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Using bispectral distribution as a feature for rotating machinery fault diagnosis

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ABSTRACT

The vibration signals of rotating machinery present a strongly non-linear and non-Gaussian behavior, and bispectrum is well suitable to analyze this kind of signals. Due to modulation or smearing, it is hard to extract the accurate frequency-based features from the bispectrum. A bispectral distribution for machinery fault diagnosis is developed in this paper. The binary images extracted from the bispectra are taken as features to construct the target templates, then, the nearest template classifier is constructed to achieve pattern recognition and fault diagnosis. The computing speed of this method is very high because the proposed algorithm just calculates the number of "1". Finally, roller bearing and gear fault diagnosis are performed as examples, respectively, to verify the feasibility of the proposed method.

1. Introduction

The safety, reliability, efficiency and performance of rotating machinery are major concerns in industry. The task of condition monitoring and fault diagnosis of rotating machinery is significant. Many methods are used widely in many industries in predictive maintenance. Vibration analysis-based method is the most principal and effective method. It consists of three steps: (1) to measure the vibration responses; (2) to extract the fault feature; (3) to diagnose the defect [1,2]. The presence of a defect of rotating machinery always causes significant increase in the vibration level. Those vibration responses can be measured by testing and measurement systems [3]. However, Vibration signal collected from rotating machinery with defects is difficult to indicate faults directly. Signal preprocessing and feature extraction are usually taken in the processing of fault diagnosis. There are many signal processing techniques. The common method is the fast Fourier transform (FFT) to obtain the power spectrum with the frequency components of the entire signal. It is easy to figure out from the formula of FFT in which the time range of integral is from minus infinity to plus infinity [4]. The useful information contained in the power spectrum, however, is essentially in the second order statistics. This only suffices for a complete statistical description of a Gaussian process. It is well known that the raw signals of vibration are composed of a large amount of non-stationary and non-Gaussian signals in rotating machinery. As power spectral analysis has drawback of discarding all phase information. Higher Order Statistics/Spectra (HOS) are easy to extract information due to deviation from Gaussianity, to recover the true phase character of the signals, and to detect and quantifying nonlinearities in the time series [5–7]. These characters make it well suitable to analyze non-stationary and non-Gaussian signals. As a result, HOS methods have been applied with partial success to rotating machinery condition monitoring and fault diagnosis. Howard [8] used the bispectrum and the trispectrum for machine vibration condition monitoring and demonstrated the applicability of the higher order spectral techniques to detect amplitude and phase modulation. Sinha [9] developed higher order spectra for crack and misalignment identification in the

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shaft of a rotating machinery and received a good result. Wang and Jamestoo [10] used higher order spectra as preprocessor to extract the features and neural network as a classifier for rotating machinery fault diagnosis. All of these studies attempted to match spectral lines with a priori known defect frequencies that are characteristic of the affected machinery components. There may be some problems. For example, the modulation sidebands or smearing due to fluctuations in machine speed can produce complicated patterns, which make the interpretation of the frequencies become difficult. A peak in the bispectrum may represent true components of the analyzed signal, a false image produced by the interference of other components, and even a mixture of the above. These make accurate frequency-based features hard to extract. In this paper, a bispectral distribution for machinery fault diagnosis is developed. The binary images extracted from the bispectra are taken as features to construct target templates, then, an objective function is constructed as a classifier to achieve pattern recognition and diagnosis. Application of these techniques to roller bearing and gear fault diagnosis are presented herein.

2. The introduce of HOS and bispectrum

The first and second-order statistics, such as mean, variance, autocorrelation and power spectrum [1,2] are popular signal processing tools and have been used extensively for data analysis. However, they are subject to describe liner and Gaussian processes. In practice, most of the situations with nonlinear and non-Gaussian behavior can be conveniently studied using HOS [11,12].

Higher-than-second-order moment, cumulant and spectra are defined as higher order moment, cumulant and spectra, respectively. They are general designation as HOS. Just as the power spectrum is the frequency domain counterpart of the second-order cumulant of a signal and represents the decomposition or spread of the signal energy over the frequency channels obtained from the Fourier transform, the kth-order spectrum is defined as the $k-1$ dimensional Fourier transform of the kth-order cumulant [12]. It is expressed by:

$$C(\varpi_1, \varpi_2, \cdots, \varpi_{n-1}) = \sum_{\tau_1=-\infty}^{+\infty} \cdots \sum_{\tau_{n-1}=-\infty}^{+\infty} c_{kx}(\tau_1, \cdots, \tau_{k-1}) \cdot \exp\{-j(\varpi_1\tau_1 + \ldots + \varpi_{k-1}\tau_{k-1})\} \tag{1}$$

where $C(\varpi_1, \varpi_2, \ldots, \varpi_{n-1})$ is the kth-order spectrum, and $c_{kx}(\tau_1, \ldots, \tau_{k-1})$ is the kth-order cumulant.

The bispectrum is the frequency domain representation of the third-order cumulants. It can be expressed as follows:

$$B(\varpi_1, \varpi_2) = \sum_{\tau_1=-\infty}^{+\infty} \sum_{\tau_2=-\infty}^{+\infty} c_{3x}(\tau_1, \tau_2) \exp\{-j(\varpi_1\tau_1 + \varpi_2\tau_2)\} \tag{2}$$

where $B(\varpi_1, \varpi_2)$ is the bispectrum, $c_{3x}(\tau_1, \tau_2)$ is the third-order cumulant.

The bispectrum is a complex quantity with information of magnitude and phase. It can be plotted against two independent frequency variables, ϖ_1 and ϖ_2 in a three-dimensional (3D) plot. Compared with the discrete power spectrum with a point of symmetry at the folding frequency, the bispectrum also has 12 regions of symmetries in the (ϖ_1, ϖ_2) plane [13,14]. Additionally, the bispectrum can be used to solve practical problems effectively, and the reasons are expressed as follows:

(1) *Gaussian processes:* If $x(t)$ is a stationary zero-mean Gaussian process, its bispectrum $B(\varpi_1, \varpi_2)$ is identically zero.
(2) *Linear phase shifts:* While the power spectrum suppresses all phase information, the bispectrum does not.
(3) *Non-Gaussian white noise:* Its bispectrum is flat.

3. Feature extraction and classification

3.1. The bispectral binary image extracted

Assuming that $B(\varpi_1, \varpi_2)$ is the bispectrum of the vibration signal $x(t)$, due to three-dimensional distribution, the bispectrum has a huge related calculation. At the same time, the bispectral amplitudes are close to zero in some regions which may bring redundant calculation. In order to reduce computation load, the simplest feature should be selected to ensure classifying correctly. The binary image $F_x(\varpi_1, \varpi_2)$ obtained by the threshold value is selected as the feature. This process is expressed as follows:

$$F_x(\varpi_1, \varpi_2) = \begin{cases} 1 & B_x(\varpi_1, \varpi_2) \geqslant T \\ 0 & B_x(\varpi_1, \varpi_2) < T \end{cases} \tag{3}$$

where T is the threshold value. Generally, it is the mean of $B_x(\varpi_1, \varpi_2)$

$$T = \frac{1}{N \times N} \sum_{m=0}^{N-1} \sum_{n=0}^{N-1} B_x(\varpi_1, \varpi_2) \tag{4}$$

The binary image $F_x(\varpi_1, \varpi_2)$ has made full use of the bispectral distribution information and no longer involves the amplitude information.

3.2. The target template constructed

Assuming that there are c classes samples, and each class includes m training samples. The target template is defined as $P_i = \{C_i, D_i\}$ $(i = 1, 2, \ldots, c)$. It can be obtained from the following formulas:

$$C_i(\varpi_1, \varpi_2) = \bigcap_{k=1}^{m} \{F_{ik}(\varpi_1, \varpi_2)\} \tag{5}$$

$$D_i(\varpi_1, \varpi_2) = \bigcup_{k=1}^{m} \{F_{ik}(\varpi_1, \varpi_2)\} \tag{6}$$

where $C_i(\varpi_1, \varpi_2)$ and $D_i(\varpi_1, \varpi_2)$ are defined as the core and domain of the ith class, respectively. $F_{ik}(\varpi_1, \varpi_2)$ is the binary image of the kth samples of the ith class.

It can be noted from Eqs. (5) and (6) that the $C_i(\varpi_1, \varpi_2)$ and $D_i(\varpi_1, \varpi_2)$ represent as the common and scope of bispectral distribution of the ith class, respectively.