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Normalized wavelet packets quantifiers for condition monitoring

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ABSTRACT

Normalized wavelet packets quantifiers are proposed and studied as a new tool for condition monitoring. The new quantifiers construct a complete quantitative time––frequency analysis: the *Wavelet packets relative energy* measures the normalized energy of the wavelet packets node; the *Total wavelet packets entropy* measures how the normalized energies of the wavelet packets nodes are distributed in the frequency domain; the *Wavelet packets node entropy* describes the uncertainty of the normalized coefficients of the wavelet packets node. Unlike the feature extraction methods directly using the amplitude of wavelet coefficients, the new quantifiers are derived from probability distributions and are more robust in diagnostic applications. By applying these quantifiers to Acoustic Emission signals from faulty bearings of rotating machines, our study shows that both localized defects and advanced contamination faults can be successfully detected and diagnosed if the appropriate quantifier is chosen. The Bayesian classifier is used to quantitatively analyse and evaluate the performance of the proposed quantifiers. We also show that reducing the Daubechies wavelet order or the length of the segment will deteriorate the performance of the quantifiers. A two-dimensional diagnostic scheme can also help to improve the diagnostic performance but the improvements are only significant when using lower wavelet orders.

1. Introduction

Failure of rolling element bearings will cause machine malfunction and may quickly lead to catastrophic failure of the machinery if no early maintenance is undertaken. Premature bearing failures can be caused by a large number of factors which can be systematically divided into four groups for study [1]: design, production technology, operation and change of condition (DPTOCC). The design factors are taken by a designer to give the background for the bearing production, including all the details connected with the shape of the structure, bearing selection and imperfection limits. The factors connected with the production are called production technology factors, which may or may not fulfil the design factors. The factors connected with bearing operation are named operation factors, including load, rotation speed and environment condition (dustiness, moisture and so on). The change of condition comes from a fault occurring during operation of bearing, such as localized defect, distributed defect and contamination fault. In this paper, the localized defect and contamination fault will be studied. These factors will lead to DPTOCC inferring diagnostic information of a bearing system. The development of modern signal processing techniques for bearing faults detection using vibration signals is given in [2–6]. Acoustic Emission (AE) (i.e. structure-borne ultrasound) measurements are a subject of great recent interest because of their improved sensitivity for some advanced faults compared to the traditional vibration measurements [7].

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Localized bearing defects include cracks, pits and spalls on the rolling surfaces. The vibration signals caused by localized defects can be modelled as a second-order cyclostationary process [8]. Many methods have been proposed and studied for localized defects detection, such as the high-frequency resonance technique [9] and cyclostationary signal analysis [6]. The frequency of the periodic impacts, termed as the bearing Characteristic Defect Frequency (CDF), can be estimated by equations of shaft speed, bearing geometry and defect location [3]. Signal processing methods on frequency domain for localized defects detection are used for trying to find out if significant power exists at the CDFs. Surface-initiated damage due to contamination is one of the main reasons for early bearing failure. At an early stage, the contamination fault does not produce any harmonics of shaft speed frequency at low frequencies and there is often no obvious CDF being modulated at high frequencies.

The Wavelet Transform (WT) is the time-scale analysis method with octave decomposition and the advantage of wavelet analysis lies in detecting transient changes [10,11]. The applications of the WT for condition monitoring have been developed quickly over the last 10 years [12]. As an extension of Discrete Wavelet Transform (DWT), Discrete Wavelet Packets Transform (DWPT) is a powerful and versatile quantitative joint time–frequency analysis method for condition monitoring. This paper proposes and studies normalized wavelet packets quantifiers as a new tool for the detection and diagnosis of localized bearing defect and contamination fault. Unlike the feature extraction methods, which use the amplitude of wavelet coefficients, these new quantifiers are derived from probability distributions and are more robust for diagnostic applications.

This paper is organized as follows: Section 2 provides an overview of the methodology. Section 3 describes the experiment set-up and data acquisition. Section 4 shows the results and performance evaluation of applying the new quantifiers to AE signals from faulty bearings of rotating machines. We discuss the results in Section 5 and finally report conclusions in Section 6.

2. Methodology

2.1. Discrete wavelet packets transform

The DWPT yields time–frequency decomposition by simply decomposing the details of DWT coefficients into finer and finer dyadic frequency bands [10]. By flexibly choosing the nodes from DWPT, we can have better insight of the signal time–frequency structure. The basis of DWPT can be flexibly chosen for practical implementation considerations; some packet nodes which concentrate the contaminating noises can be easily eliminated; the computational time for DWPT is fast because it is supported by the fast filter bank algorithm.

The DWPT generates a wavelet packets table or wavelet packets tree. The wavelet node (j, n) corresponds to the vector $\mathbf{W}_{j,n}$ of wavelet packets coefficients where $j = 1,\ldots J_0$ is the depth of the node and $n = 0,\ldots,2^j-1$ is the number of nodes that are on its left at the same depth. The collection of nodes forming the indices of wavelet packets table will be denoted by $T \equiv \{(j, n)\colon j = 1,\ldots J_0;\ n = 0,\ldots,2^j-1\}$. The coefficient $W_{j,n,t}$ of node (j, n) at time t can be written in terms of a filtering of signal $\mathbf{S}$ with appropriate downsampling [11]:

$$W_{j,n,t} = \sum_{l=0}^{L_j-1} u_{j,n,l} S_{2^j(t+1)-1-l \text{ modulo } N}, \quad t = 0, 1, \ldots, N_j - 1, \tag{1}$$

where N_j is the length of coefficients vector $\mathbf{W}_{j,n}$ at level j and $N_j = N/j$, L_j is the filter width at j level $L_j = (2^j-1)(L-1)+1$ and $u_{j,n,l}$ is the filter for node (j, n).

$\|\mathbf{W}_{j,n}\|^2$ can be interpreted as the energy portion in the frequency band $[f_s \cdot n/2^{j+1}, f_s \cdot (n+1)/2^{j+1}]$, that is

$$\|\mathbf{W}_{j,n}\|^2 = E_{j,n} = \sum_{t=0}^{N_j-1} \mathbf{W}_{j,n,t}. \tag{2}$$

2.2. New wavelet packets quantifiers

Since the DWPT is an orthonormal transform, the terminal wavelet packets nodes $(\hat{j}, \hat{n})$ preserve the energy of signal $\mathbf{S}$, that is

$$\|\mathbf{S}\|^2 = \sum_{\hat{j}=1}^{J_0} \sum_{\hat{n}=0}^{2^{\hat{j}-1}} \|\mathbf{W}_{\hat{j},\hat{n}}\|^2. \tag{3}$$

We can eliminate terminal nodes for denoising purpose (e.g. after wavelet packets composition of AE signals, the energy of the nodes corresponding to low frequencies noise will be set to zero). In this case, the total energy of the remaining terminal nodes collection C is

$$E_{\text{tot}} = \sum_{(\hat{j},\hat{n}) \in C} E_{\hat{j},\hat{n}}. \tag{4}$$