Mechanical Systems and Signal Processing 103 (2018) 76–88

Contents lists available at ScienceDirect

Mechanical Systems and Signal Processing

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

Amplitude-cyclic frequency decomposition of vibration signals for bearing fault diagnosis based on phase editing

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ARTICLE INFO

Article history:
Received 17 May 2017
Received in revised form 2 August 2017
Accepted 29 September 2017

Keywords:
Phase editing
Diagnostics of defective bearings
Spectral correlation
Enhanced squared envelope spectrum
Variable speed

ABSTRACT

In rotating machine diagnosis different spectral tools are used to analyse vibration signals. Despite the good diagnostic performance such tools are usually refined, computationally complex to implement and require oversight of an expert user. This paper introduces an intuitive and easy to implement method for vibration analysis: amplitude cyclic frequency decomposition. This method firstly separates vibration signals accordingly to their spectral amplitudes and secondly uses the squared envelope spectrum to reveal the presence of cyclostationarity in each amplitude level. The intuitive idea is that in a rotating machine different components contribute vibrations at different amplitudes, for instance defective bearings contribute a very weak signal in contrast to gears. This paper also introduces a new quantity, the decomposition squared envelope spectrum, which enables separation between the components of a rotating machine. The amplitude cyclic frequency decomposition and the decomposition squared envelope spectrum are tested on real word signals, both at stationary and varying speeds, using data from a wind turbine gearbox and an aircraft engine. In addition a benchmark comparison to the spectral correlation method is presented.

1. Introduction

In a rotating machine when a rolling element bearing has a defect it does not operate smoothly but produces a series of impacts throughout its rotation. The impacts generate vibrations which propagate through the machine from the bearing to the vibration transducer. Diagnosis of a defective bearing is subject to the observation of such vibrations. The literature on signal processing methods for the ad hoc treatment of vibrational signals is abundant, as are mathematical models for the expected vibrations from defective bearings [1,2]. In particular it is commonly accepted that the signal from a defective bearing is cyclostationary and that the most appropriate tool for its analysis is Spectral Correlation (SC). Specifically [3] shows that the integral over all spectral frequencies of the SC is equivalent to the spectrum of the squared envelope, therefore it is related to the high resonant frequency technique [4]. Recently Antoni et al. [5] introduced an algorithm for the fast computation of the SC. The algorithm was successfully used to detect faulty bearings on machines operating both at stationary and non-stationary speeds.

The SC achieves detection of a defective bearing exploiting two aspects of a vibrational signal, namely its statistical properties and the separation of the vibrations in spectral frequency. The first aspect uses the presence of peaks in the cyclic

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https://doi.org/10.1016/j.ymssp.2017.09.044
0888-3270/

domain for a series of impacts from the defective bearing. The latter exploits the fact that vibrations from different components of the machine occupy different spectral bands. Usually gears contribute peaks at low frequencies versus the high resonant frequencies excited by the impacts from a defective bearing. The combination of these two aspects in the SC allows detection of the defective bearing without any preceding steps for suppression of vibrations from gears or other unwanted components. Therefore a 2-dimensional decomposition simplifies, conceptually and practically, the usual procedure of first pre-processing the vibration signal and afterwards calculating the Squared Envelope Spectrum (SES) [6].

This paper introduces a novel method to decompose a vibrational signal in a 2-dimensional map. The method is implemented using Phase-Editing (PE) [7] to threshold spectral amplitudes at different levels. It exploits the fact that components of a vibrational signal can be separated according to their amplitudes independently from their frequency in the spectrum. For instance, in the case of a small defect on a bearing, vibrations from the gears contribute a series of high amplitude peaks, while the impacts from the bearing contribute a low amplitude resonance around the excited resonant frequency. The SES is then calculated for each threshold level, in order to observe peaks in the cyclic domain. Therefore the proposed method decomposes the vibrational signal in a 2-dimensional map of which the characteristic dimensions are: the spectral amplitude level up to which the signal has been thresholded and its corresponding cyclic content. The name of the proposed method is Amplitude-cyclic frequency Decomposition (AD).

Differently from phase editing [7], AD does not require the optimisation step for the selection of the best threshold level, in addition the 2-dimensional map allows the simultaneous visualisation of the cyclic content of vibrations from gears and bearings at different spectral amplitudes. The method does not require any pre-processing of the vibration signal and it can be applied also to machines operating at non-stationary speeds. Only one parameter has to be tuned, namely the number of thresholds. In addition the computational cost for each threshold level of the AD consists of four computations of the fast Fourier transform of the vibration signal. For these reasons AD is well suited for an automated detection scheme.

The paper is structured as follows: Section 2 introduces the method and, by means of a numerical simulation, compares the performance of AD with that of SC. Section 3 presents the results of AD applied to three experimental data sets: a laboratory set-up characterised by largely varying speed, a wind turbine gearbox, and a civil aircraft engine. Comparison with the results obtained from SC is presented for the three cases. Section 4 draws some conclusions.

2. Methods

This section shows how to obtain the amplitude-cyclic frequency decomposition of the raw vibration signal $x[k]$, with Fourier transform $\hat{x}[j]$ where $k, j = \{0, \dots, N_k - 1\}$ are the indices in the time and frequency domains, respectively.

Firstly $x_{AD}[k, l]$ is computed using the phase editing method to threshold $|\hat{x[j]}|$ at N_l levels [7]:

$$x_{AD}[k, l] = x[k] - \text{Real}\left(p^{(l)}[k]\right). \tag{1}$$

where $l = \{0, \dots, N_l - 1\}$ is the index of the threshold level and $p^{(l)}[k]$ is the phase edited vector obtained for the l level. For each level the phase editing method suppresses spectral components with amplitude smaller than the selected threshold and can be seen as a denoising procedure. This is achieved rotating in the complex plane pairs of conjugate vectors of $\hat{x}[j]$. The degree of rotation is defined by the ratio between the amplitude of the vector and the value of the threshold level. Specifically, if the conjugate vectors have an amplitude smaller than the threshold they are significantly rotated, while in the opposite scenario, the vectors are rotated of a small quantity. As a final step the Inverse Fourier Transform (IFT) is calculated on this modified spectrum, adding pairs of complex vectors which cancel out or reinforce accordingly to the degree of rotation. The result of this operation is a denoised complex signal in the time domain of which the real part only is retained. Following this procedure, in Eq. (1) $p^{(l)}[k]$ is defined as the IFT of the modified amplitude spectrum of the raw vibration signal:

$$p^{(l)}[k] = \text{IFT}\{\hat{p}^{(l)}[j]\} = \text{IFT}\left\{|\hat{x}[j]| \exp\left\{i\angle\left(\hat{x}[j] + L^{(l)}[j]\right)\right\}\right\} \tag{2}$$

where $L^{(l)}[j]$ is the threshold vector for the level l. In Eq. (2) $L^{(l)}[j]$ is an antisymmetric vector:

$$L^{(l)}[j] = \begin{cases} +\lambda^{(l)} & 0 \leqslant j < N_k/2 \\ -\lambda^{(l)} & N_k/2 \leqslant j \leqslant N_k - 1 \end{cases} \tag{3}$$

where for each l the constant $\lambda^{(l)}$ is found in an automated way from $\hat{x}[j]$:

$$\lambda^{(l)} = \hat{x}_M \left(\frac{\hat{x}_m}{\hat{x}_M}\right)^{l/(N_l-1)} \tag{4}$$

with $\hat{x}_M = \max_{0 \leqslant j < N_k/2}\{|\hat{x}[j]|\}$ and $\hat{x}_m = \min_{0 \leqslant j < N_k/2}\{|\hat{x}[j]|\}$.

Barbini et al. in [7] showed that in the case of a single threshold level, for each frequency index $j = n \leqslant N_k/2$, PE returns the sinusoidal component:

$$x_{pe,n}[k] = x_n[k] - \text{Real}\{p_n[k]\} = K[n]\frac{2|\hat{x}[n]|}{N} cos\left(\frac{2\pi}{N}nk + \angle\hat{x}[n] + \theta[n]\right) \tag{5}$$