Mechanical Systems and Signal Processing 52-53 (2015) 293–308

Contents lists available at ScienceDirect

Mechanical Systems and Signal Processing

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

A general sequential Monte Carlo method based optimal wavelet filter: A Bayesian approach for extracting bearing fault features

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ARTICLE INFO

Article history:
Received 24 February 2014
Received in revised form
27 June 2014
Accepted 7 July 2014
Available online 20 August 2014

Keywords:
Bearing
Fault diagnosis
Monte Carlo methods
Optimization
Wavelet transforms
Vibrations

ABSTRACT

A general sequential Monte Carlo method, particularly a general particle filter, attracts much attention in prognostics recently because it is able to on-line estimate posterior probability density functions of the state functions used in a state space model without making restrictive assumptions. In this paper, the general particle filter is introduced to optimize a wavelet filter for extracting bearing fault features. The major innovation of this paper is that a joint posterior probability density function of wavelet parameters is represented by a set of random particles with their associated weights, which is seldom reported. Once the joint posterior probability density function of wavelet parameters is derived, the approximately optimal center frequency and bandwidth can be determined and be used to perform an optimal wavelet filtering for extracting bearing fault features. Two case studies are investigated to illustrate the effectiveness of the proposed method. The results show that the proposed method provides a Bayesian approach to extract bearing fault features. Additionally, the proposed method can be generalized by using different wavelet functions and metrics and be applied more widely to any other situation in which the optimal wavelet filtering is required.

1. Introduction

Vibration based bearing fault diagnosis is a hot topic in a recent decade because bearings are widely used in various machines, such as cooling fans [1,2], motors [3–5], trains [6,7], etc., to support rotating shafts and they are prone to suffer localized faults. When a bearing has a localized defect either on its outer race or its inner race, a series of random transients caused by rollers striking a defect surface are generated [8]. It is experimentally proven that wavelet transforms are naturally able to match the transients caused bearing localized faults [9].

When wavelet transforms are used, two aspects are extremely of concern. The first aspect is how to choose a proper wavelet function. The second aspect is how to choose proper wavelet parameters. Because the shape of a Morlet wavelet function is similar to the transients generated by bearing localized faults, optimization of the Morlet wavelet function for

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http://dx.doi.org/10.1016/j.ymssp.2014.07.005
0888-3270/

highlighting the transients corrupted by heavy noises attracts much attention in the recent years [10–18]. At the beginning, Lin and Qu [10] suggested that a wavelet entropy could be used to tune the shape of a Morlet wavelet function for matching bearing fault transients. To optimize a complex shifted Morlet wavelet function for matching bearing fault transients, Nikolaou and Antoniadis [11] proposed three different criteria to guide parameter selection. Qiu et al. [12] developed a method which combined Shannon entropy with a periodicity detection method to choose Morlet wavelet parameters for bearing fault diagnosis. He et al. [13] considered a differential evolution to automatically choose the optimal parameters of a complex Morlet wavelet. To reduce in-band noises existing in the signal filtered by the optimal complex Morlet wavelet, they further introduced a maximum likelihood estimation based soft-threshold method. Su et al. [14] used a genetic algorithm with an objective function of Shannon entropy to optimize a Morlet wavelet to extract bearing fault features. Bozchalooi and Liang [15] introduced a smoothness index, namely the ratio of a geometric mean to an arithmetic mean, to guide the parameter selection of a complex Morlet wavelet. Besides, they mathematically proved the upper bound of the smoothness index for processing bearing fault signals. Sheen [16] designed the proper parameters of a Morlet wavelet to retain one of resonance modes in terms of known resonance frequencies. Ericsson et al. [17] applied a Morlet based wavelet technique to process bearing fault signals and concluded that wavelet transforms are highly suitable to bearing fault diagnosis. Recently, Tse and Wang [18] introduced a new metric, called sparstiy measurement, to optimize the parameters of a complex Morlet wavelet to detect bearing localized faults.

In this paper, a general sequential Monte Carlo method, particularly a general particle filter, is introduced to optimize a complex Morlet wavelet filter for extracting bearing fault features. The contributions of this paper are illustrated as follows. First, a state space model of wavelet parameters is built. Second, the general particle filter is used to optimize the complex Morlet wavelet filter. Third, a joint posterior probability density function of wavelet parameters is mathematically derived. Moreover, the graphical relationship between center frequency and bandwidth is obtained by observing the joint posterior probability density function of wavelet parameters. At last, based on the joint posterior probability density function of wavelet parameters, the approximately optimal center frequency and bandwidth are determined and are used to perform an optimal filtering for enhancing the signal to noise ratio of bearing fault signals and extracting bearing fault features. According to our literature review, the use of the general particle filter for prognostics attracts much attention [19–29]. However, the use of the general particle filter for solving an optimization problem is very limited [30,31]. For prognostics, especially estimation of remaining useful life, a general procedure for the use of the general particle filter is summarized as follows. First, a state space model is built to reflect the health evolution of a component or system. Then, based on some known observations, the states used in the state space model are posteriorly updated by using the general particle filter. At last, a remaining useful life is derived by extrapolating the established state space model to a specified alert of failure threshold. For optimization, Zhou et al. [30] illustrated that a general particle filter was feasibly used to optimize a one-dimensional optimization problem. Based on Zhou's work, Eroğlu and Seçkiner [31] applied a general particle filter to get an optimized wind farm layout. So far, there is a still gap in research on optimization of a wavelet filter using the general particle filter for extracting bearing fault features. Additionally, because wavelet transforms are widely used in processing various signals, the proposed method can be generalized to analyze the local features hidden in other kinds of signals.

The rest of this paper is organized as follows. In Section 2, the principle of wavelet transforms and a general particle filter method are introduced. A general particle filter method based optimal wavelet filtering for extracting bearing fault features is presented in Section 3. Case studies related to simulated and real bearing fault signals are investigated in Section 4. Conclusions are drawn in Section 5.

2. Brief introduction of wavelet transforms and a general particle filter

2.1. Wavelet transforms

A wavelet transform $Wc(u,s)$ aims to measure a local similarity between a wavelet function (an artificial impulse function of zero average) $\psi(t)$ at scale s and translation position u and a real signal $c(t)$. According to this concept, the wavelet transform can be mathematically defined by an inner product operation [32]:

$$Wc(u,s) = \left\langle c(t), \frac{1}{\sqrt{s}}\psi\left(\frac{t-u}{s}\right)\right\rangle = \int_{-\infty}^{+\infty} c(t)\frac{1}{\sqrt{s}}\psi'\left(\frac{t-u}{s}\right)dt, \tag{1}$$

where ψ' is the complex conjugate of ψ and $\langle\cdot\rangle$ is the inner product operator.

Considering the relationship between an inner product operation and a convolution operation, the wavelet transform is redefined as follows:

$$Wc(u,s) = \int_{-\infty}^{+\infty} c(t)\frac{1}{\sqrt{s}}\psi'\left(\frac{t-u}{s}\right)dt = \int_{-\infty}^{+\infty} c(t)\frac{1}{\sqrt{s}}\psi'\left(-\frac{u-t}{s}\right)dt = c(u)*\frac{1}{\sqrt{s}}\psi'\left(\frac{-u}{s}\right), \tag{2}$$

where * is the convolution operator. Considering a fact that the convolution of two signals can be fast calculated by taking the inverse Fourier transform of the product of the Fourier transforms of the two signals, the computing time of the wavelet