Mechanical Systems and Signal Processing 72-73 (2016) 80–91

Contents lists available at ScienceDirect

Mechanical Systems and Signal Processing

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

Novel Gauss–Hermite integration based Bayesian inference on optimal wavelet parameters for bearing fault diagnosis

Dong Wang*, Kwok-Leung Tsui, Qiang Zhou

Department of Systems Engineering and Engineering Management, City University of Hong Kong, Tat Chee Avenue, Kowloon, Hong Kong, China

ARTICLE INFO

Article history:
Received 18 August 2015
Received in revised form
8 October 2015
Accepted 13 November 2015
Available online 30 November 2015

Keywords:
Bearing fault diagnosis
Gauss–Hermite integration
Kurtogram
Bayesian inference
Wavelet transform

ABSTRACT

Rolling element bearings are commonly used in machines to provide support for rotating shafts. Bearing failures may cause unexpected machine breakdowns and increase economic cost. To prevent machine breakdowns and reduce unnecessary economic loss, bearing faults should be detected as early as possible. Because wavelet transform can be used to highlight impulses caused by localized bearing faults, wavelet transform has been widely investigated and proven to be one of the most effective and efficient methods for bearing fault diagnosis. In this paper, a new Gauss–Hermite integration based Bayesian inference method is proposed to estimate the posterior distribution of wavelet parameters. The innovations of this paper are illustrated as follows. Firstly, a non-linear state space model of wavelet parameters is constructed to describe the relationship between wavelet parameters and hypothetical measurements. Secondly, the joint posterior probability density function of wavelet parameters and hypothetical measurements is assumed to follow a joint Gaussian distribution so as to generate Gaussian perturbations for the state space model. Thirdly, Gauss–Hermite integration is introduced to analytically predict and update moments of the joint Gaussian distribution, from which optimal wavelet parameters are derived. At last, an optimal wavelet filtering is conducted to extract bearing fault features and thus identify localized bearing faults. Two instances are investigated to illustrate how the proposed method works. Two comparisons with the fast kurtogram are used to demonstrate that the proposed method can achieve better visual inspection performances than the fast kurtogram.

1. Introduction

Rolling element bearings are frequently used in various machines to support rotating shafts. Their failures may cause unexpected machine breakdowns and thus result in economic loss. To prevent bearing failures, bearing fault diagnosis should be conducted as early as possible. If a bearing has a defect on either an outer race or an inner race, impulses are repeatedly generated by rollers striking the defect surface [1,2]. Because of slippage of rollers, these impulses are not strictly periodic but slightly random [3].

Besides spectral kurtosis [4] and its variants [5–8], wavelet transform [9,10] has proven to be one of the most effective and efficient methods for bearing fault diagnosis. The major idea of wavelet transform aims to calculate the inner product between an artificial wavelet at different translations and scales and a signal to be analyzed. If the artificial wavelet is properly chosen to

* Corresponding author.
E-mail addresses: dongwang4-c@my.cityu.edu.hk (D. Wang), kltsui@cityu.edu.hk (K.-L. Tsui), q.zhou@cityu.edu.hk (Q. Zhou).

http://dx.doi.org/10.1016/j.ymssp.2015.11.018
0888-3270/

be highly similar with impulses caused by localized bearing faults, the inner product operation can highlight impulses hidden in bearing fault signals. Additionally, optimization of wavelet parameters attracts much attention in the past years so as that wavelet transform can achieve better visual inspection performances. One of the most popular artificial wavelets is Morlet wavelet generated by the frequency modulation of a Gaussian window. Lots of studies [11–16] have been conducted to demonstrate the effectiveness and efficiency of Morlet wavelet. In addition to Morlet wavelet, anti-symmetric real Laplace wavelet (ARLW) [17] or impulse response wavelet (IRW) [18] has been used to diagnose different bearing faults. Particularly, in recent work [19], anti-symmetric real Laplace wavelet was used to approximate each of impulses caused by bearing outer race or inner race defects. The reconstruction of the anti-symmetric real Laplace wavelets peeled off from bearing fault signals and its comparison with a strict periodic multiple-transient model [20] experimentally demonstrated that bearing fault signals are not periodic but slightly random. Besides, the observations obtained from the results experimentally show that the anti-symmetric real Laplace wavelet is highly similar with impulses caused by localized bearing faults.

To further explore the anti-symmetric real Laplace wavelet, a novel Gauss–Hermite integration based Bayesian inference method is proposed in this paper to estimate the posterior distribution of anti-symmetric real Laplace wavelet parameters and find optimal wavelet parameters. The idea of Bayesian inference on the posterior distribution of wavelet parameters was newly reported in Refs. [21,22], in which a general particle filter based Bayesian inference method and its improvements were proposed. Even though the general particle filter based Bayesian inference can achieve a good visual inspection performance for bearing fault diagnosis, it requires many random particles to infer the posterior distribution of wavelet parameters, which results in extensive calculation times. Compared with the general particle filter based Bayesian inference methods, the advantages of the novel Gauss–Hermite integration based Bayesian inference method are summarized as follows. Firstly, only a few sigma points established by Hermite polynomial are used to propagate through a non-linear state space model proposed in this paper. It means that calculation times used in this paper are largely shortened. Secondly, the Gauss–Hermite integration based Bayesian inference method is based on an assumption that the joint posterior distribution of wavelet parameters and hypothetical measurements follows a joint Gaussian distribution. The reasons for the use of the joint Gaussian distribution are explained as follows. Recalling the fast kurtogram, it is known that it can be used to find an approximately optimal filter for retaining one of the resonant frequency bands so as to extract bearing fault features. Simply speaking, the fast kurtogram well provides an initial guess for finding a pair of optimal filter parameters including center frequency and bandwidth. Because initial parameters of the non-linear state space model in this paper are able to be initialized by the fast kurtogram, it is reasonable to use the joint Gaussian distribution to generate Gaussian perturbations around the initial parameters of the non-linear state space model for finding optimal anti-symmetric real Laplace wavelet parameters. Moreover, the analytical expression of the posterior distribution of anti-symmetric real Laplace wavelet parameters is determined. It means that the predicting and updating equations of the distribution of wavelet parameters analytically exist. Additionally, it should be noted that the first hypothetical measurement is an initial kurtosis value provided by the fast kurtogram. Other hypothetical measurements are generated by monotonically increasing extrapolations of the first hypothetical measurement. Because the other hypothetical measurements are higher than the initial hypothetical measurement provided by the kurtogram, the posterior estimate of wavelet parameters by using the proposed method can result in optimal wavelet filter parameters, which are better than that provided by the fast kurtogram. Other possible hypothetical measurement metrics are smoothness index [16], sparse measurement [14], Shannon entropy [23], etc., which are potentially used to replace the kurtosis metric used in this paper. Thirdly, optimal wavelet parameters are easily found according to the mean of the posterior distribution of wavelet parameters, namely the mean of the joint Gaussian distribution. Fourthly, resampling methods are not required in this paper because the weights of the sigma points used in the novel Gauss–Hermite integration based Bayesian inference method are deterministically established and do not degenerate over time.

The organization of this paper is given as follows. Anti-symmetric real Laplace wavelet transform and Gauss–Hermite integration are simply reviewed in Section 2. The novel Gauss–Hermite integration based Bayesian inference method is proposed in Section 3 to diagnose localized bearing faults. Two instances are studied in Section 4 to illustrate how the proposed method works. Besides, two comparisons with the fast kurtogram are used to highlight the better visual inspection performances of the proposed method. Conclusions are drawn in Section 5.

2. Introduction of anti-symmetric real Laplace wavelet transform and Gauss–Hermite integration

2.1. Anti-symmetric real Laplace wavelet transform

Anti-symmetric real Laplace wavelet transform $Wc(u,\gamma,\sigma)$ calculates the inner product between an anti-symmetric real Laplace wavelet $\psi(t)$ and a real signal $c(t)$ to be analyzed [18,20,24]:

$$Wc(u,\gamma,\sigma)=\left\langle c(t),\psi_{\gamma,\sigma}(t-u)\right\rangle=\int_{-\infty}^{+\infty}c(t)\psi_{\gamma,\sigma}(t-u)dt=c(t)*\psi_{\gamma,\sigma}(-t)=F^{-1}(C(f)\times\Psi(f)),\tag{1}$$

where $\langle\cdot\rangle$ is the inner product operator; $*$ is the convolution operator; F^{-1} denotes inverse Fourier transform; $C(f)$ and $\Psi(f)$ are the Fourier transforms of $c(t)$ and $\psi_{\gamma,\sigma}(-t)$, respectively; σ and γ are the half-power bandwidth and the center frequency, respectively. Anti-symmetric real Laplace wavelet $\psi(t)$ is defined as follows:

$$\psi_{\gamma,\sigma}(t)=\mathrm{e}^{-\pi\sigma|t|}\sin(2\pi\gamma t).\tag{2}$$