AN ENHANCED TECHNIQUE FOR REACTOR COOLANT PUMP ABNORMALITY MONITORING USING CONTINUOUS WAVELET TRANSFORM BASED SPARSE CODE SHRINKAGE DE-NOISING ALGORITHM

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Abstract

Detection of the weak signature of degradation of the Reactor Coolant Pump (RCP) at early stage gives more time for maintenance reaction, safety decision-making and also provides economic benefits. An integrated and improved method to detect and identify abnormality using continuous wavelet transform based sparse code shrinkage de-noising algorithm is suggested in this work. For RCP roller bearings, periodic impulses indicate the occurrence of faults in the components. However, it is difficult to detect the impulses because they are rather weak and are often immersed in heavy noise. Existing wavelet threshold de-noising methods do not work well because they use orthogonal wavelets, which do not match the impulse very well and do not utilize prior information on the impulse. Therefore, in order to suppress any undesired information and highlight the features of interest, a new method for wavelet threshold de-noising is proposed in this paper. It employs an adapted Morlet wavelet as the basic wavelet for matching the impulse and also uses the Maximum Likelihood Estimation (MLE) for thresholding by utilizing prior information on the probability density function (pdf) of the impulse. By using MLE de-noising method, the inspected signal is analyzed in a more exact way even with a very low signal-to-noise ratio.

1. INTRODUCTION

NUR Reactor reached its first criticality in 1989. In the context of its modernization program and ageing management for its safety operation, increasing its availability and for extending its useful life, it was decided, among others actions, an improvement of the installation maintenance activities. In this way it was recommended a development of a strategy of vibration monitoring for the reactor primary coolant pump: first due to a safety necessity, in order to reduce the LOFA probability as it is explained in the installation Safety Analysis Report, and then to increase the reactor availability by the early detection of mechanical problems. The objective of this work was to create a diagnostic and vibration monitoring strategy for the hydraulic pump Reactor primary cooling loop. This strategy includes the determination of the defects to be observed and the vibration signal analysis techniques to be used. Usually, vibration signals are acquired from accelerometers mounted on the outer surface of a bearing case. The signals include vibrations from bearings, and from many other running parts. Damage to these parts usually causes the vibration level of the system to increase. However, the signals are always complex and it is difficult to diagnose a machine from such vibration signals. Thereby, until now, the Fast Fourier Transform (FFT) has been widely used in the vibration analysis of rotating machines and it is considered as a deterministic tool. Nevertheless, spectral analysis based on FFT has limitations; since weak signals, non-stationary signals and the effect of time-varying load can not be highlighted.

Besides, periodic impulses which indicate damaged races or rollers of roller bearings cannot be detected easily with the frequency spectrum because they are short in time duration and usually hidden in noises unless the crack is very big. Hence, de-noising and extraction of the weak signature from the noisy signal are crucial to fault prognostics, in which case features are often very weak and masked by the background noise. Consequently, in order to compensate spectral analysis weakness, the following method based on time–frequency analysis is adopted.

2. REVIEW OF WAVELET TRANSFORM

The wavelet transform of a finite energy signal x(t) with the analyzing wavelet $\psi(t)$ is the convolution of x(t) with a scaled and conjugated wavelet. Let $\psi_{a,b}(t)$ the daughter wavelets of the mother wavelet $\psi(t)$, which is derived by varying both the scale factor a and the shifting parameter b:

$$\psi_{a,b}(t) = \frac{1}{\sqrt{a}}\psi\left(\frac{t-b}{a}\right) \tag{1}$$

The wavelet transform is defined as:

$$W_{\psi}(a,b) = \langle x(t), \psi_{a,b}(t) \rangle = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} x(t) \psi^*_{a,b}(t) dt$$
(2)

 $W_{\psi}(a, b)$ represents the wavelet transforming coefficients derived from the signal x(t). The parameters of translation b and dilation a, may be continuous or discrete, the asterisk stands for complex conjugate. The factor $1/\sqrt{a}$ is used to ensure energy preservation. Eq. (2) indicates that the wavelet analysis is a time-frequency analysis, or a time-scaled analysis of a signal through dilation and translation. Wavelet transform is also reversible, which provides the possibility to reconstruct the original signal. A universal reconstruction equation for any type of wavelet is [5]:

$$x(t) = \frac{1}{C_{\psi}} \iint W_{\psi}(a,b)\psi_{a,b}(t)\frac{da}{a^2}db \qquad \text{with} \qquad C_{\psi} = \int_0^\infty \frac{|\Psi(f)|^2}{|f|}d\omega < \infty$$
(3)

3. MECHANICAL IMPULSE MODELLING

The system subjected to an impact load may be formulated as a single degree of freedom system which has the form of [9], [10]:

$$M\frac{d^{2}x}{dt^{2}} + C\frac{dx}{dt} + Kx = F\delta(t) \qquad \text{with} \qquad \delta(t) = \begin{cases} 1, & t = b \\ 0, & otherwise \end{cases}$$
(4)

Where x represents the displacement, M the concentrated mass, C the damping coefficient, K the stiffness of the system, F is a constant, and δ the instant impulse. The solution for Eq. (4) is [9], [10]:

$$x(t) = \frac{F + Mv_0}{M\omega_d} e^{-\zeta\omega_n t} \cos(\omega_d t) + \frac{x_0}{(1 - \zeta^2)^{1/2}} e^{-\zeta\omega_n t} \sin(\omega_d t - \psi)$$
(5)

 x_0 and v_0 indicate the initial displacement and velocity of the system, respectively. When the initial displacement and velocity of the system are zero Eq. (5) can be rewritten as [9], [7]:

$$x(t) = Ae^{-\zeta \omega_n t} \cos(\omega_d t) \qquad A = \frac{F}{M\omega_d}$$
(6)

4. CHOICE OF THE ANALYZING WAVELET

Eq. (6) indicates that the impulsive feature, which is caused by external impact load, is characterized by an oscillation with decaying amplitude. So according to the matching mechanism of wavelet transform, Morlet wavelet which is presented in Figure 2, could be a more suitable wavelet function for extracting such types of features because Morlet wavelet has a more similar shape to the impulsive feature. Morlet wavelet is derivative of a Gaussian function, so these wavelets have Gaussian window in frequency domain. In time domain, the Morlet wavelet can be expressed as [3]:

$$\psi(t) = exp^{-t^2/2}exp^{j\omega_0 t} \tag{7}$$

Where ω_0 is the central wavelet frequency. It is shown that the function decays exponentially on both sides. The modified Morlet wavelet function used in this paper is:

$$\psi(t) = \exp^{-\beta^2 t^2/2} \left(\exp^{j\omega_0 t} - \exp^{-(\omega_0)^2/2} \right) \tag{8}$$

The time expression of the Morlet wavelet can be further transformed to the frequency domain by applying Fourier transform, as shown below:

$$\Psi(\omega) = \Psi^*(\omega) = \sqrt{2\pi} \left(exp^{-(\omega - \omega_0)^2/2\beta^2} - exp^{-(\omega^2 + \omega_0^2)/2\beta^2} \right)$$
(9)

Which is an impulse frequency response with arbitrary centre frequency ω_0 . β is the shape parameter. When we let $\omega = 0$; the frequency response is $\Psi(\omega) = 0$. It is implied that $\int_{-\infty}^{\infty} \psi(t) dt = 0$. Thus, the mother analysis wavelet $\psi(t)$ satisfies the admissibility conditions. By applying the Fourier Parseval formula, wavelet transform of a signal x(t) using Morlet wavelet as analysis function can take the following alternative form:

$$W_{\psi}(a,b) = \frac{\sqrt{a}}{\sqrt{2\pi}} \int_{-\infty}^{+\infty} X(\omega) \Big(exp^{-(a\omega-\omega_0)^2/2\beta^2} - exp^{-(a^2\omega^2+\omega_0^2)/2\beta^2} \Big) e^{j\omega b} d\omega$$
(10)

It is obvious from Eq. (8) that the shape of the basic wavelet is controlled by parameter β . When β tends to be infinite, the Morlet wavelet becomes a Dirac function with the finest time resolution. With β tending to be 0, the Morlet wavelet becomes a cosine function which has the finest frequency resolution. Therefore, there is always an optimal β with the best time-frequency resolution for a certain signal localized in the time-frequency plane. An approach to find the appropriate parameters β that can construct an optimal wavelet transform is proposed in the next section. This modified Morlet wavelet function offers a better compromise in terms of localisation, in both time and frequency for a signal, than the traditionally Morlet wavelet function.

5. OPTIMAL MORLET WAVELET FOR IMPULSE DETECTION

The sparseness of wavelet coefficients is often used as the rule for evaluating the efficiency of wavelet transforms. The wavelet corresponding to the fewest and dominant wavelet transformation coefficients of a signal is ideal. Therefore, a variety of sparseness measurement criteria are proposed by researchers, such as: L_0 norm, L_p norm, Shannon entropy and kurtosis, etc. Among them, Shannon entropy is one of the well-adopted

sparseness criterion. Thereby, wavelet transform coefficients with minimal Shannon entropy can be treated as the sparsest result. Therefore, the corresponding shape factor β can be adopted as the optimal result. Shannon entropy is defined as [6]:

$$E_n = -\sum_i d_i * \log d_i \qquad \sum_{i=1}^n d_i = 1 \quad \text{and} \quad d_i = \frac{c_i}{\sum c_j} \tag{11}$$

Where c_i are wavelet coefficients. For different scales, these coefficients could be calculated from Eq. (10) which is convolution of x(t) and $\psi(t)$.

6. SPARSE CODE SHRINKAGE THRESHOLD USING THE OPTIMAL MORLET WAVELET TRANSFORM

The underlying model for the noisy signal is basically of the following form [3], $x(n) = s(n) + \sigma w(n)$. The objective of de-noising is to suppress the noise part w(n) of the signal x(n) and to recover s(n). The basic idea behind wavelet thresholding is that the energy of the signal to be identified will concentrate on a few wavelet coefficients while the energy of noise will spread throughout all wavelet coefficients.

In view of this, Hyvärinen has proposed a so-called sparse code shrinkage method 'SCS' to estimate non-Gaussian data under noisy conditions. It is based on the MLE principle and is successfully used for image de-noising. It demands that the non-Gaussian variable follow a sparse distribution. The pdf of a sparse distribution is characterized with a spike at point zero. To represent a sparse distribution, Hyvärinen proposes the following function form for a very sparse pdf [1], [2]:

$$p(s) = \frac{1}{2d} \frac{(\alpha+2)[\alpha(\alpha+1)/2]^{(\alpha/2+1)}}{\left[\sqrt{\alpha(\alpha+1)/2} + |s/d|\right]^{(\alpha+3)}}$$
(12)

Where: $d = \sqrt{E\{s^2\}}$ is the standard deviation of the impulse to be isolated and $\alpha = \frac{2-k+\sqrt{k(k+4)}}{2k-1}$ is the parameter controlling the sparseness of the pdf with $k = d^2 p_s(0)^2$. For an impulse whose pdf can be represented by Eq.(12), Hyvärinen proposes the following thresholding rule [1], [2]:

$$g(u) = \operatorname{sign}(u) \max\left(0, \frac{|u| - ad}{2} + \frac{1}{2}\sqrt{(|u| + ad)^2 - 4\sigma^2(\alpha + 3)}\right)$$
(13)

Where: $a = \sqrt{\alpha(\alpha + 1)/2}$, σ is the standard deviation of the noise. The function g(u) in Eq. (13) does not change much when α and d vary within a reasonable range [1]. The reconstruction results from shrunken wavelet coefficients using the thresholding rule given in Eq. (13) represent an approximation to the impulse.

7. SIMULATION STUDY

The impulses generated by damaged mechanical components often exhibit the shapes shown in Figure 1.a.



Fig. 1a. Simulated impulses; 1b. Simulated impulses with heavy background Gaussian noise.

The signal shown in Fig. 1.b is used to test the effectiveness of the proposed method to extract weak periodical impulses from the vibration signals with heavy background noise. The optimal Morlet wavelet is constructed based on the optimization algorithm. The minimal value of Shannon entropy is the optimal selection of β . The optimal parameter is found as: $\beta = 0.7$. Then, the SCS method is employed to further remove the noise and isolate the impulses. The extracted impulses are presented in Fig.2.a, from which it is observed that all the impulses immersed in noise are picked out.



Fig. 2a. Result by MLE thresholding; 2b. Result by Donoho's soft-thresholding.

To further prove the superiority of the proposed method, we also processed the simulation signal using Donoho's 'soft-thresholding de-noising', in which db4 wavelet is employed as the basic wavelet. Its de-noising result is shown in Figure 2.b. Though several true impulses are extracted, a lot of fake impulses also exist, which would affect the recognition of true impulses. However, the proposed approach isolates all the true impulses, and no fake impulses exist in the result Figure 2.a. The obtained results have shown that the proposed approach is very effective in the extraction of weak periodical impulses under heavy noise, and its performance is much better than the traditional methods.

8. EXPERIMENTAL RESULTS

To investigate the effectiveness of SCS de-noising method a series of vibration signals collected from a test rig and from a real machine which is the hydraulic pump of NUR Reactor primary cooling loop system as shown in figures Figure 3 and Figure 4 were analyzed for detecting faults. Vibration signals are collected from accelerometer mounted on the bearing housing.



Fig.3. Photograph of the test rig.

Fig.4. Tested hydraulic pump

A radial acceleration signal was picked up from the top of the tested bearing casing by a B&K 4371 transducer. Afterward, the signal is amplified and band-pass filtered by a B&K charge amplifier into the frequency range from 0.2 Hz to 20 kHz and recorded on the dual channel frequency analyzer B&K 2133. Acquisitions were transferred to the PC where Matlab programs were implemented to execute signal analyses and wavelet transforms calculations. Fault characteristic frequencies of bearings for fixed outer race related to common failures are geometrically estimated and reported by below formulas as follows:

$$f_i = \frac{N}{2} f_r \left(1 + \frac{d}{D_p} \cos \phi \right)$$
 and $f_e = \frac{N}{2} f_r \left(1 - \frac{d}{D_p} \cos \phi \right)$ (14)

Where f_r is the shaft revolution frequency, f_i and f_e are respectively, the inner and outer race defect frequency, N is the number of rolling elements, ϕ represents the contact angle, d and D_p are, respectively, the ball and the pitch diameters. Based on the geometric parameters and the rotational speed of ball bearings, fault characteristic frequencies of bearings are estimated and listed in the following Table 1.

Bearing type	(Test rig bearing) SNR 1205	(RCP bearing 1) SKF 6309	(RCP bearing 2) SKF 7309
Rotating speed (tr/min)	2986	2968	2968
Number of rolling elements	N = 12	N = 8	<i>N</i> = 12
Rotating frequency	$f_r = 49.77 \ Hz$	$f_r = 49.47 \ Hz$	$f_r = 49.47 Hz$
Ball Passing Frequency Inner Race - BPFI	$f_i = 353.99 \ Hz,$ $P_i = 0.0028 \ sec$	$f_i = 245.52 \ Hz$	$f_i = 352.31 Hz$
Ball passing Frequency Outer Race - BPFO	$f_e = 243.16 \ Hz,$ $P_e = 0.0041 \ sec$	$f_e = 151.21 Hz$	$f_e = 241.29 Hz$

Time and spectral amplitude representing the effect of the crossing of the balls over artificial spall in the test rig bearing is presented in Figure 5.



Fig.5. Vibration signal of the tested bearing and Power spectrum of the vibration signal.



Fig.6. Vibration signal waveform and power spectrum of RCP roller bearing.

On the grounds of these observations, it appears clear that the effectiveness of the spectral analysis for the bearing diagnostics proves inadequate to operate correct monitoring. The bearing faults cannot be diagnosed with certainty since spectra provide peaks, located at the fault characteristic frequencies, whose amplitudes are comparable to the corresponding ones related to the bearing in sound condition. Noise prevails over the effect of periodic impulses. Thereby, Donoho's soft-thresholding de-noising has been used to process the signals. One can note that no periodic impact is highlighted as presented in Fig. 7.a and Fig. 7.b below.



Fig. 7. The purified signals obtained by Donoho's soft-thresholding. (a): Test rig bearing signal, (b): RCP bearing signal.

Irregular intervals of the presented signal amplitude in Figure 7.a are not able to isolate the phenomenon by extracting characteristic defect period. However, through the inverse wavelet transform of the thresholded modulus, the reconstructed signal after de-noising by SCS method on the test rig bearing signal is shown in Figure 8.a. Distinct evenly spaced impulses can be observed from the reconstructed signal.



Fig.8. The purified signals obtained by the de-noising method based on adaptive Morlet wavelet and SCS; (a): Test rig bearing signal, (b): RCP bearing signal

The measured distance between two successive impulse peaks of the presented diagrams represents the characteristic defect period, i.e. the inverse of the characteristic frequency. Quasi-periodic intervals equal to 4.1 ms can be found in the figure. These quasi-periodic intervals are equivalent to the inverse of the ball-passing frequency outer-race (BPFO) which is 141 Hz as listed in Table 1. Hence, it can be concluded that the impulses are caused by the outer-race defect. Finally, it is worthwhile to observe from Fig.8.a, that only defect-induced impulse clusters are retained in the reconstructed signal. This indicates the effectiveness of the proposed algorithm in cancelling out the environmental noise even with small defect.

Thereby, the result of SCS de-noising method on RCP bearing signal is plotted in the Figure 8.b. One can observe on reconstructed signal using SCS de-noising method some random peaks without fixed periodicity, which are not related to faulty impulses. It can be concluded now that the reconstructed signal shown in Figure 8.b is the characterised signal pattern of the bearing without raceway defects on bearings. In view of that, by considering the results obtained, the proposed algorithm shows a great promise in highlighting the defect-induced impact in the vibration signals for bearing fault diagnosis.

9. CONCLUSION

The wavelet de-noising method proposed in this paper not only employs the adaptive Morlet wavelet based beta-optimization, as the basic wavelet, but also utilizes prior information on the pdf of the signals to be identified. The new adaptive SCS thresholding rule is effective at extracting the impulsive features buried in the noisy signals even when the SNR is very low. In applications, the SCS thresholding method can be used directly to detect impulses, because the pdf of any impulse signal is always very sparse. such results helps the machine operators not only in detecting the existence of faults on bearing at its initial stage, but also in identifying the causes of faults by using the information of the time intervals which is provided by reconstructed signal.

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