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A method for extracting weak impact signal in NPP based on adaptive Morlet wavelet transform and kurtosis

Yanlong Cao [a, b], Mingzhou Liu [b], Jiangxin Yang [b, *], Yanpeng Cao [b], Weinan Fu [b]

[a] State Key Laboratory of Fluid Power Transmission and Control, College of Mechanical Engineering, Zhejiang University, Hangzhou, 310027, China
[b] Key Laboratory of Advanced Manufacturing Technology of Zhejiang Province, College of Mechanical Engineering, Zhejiang University, Hangzhou, 310027, China

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ABSTRACT

The monitoring and detecting of loose parts in the reactor coolant system is vital for the safe operation of a NPP (Nuclear Power Plant). The impact signal stimulated by the loose part hitting on other parts is used to analyze the mass and the position of the loose part. However, the impact signal is always interfered by the strong background noise caused by the vibration of primary circuit and other components. In order to remove the interfering noise and enhance the weak impact features, a modified denoising and extracting method based on adaptive Morlet wavelet transform and kurtosis is proposed in this paper. Firstly, the Morlet wavelet parameters are optimized using a modified algorithm based on the Shannon entropy. Then, the wavelet coefficients that contains the most information of impact are selected using the kurtosis index. Finally, after denoising the selected coefficients using the adaptive soft-thresholding method, the impact signal is reconstructed through the ICWT. The proposed method is tested through simulation experiment which takes steel balls as the real loose parts, and results show that it maintains good performance under low SNR. In addition, the proposed method is compared with another two denoising methods and shows much greater performance.

1. Introduction

Nowadays, nuclear energy has been widely used all over the world. The secure operation of a NPP has drawn more and more attentions. The prime circuit and the pressure vessels of the RCS are filled with high pressure cooling water for controlling the temperature of the reactor. Due to continuous scouring of the cooling water, parts like nuts or other fasteners inside the reactor may become loose or ever drop. Once a part in the RCS looses and drops, it hits the inwall of reactor pressure vessel and other components, which may cause serious damage to the nuclear power plant. So it is necessary to monitor the dropping of loose parts (Bechtold and Kunze, 1999; Morel and Puyal, 1991; Hanling et al., 1998; Lenain and Carlos, 2004; Tjhai et al., 2010; Zigler et al., 1985). The loose part monitoring system (LPMS), designed to monitor abnormal vibration signals from the reactor, is one of the most important elements which ensure the safe operation of nuclear power plant. Acceleration sensors are installed on the outwall of the reactor pressure vessels to detect the vibration caused by the loose parts' hitting on the inwall. Then the impact signals transduced from the sensors are used to analyze the mass and the position of the loose part by the LPMS. However, the machine activity and the circulating high pressure cooling water cause vibration of the prime circuit and the pressure vessel, which means the signals acquired by the LPMS are mixed with strong background noise. The influence of noise makes it more difficult to monitor and discover the impact signal. In addition, it decreases the precision of the subsequent analyzing. So, how to extract the relatively weak impact signal from strong background noise and enhance the SNR has always been a hot research issue. Researchers have made some achievements for the impact signal extraction, such as signal whitening using auto-regression model (Cao et al., 2012a, 2012b), method based on the eigenvector algorithm (EVA) (Yang et al., 2016), and methods based on wavelet transform (Lixian et al., 2004; Figedy and Oksa, 2005).

The vibration signal acquired from the RCS by LPMS is non-stationary because the frequency feature is time-varying. Wavelet analysis is a powerful time-frequency analysis method, which is especially suitable for non-stationary signal processing. It is widely used in the field of mechanical fault diagnosis (Lixian et al., 2004;

* Corresponding author.
E-mail address: yangjx@zju.edu.cn (J. Yang).

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Figedy and Oksa, 2005; Loutridis, 2006; Junsheng et al., 2005; Yang and Ren, 2004; Chanerley and Alexander, 2007; Qin et al., 2010). The Morlet wavelet is widely used as the mother wavelet for impulsive signal extraction at present because of its similarity with the impulse-like features of fault signals. In addition, its center frequency and bandwidth is adjustable. However, the parameters of the Morlet wavelet needs to be optimized in order to achieve optimal match with the signal. Bozchalooi and Liang (2007) proposed a new measurement index called the 'smoothed index' to find the optimized wavelet shape parameter and scale, but it was time consuming for it searched for the minimum on a two dimensional surface. Lin and Qu (2000) optimized the bandwidth parameter using the Shannon entropy, but they didn't optimize the center frequency. Nikolaou and Antoniadis (2002) combined the minimal Shannon entropy criterion and magnification factor criterion for the parameter optimization. Zhang et al. (2015). determined the center frequency using Local mean decomposition (LMD) and the bandwidth with minimum Shannon entropy criterion. Similar approaches have been proposed by other researchers (Liu et al., 2014; Barszcz and JabŁoński, 2011; Wang et al., 2013; He et al., 2009).

However, the impact feature has more energy distribution at higher frequency band. If the value of center frequency of the Morlet wavelet is set to be large, then the sample number of the wavelet should be large enough to satisfy the Nyquist Sampling Theorem. It will cost a large amount of calculation for the convolution. So the wavelet parameter optimization method based on minimum Shannon entropy criterion is modified by a mapping relationship in this paper. In this way, the search range of center frequency is diminished and so as the calculation of wavelet transform.

On the issue of weak impact signal extraction, a modified denoising and extracting method based on adaptive Morlet wavelet transform and kurtosis is proposed in this paper. Firstly, the center frequency and bandwidth parameter of the Morlet wavelet are optimized using the modified adaptive algorithm. Then the kurtosis of coefficients at each scale is calculated and is used to select the scales at which it exceeds the threshold. The corresponding coefficients are denoised based on Donoho's soft-thresholding method. Finally, the impact signal is reconstructed by ICWT from the denoised coefficients. The effectiveness and stability of the proposed method is testified by performances under different SNR. Comparison with another two denoising methods shows great superiority of the proposed method.

2. Method

2.1. Adaptive Morlet wavelet transform

The CWT (continuous wavelet transform) is the convolution of signal $x(t)$ and conjugated mother wavelet $\psi(t)$, which integrates all time of the signal multiplied by scaled, shifted versions of the mother wavelet, that is

$$W(a,\tau)=\frac{1}{\sqrt{a}}\int_{-\infty}^{\infty}x(t)\psi^{*}\left(\frac{t-\tau}{a}\right)\mathrm{d}t \tag{1}$$

where a is scale factor, τ is shifting factor and * denotes complex conjugation. $\frac{1}{\sqrt{a}}$ is used to ensure energy conservation. According to the convolution properties of Fourier transform, Eq. (1) can also be represented as

$$W(a,\tau)=\sqrt{a}F^{-1}\left\{X(f)\Psi^{*}(af)\right\} \tag{2}$$

where $X(f)$ and $\Psi^{*}(af)$ are the Fourier transform of $x(t)$ and $\psi^{*}\left(\frac{t-\tau}{a}\right)$, respectively. F^{-1} denotes the inverse Fourier transform. CWT is a time-frequency analysis method and it can be regarded as a special bandpass filtering process, which changes the frequency band by changing the analysis scale a. The mother wavelet dilate or shrink as the scale changes, and so as the time and frequency resolution. Thus the wavelet coefficients $W(a,\tau)$ gives information on $x(t)$ at different levels of resolution and also measures the similarity between the signal $x(t)$ and the mother wavelet $\psi(t)$ at each scale.

Since the shape of the Morlet wavelet is similar to the impulsive signal, it has been widely applied to detect the impact signals in mechanical systems. The Morlet wavelet can be defined as

$$\psi(t)=\frac{1}{\sqrt{\pi f_b}}\exp\left(-t^2\big/f_b\right)\cos(2\pi f_c t) \tag{3}$$

where f_b is the bandwidth parameter, f_c is the center wavelet frequency. The time domain waveform of the Morlet wavelet is a cosine wave decaying exponentially on both sides. The Fourier transform of the Morlet wavelet is written as

$$\Psi(f)=e^{-\pi^2 f_b (f-f_c)^2} \tag{4}$$

It shows that the Morlet wavelet has a shape of Gaussian window, the corresponding frequency band of which is $[f_c-1/2\sqrt{f_b},f_c+1/2\sqrt{f_b}]$. Thus, the Morlet wavelet can be regarded as a bandpass filter with changeable center frequency and bandwidth. The time and frequency resolution of the wavelet coefficients vary with the two parameters. The larger the center frequency f_c is, the quicker the oscillation of the Morlet wavelet. The frequency resolution decreases as the center frequency of wavelet increases. The bandwidth parameter controls the oscillation attenuation of the Morlet wavelet. The larger the f_b is, the more slowly the Morlet wavelet attenuates. When f_b tends to 0, the Morlet wavelet becomes a Dirac function which has the finest time resolution, and when f_b tends to be infinity, the Morlet wavelet degenerates to a cosine function which has the finest frequency resolution. So, the parameters need to be optimized in order to get the best time-frequency resolution.

Since “sparsity” is usually used as the rule for evaluating the wavelet and optimizing the wavelet parameter, the best parameters can be determined when the wavelet coefficients are sparsest. Shannon entropy is used to measure the sparsity, which is calculated as

$$H(f)=-\sum_{i=1}^{M}p_i\log p_i \tag{5}$$

where f is the parameter prepared to be optimized, M is the number of the scales, p_i is the distribution sequence obtained from wavelet coefficients, which is calculated by

$$p_i(f)=\left|W(a_i,\tau)\right|\Big/\sum_{j=1}^{M}\left|W(a_j,\tau)\right| \tag{6}$$

which satisfies $\sum_{i=1}^{M}p_i=1$.

For each given value of bandpass parameter f_b and center frequency f_c, there is a responding value of Shannon entropy. Then the curve of the relation between the entropy and f_b , and the one between the entropy and f_c can be obtained. The parameters corresponding to the minimum entropy are the optimal ones.

However, for a signal with high sampling frequency, the sampling