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Extraction of weak crack signals based on sparse code shrinkage combined with wavelet packet filtering

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ABSTRACT

Early crack signals in critical infrastructure components of major equipment are hardly to be extracted due to its low signal noise ratio (SNR). A de-noising method combined wavelet packet (WP) technology with sparse code shrinkage (SCS) is proposed in this study. Firstly, WP reconstruction technology is used to reserve the crack signal with a specified frequency range. That is, the signal is decomposed by Meyer wavelet into five layers, and the signal with the frequency range from 187.5 kHz to 609.375 kHz is reserved. Then SCS method removes noise within the specified frequency range. Namely, the probability density function (PDF) of the signal independent coefficients is estimated via the generalized Gaussian model (GGM) in the independent component analysis (ICA) space. The nonlinear de-noising is finished by utilizing maximum a posteriori (MAP) estimate. The results obtained by the combined method are compared with those generated by the SCS method and the WP de-noising method. It demonstrates that the combined method is the best one among the three methods in extracting weak signals. Its output SNR is −2.38 dB and the correlation coefficient (CC) is 0.54 when the input SNR is −20 dB. They are higher than those obtained by the SCS method (SNR −4.46 dB and CC 0.51). The WP method is the worst (SNR −3.54 dB and CC −0.003). Therefore, the combined method is quite suitable for weak signal extraction.

1. Introduction

Key components of mechanical equipment, such as wind turbine gearboxes, Francis turbine runners and Turbine rotors, are more prone to incur cracks and other faults, which can spell failure of entire devices and even give rise to serious security incidents. Accordingly, it is of great significance to detect and predict early faults in key components by taking advantage of acoustic emission (AE), which can ensure stable operation of these devices and reduce economic losses.

Early crack signals are usually weak and prone to be interfered by various noise [1,2]. For the sake of filtering out noise and recovering source signals from the received signals, noise reduction methods [3–6] mainly including time-domain analysis, frequency-domain analysis and time–frequency domain analysis have developed in recent years. Crack signals are generally non-stationary, whereas wavelet analysis is one of the most effective ways to deal with a non-stationary random signal. It assumes that the main frequency range of signals and noise is different, which can filter out noise by selecting a suitable filter while useful signals are retained [7]. However, this method is hardly to remove the noise that had the same frequency range with the useful signals. Furthermore, wavelet basis functions are specific. Sparse code shrinkage (SCS) [8,9] based on independent component analysis (ICA) has essential benefits over wavelet method. That is, it cannot be affected by noise with the same frequency range and is free from the interference owing to the strength of noise. Indeed, the basis function and shrinkage function are determined solely by the statistical properties of the signal alone [10]. Only a few neurons are active simultaneously after ICA transform. These neurons with substantial activities are retained and the components (purely noise) with small absolute values are set to zero. Then the noise is removed. The principle of SCS is firstly using ICA to find a basis functions matrix, which requires noise-free source signals as a prior knowledge [11–13]. Actually, the source signals generally

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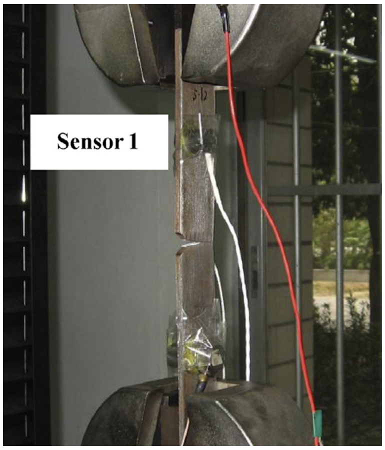

Fig. 1. Crack signal produced by tensile test.

cannot be obtained in advance, which makes the method be restricted in practical applications. Therefore, a noisy ICA model is used to choose the basis for sparse coding.

In this study, a de-noising method combined wavelet packet (WP) technology with SCS (i.e. the combined method) is used to extract weak crack signals due to their better noise reduction capability. WP technology is used to remove noise with the frequency range outside crack signals firstly. Then, the noise within the frequency band is removed by the SCS method. That is, the probability density functions (PDFs) of independent coefficients are estimated by the generalized Gaussian model (GGM) [14,15]. Then the basis functions of the crack signals are obtained by noisy mixture signals in a noisy ICA model. Finally, the crack signals are extracted by maximum a posteriori (MAP) [16] directly in ICA space.

In this study, the de-noising theory combined wavelet with SCS theory is introduced firstly. Then the experimental procedure is carried out in the following section. The results are compared with those obtained by the SCS method and the WP method.

2. De-noising theory

2.1. WP de-noising theory

WP analysis decomposes signals in a whole frequency range that differs from the binary discrete wavelet transformation. Each WP includes the information of signals with a specific frequency band, which are in diverse time windows and at various resolutions. Some packets contain important information while other packets are relatively useless.The crack signal $S(t)$ is decomposed into i levels according to the following equation [17],

$$\begin{cases} d^{(0,0)}(t) = S(t) \\ d^{(i+1,2j+1)} = \sum_k h(k-2t)d^{(i,j)}(t) \\ d^{(i+1,2j)} = \sum_k g(k-2t)d^{(i,j)}(t) \end{cases} \tag{1}$$

where $d^{(i,j)}$ represents the jth WP coefficients in the ith level; $i = 0, 1, 2, \ldots$; $j = 0, 1, \ldots, 2^i - 1$; $t = 1, 2, \ldots, 2^{I-i}$; $I = \log_2 N$; N is the number of t; h and g are decomposition filters. h is pertinent to the scaling function and g is pertinent to the wavelet function.

The WP coefficients are reconstructed into signals with different frequency bands. S_{i0} represents the reconstructed signal of $d^{(i,0)}$. Similarly, S_{ij} represents the reconstructed signal of $d^{(i,j)}$. Then, the total signal is

$$S = S_{i0} + S_{i1} + \cdots + S_{ij} + \cdots + S_{i,2^i-2} + S_{i,2^i-1} \tag{2}$$

2.2. SCS de-noising theory

ICA model with additive noise can be expressed as,

$$\boldsymbol{x} = \mathbf{A}\boldsymbol{s} + \boldsymbol{n} \tag{3}$$

where $\boldsymbol{n} = [n_1, \ldots, n_n]^T$ is a noise vector, $\boldsymbol{x}$ is an observed noisy signal vector, $\boldsymbol{s}$ is a pure signal vector. $\boldsymbol{n}$ and $\boldsymbol{s}$ are assumed independent of each other. The inverse of Eq. (3) is,

$$\boldsymbol{y} = \mathbf{W}\boldsymbol{x} = \boldsymbol{s} + \mathbf{W}\boldsymbol{n} \tag{4}$$

where $\mathbf{W} = \mathbf{A}^{-1}$ is a decoupling matrix and $\boldsymbol{y}$ is the estimated value of $\boldsymbol{s}$. The infomax optimization algorithm [18] is used to extract $\mathbf{W}$. Namely,

$$\mathbf{W} \leftarrow \mathbf{W} + \eta(\mathbf{I} - \varphi(\boldsymbol{s})\boldsymbol{s}^T)\mathbf{W} \tag{5}$$

where η is a learning rate factor and $\varphi(\boldsymbol{s}) = \frac{\partial \log F(\boldsymbol{s})}{\partial \boldsymbol{s}}$ is a transcendental function. $F(\boldsymbol{s})$ is the PDF, whose model is extremely vital and directly determines de-noising effects. The GGM is used in the study and expressed as

$$F(s; \alpha, \beta, \mu) = \left(\frac{\alpha}{2\beta\Gamma(1/\alpha)}\right) e^{\left(-\left|\frac{s-\mu}{\beta}\right|^{\alpha}\right)} \tag{6}$$

where $\beta = \sqrt{\frac{\sigma^2 \Gamma(1/\alpha)}{\Gamma(3/\alpha)}}$ is a scale parameter. $\Gamma(\cdot)$ is the Gamma function. μ, σ^2 and α are the mean, variance and shape parameter of the generalized Gaussian distribution, respectively, which are estimated using maximum likelihood criterion according to the observed signal $\boldsymbol{x} = [x_1, x_2, \ldots, x_N]$. Namely,

$$L(\boldsymbol{x}; \mu, \sigma, \alpha) = \log \prod_{i=1}^{N} F(x_i; \mu, \sigma, \alpha) \tag{7}$$

where $\boldsymbol{x}$ is an $M \times N$-dimensional matrix constructed by a single channel signal through splitting the column.

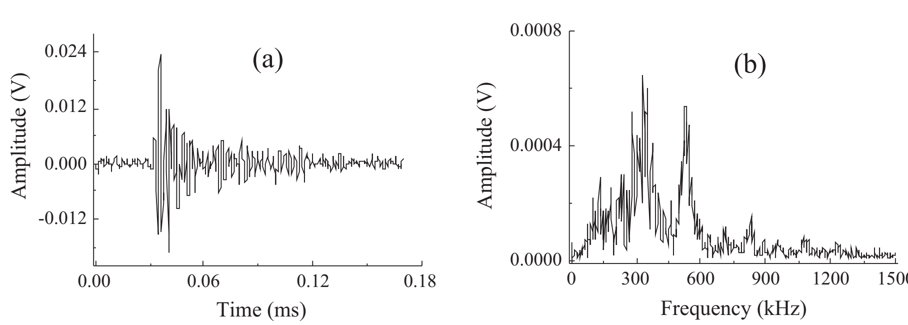

Fig. 2. Waveform (a) and spectrum (b) of crack signal.