.

In this paper, a feature extraction method is proposed to obtain the fault characteristic frequency based on the auto-correlation analysis of the Fourier coefficient series, which are projections of the signal on the complex trigonometric basis. The proposed method is able to enhance the fault feature by the iterative operation in the program of the bearing fault diagnosis. The paper is organized as follows: firstly, on the basis of the orthogonal projection theory, the auto-correlation analysis of the Fourier coefficient series is proposed. Then, the proposed method is compared with the cyclostationary analysis and SEA. Finally, the simulated and experimental signals are employed to evaluate the efficacy of the proposed method.

2. Auto-correlation analysis of the Fourier coefficient series

In the following we will consider sampled signals at the sampling frequency of F_s. The discrete time is $t_n = n/F_s$ and the discrete frequency is $f_n = nF_s/N$, where F_s/N denotes the frequency resolution. For simplification, both $x(t_n)$ and $x(n)$ are used to represent the nth sampled value in the time domain, while $X(f_n)$ and $X(n)$ are used to denote the nth Fourier transform coefficient in the frequency domain.

The correlation analysis is a universal method applied in the signal processing. For example, the coefficients of the Fourier transform and the wavelet transform are the cross-correlation results of the signal between the Fourier kernel functions and the wavelet functions respectively. The auto-correlation is used to reveal the self-similarity of the signal at the different time. According to the theory of stochastic process, the one dimensional auto-correlation of the generalized stationary signal x with the length of N_1 is defined as follows:

$$R_x(m) = E\{x(n+m)x(n)^*\}, \quad n = 0, 1, \ldots, N_1-1, \; m = 0, \pm 1, \ldots, \pm(N_1-1) \tag{1}$$

where $E\{\cdot\}$ is the expectation operator and $x(n)^*$ denotes the conjugation of $x(n)$. In applications, owing to the limited length of the collected signal, only the estimation value is available and usually given by the following:

$$\hat{R}_x(m) = \frac{1}{N_1}\sum_{n=0}^{N_1-1} x(n+m)x(n)^*, \quad m = 0, \pm 1, \ldots, \pm(N_1-1) \tag{2}$$

It is worth noting that the estimation of the temporal auto-correlation is actually the auto-correlation of the orthogonal projection series on the basis functions of $\{e_n = \{\ldots, 0_{n-1}, 1_n, 0_{n+1}, \ldots\}_{N_1}, \; n = 0, 1, \ldots, N_1-1\}$. In this sense, the auto-correlation method can be generalized to the other projection series which is obtained by different orthogonal basis functions. It is known that the coefficient series of the Fourier transform, given by Eq. (3), is the projection of the signal on the complex trigonometric basis functions.

$$X(n) = \sum_{r=0}^{N_1-1} x(r)\, e^{-j(2\pi/N_2)nr}, \quad n = 0, 1, \ldots, N_2-1 \tag{3}$$

where N_2 is the length of the Fourier coefficient series and $X(n)$ is the simplified representation of $X(2\pi n/N_2)$. The one dimensional auto-correlation of the Fourier coefficient series is imitatively proposed here

$$R_X(k) = E\{X(n+k)X(n)^*\}, \quad k = 0, \pm 1, \ldots, \pm(N_2-1) \tag{4}$$