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Analysis of Acoustic Emission Signals using Wavelet Transformation Technique

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ABSTRACT

Acoustic emission (AE) monitoring is carried out during proof pressure testing of pressure vessels to find the occurrence of any crack growth-related phenomenon. While carrying out AE monitoring, it is often found that the background noise is very high. Along with the noise, the signal includes various phenomena related to crack growth, rubbing of fasteners, leaks, etc. Due to the presence of noise, it becomes difficult to identify signature of the original signals related to the above phenomenon. Through various filtering/ thresholding techniques, it was found that the original signals were getting filtered out along with noise. Wavelet transformation technique is found to be more appropriate to analyse the AE signals under such situations. Wavelet transformation technique is used to de-noise the AE data. The de-noised signal is classified to identify a signature based on the type of phenomena.

Keywords: Acoustic emission, wavelets, wavelet transform, discrete wavelet transformation, continuous wavelet transformation, coherence estimation function

1. INTRODUCTION

Acoustic emission (AE) technique is one of the versatile nondestructive techniques widely used for materials research, online process and structural-integrity monitoring because of its potential for detection and location of dynamic events. AE is defined as the class of phenomenon whereby transient elastic waves are generated by rapid release of energy from localised sources in a material[1]. The AE occurs as a series of short impulsive packets of energy. The energy thus released from the packet travels as spherical wavefront and can be picked up from the surface of materials using highly sensitive transducers. The wave thus picked up by the transducer is converted into an electrical signal, which on suitable processing and analysis can reveal valuable information about the source.

While carrying out the AE testing, it is often found that the background noise is very high. To identify the original signal, it is necessary to understand the types of noise sources and to ensure the elimination of their influence. Different types of noise encountered during AE testing are mechanical noise, hydraulic noise, electrical (electromagnetic) noise, cyclic noise, welding noise, pseudo noise, etc.

Due to the presence of these noises, it becomes difficult to make the right interpretation of the AE signature. To analyse the AE signal, it is essential to eliminate or reduce the noise. The noise can be reduced using filters, or by decreasing the gain and/or increasing the threshold[2]. But this may affect the AE data, i.e., some of the low-amplitude AE signals may not be detected and also some of the

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AE signals may get filtered out with frequency components in the same range as that of noise.

Though various signal processing tools like Fast Fourier Transform and Windowed Fourier Transform are available for analysis of these signals, it is found that the wavelet transform (WT) is more appropriate. In this paper, wavelet transform technique is used to de-noise the transient AE waves. Further, the de-noised signal is classified based on the type of event or fault present in the original AE signal from the noise-influenced data. The results are found to be satisfactory.

2. WAVELET TRANSFORM

Wavelets are mathematical functions that cut up data into different frequency components, and then study each component with a resolution matched to its scale. These basis functions are short waves of limited duration that have an average value of zero, which are scaled wrt frequency, thus the name wavelets is used.

In general, the wavelet $\psi(t)$ is a complex valued function. A general wavelet function is defined as in Eqn (1) as:

$$\Psi_{s,\tau}(t) = |s|^{1/2}\,\psi\left[\left(\frac{t-\tau}{s}\right)\right] \quad (1)$$

This shift parameter τ, determines the position of the window in time and thus defines which part of the signal $x(t)$ is being analysed. In WT analysis, frequency variable ω is replaced by scale variable s and time shift variable t_1 is replaced by τ. The WT utilises these wavelet functions, and performs the decomposition of the signal $x(t)$ into weighted set of scaled wavelet functions $\psi(t)$. The main advantage of using wavelets is that they are localised in space[3].

The most important properties of wavelets are the admissibility and the regularity conditions and these are the properties, which gave wavelets their names. It can be shown that square integral functions $\psi(t)$ satisfying the admissibility condition, can be used to first analyse and then reconstruct a signal without loss of information.

Fourier transform has a serious drawback, that is losing time information after transforming to frequency domain. But wavelet is small wave. This small means that a wave is localised in time domain, so its energy is finite. This localised property makes possible to allow time domain analysis of given signals without loss of information. Two types of wavelet transformation techniques, viz., discrete wavelet transformation technique (DWT) and continuous wavelet transformation (CWT) technique are being used for signal analysis.

3. SIGNAL ANALYSIS METHODOLOGY

The study mainly deals with the removal of noise and recovering of signal from the noisy data using WT. Before discussing about the work, the method of de-noising is described.

3.1 De-noising of Signal

The model for the noisy signal is expressed as

$$S(n) = f(n) + \sigma\, e(n) \quad (2)$$

where time n is equally spaced. In the simplest model, suppose that $e(n)$ is a Gaussian white noise and σ is the noise level, the de-noising objective is to suppress the noise part of the signal s and to recover f. The de-noising procedure proceeds in three steps, namely: (a) decomposition, (b) detail coefficients thresholding, and (c) reconstruction. In de-noising concept, thresholding plays a major role, which is to be selected carefully.

3.1.1 *Thresholding*

The hard threshold filter H_h removes coefficients below a threshold value t_0, determined by the noise variance. This is sometimes referred to as the 'keep or kill' method. The soft threshold filter Hs shrinks the wavelet coefficients above and below the threshold. Soft thresholding reduces coefficients towards zero. Thresholding is the cause of this loss of information[4].

3.2 Signal Analysis

Test signals for different conditions are obtained. The test signals are corrupted by random noise present at all instants of time. The signals are extracted from noisy signals.

The DWT is applied on the test signal. The DWT of the test data with different wavelets are computed, and after threshold, the signal is reconstructed, and the reconstructed plots using different wavelets are displayed simultaneously. The reconstructed signals are devoid of noise but there exits slight variations between one signal and the other due to differences in the wavelets employed to decompose the test data signal. The de-noised signals[6] are then selected. If more than one signal is selected, an average of all the selected signals is computed and is displayed as the extracted signal.

The signatures of different test signals are typically low-frequency signals enveloped by relatively high-frequency background noise[7,9,10]. So to de-noise these signals, the detail coefficients are heavily thresholded. In the present study, all the detail coefficients, at all the levels, are made zero and the signal is reconstructed back.

3.2.1 Classification of Signals

The de-noised signals are further classified employing two techniques namely: (a) CWT and (b) coherence estimation function (CEF).

The CWT is superior to all other transforms in providing an exact time-frequency plot of the signal. Thus using the CWT, one can make use of the time and frequency domains information of the signal for classifying it[8]. Every time domain signal has a distinct CWT plot depending upon the times, at which various frequencies are present in the signal. So, to classify the de-noised signal as to one among the set of reference signatures, the CWT of all the waves in the set of reference signatures are also obtained using the same wavelet ('sym8' in this case) and the plots are compared using least mean square error between two signals.

The nearest neighborhood method is based on the smallest Euclidean distance between two inputs. The classification using above two methods yielded the same results for all the test data.

In the CEF method, the coherence of the de-noised signal with all the signals in the set of reference signatures is obtained and plotted. The area under the coherence curves gives an estimate of the closeness of the de-noised signal with those in the set of reference signatures in terms of frequency components present. The bigger the area, the more is the resemblance. Thus, the de-noised signal is classified. Use of both the methods increase the reliability of the classification.

3.3 Test Setup

3.3.1 Reference AE Signatures

For any kind of signature identification to be made, a reference database shall be generated. In the present work, AE signals (signatures) corresponding to the phenomenon like hydraulic noise, crack (burst) and rubbing/fretting of fasteners were recorded as reference database for event classification. The test setup was made in such a way that these signatures were recorded in noise-free environment. A sample signal was also generated using MATLAB to verify the results after processing. These reference signatures (Figs 1 to 4) were kept as a database to verify and classify the processed data recorded during the pressure vessel testing. Figures 1 to 4 show the reference AE signals from pure hydraulic noise, crack, rubbing of fasteners, and the sample signal. These signals are used to verify the processed test data wrt signature identification.

3.3.2 Test Data

Three sets of test data were recorded during pressure testing of the pressure vessel. These test data were recoded in the presence of heavy background noise. The data was processed as per the signal analysis methodology described (Section 3.2).

3.3.3 Results

The de-noised versions of the test-1 data, test-2 data, and test-3 data using various wavelets are shown in Figs 5 to 7, respectively. The subtle variations in the de-noised signals are due to different wavelets used in this study. The test signals are de-noised using sym8, coif3, db8, bior3.9, and haar

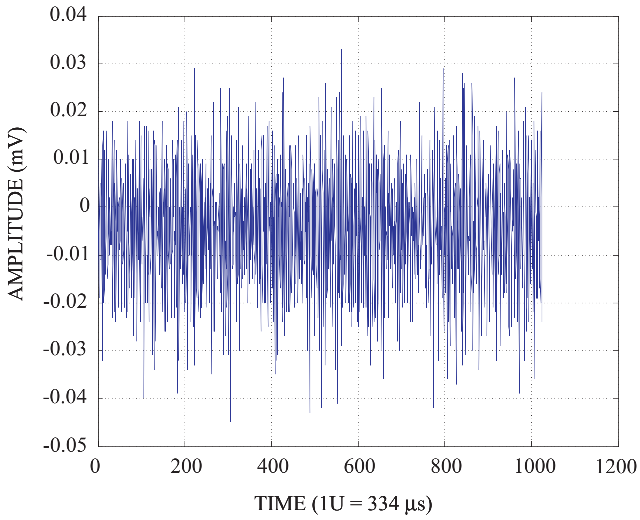

Figure 1. Reference AE signal for hydraulic noise.

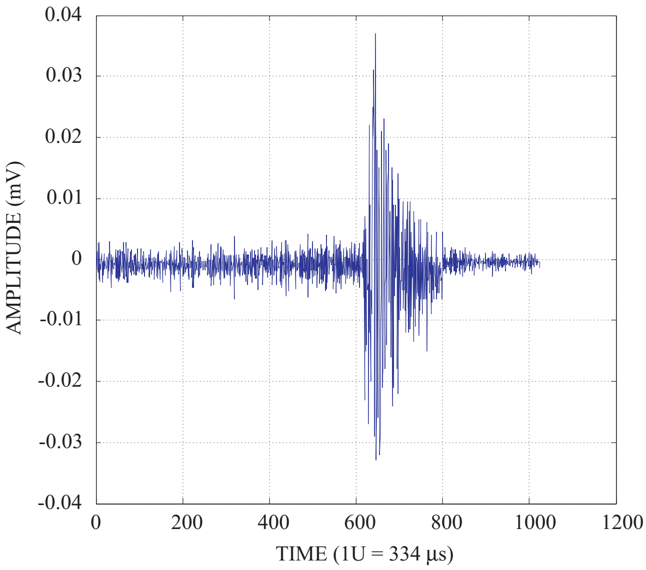

Figure 2. Reference AE signal for crack.

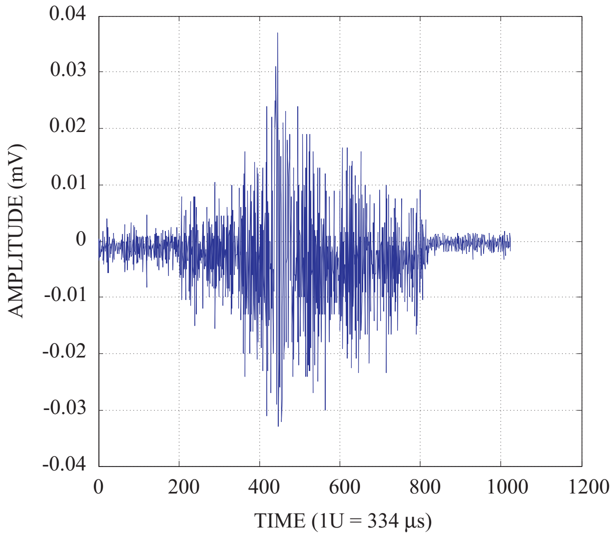

Figure 3. Reference AE signal for rubbing.

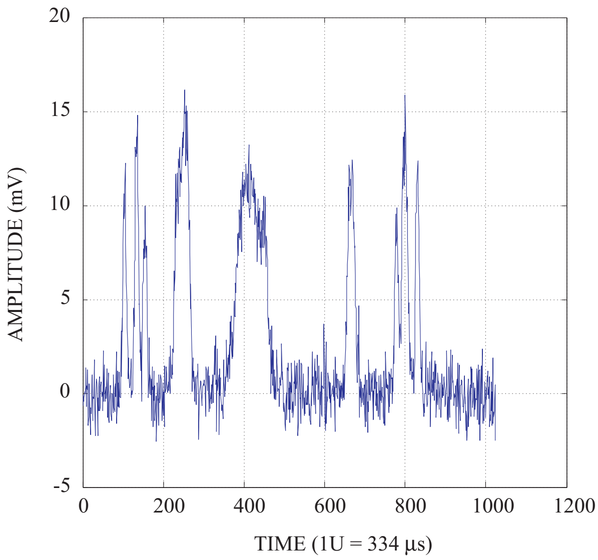

Figure 4. Reference sample signal.

wavelets. Most appropriate de-noised signal was selected as required. Whenever more than one de-noised signals were obtained from different wavelets, their average was taken.

The average of de-noised signals is shown in Figs 5-8. After de-noising the test signals, these are only classified accordingly to the type of the phenomenon occurred during the pressure test. To classify the de-noised signal and the averaged signal, the CWT of the signal was computed. The classification was done on the CWT patterns and using the CFE. The CWT of the reference signals and the de-noised signals were found to have good match, indicating that the processing methodology adopted was appropriate. The same methodology is applied in real time during pressure vessel testing to identify the phenomena related to hydraulic noise, cracks and rubbing of fasteners.

4. CONCLUSIONS

The recovery of AE signal from noisy data, acquired during pressure testing of pressure vessel, was carried out using transformation technique.

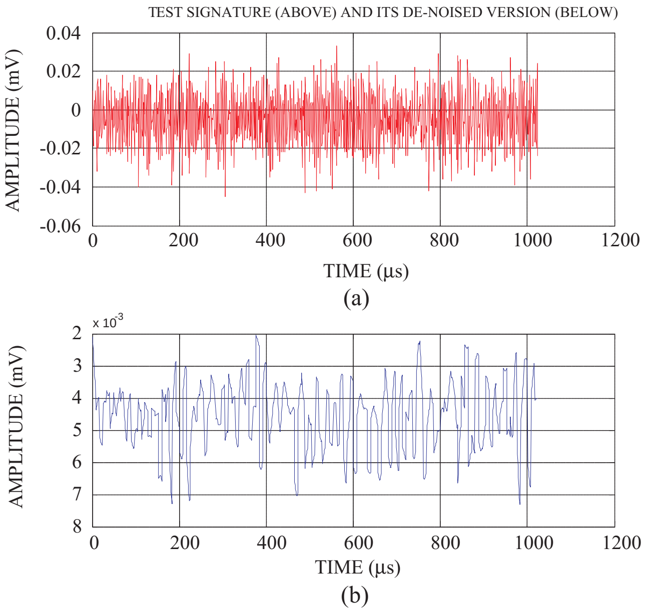

Figure 5. (a) Test-1 data and (b) de-noised data showing signal from hydraulic noise.

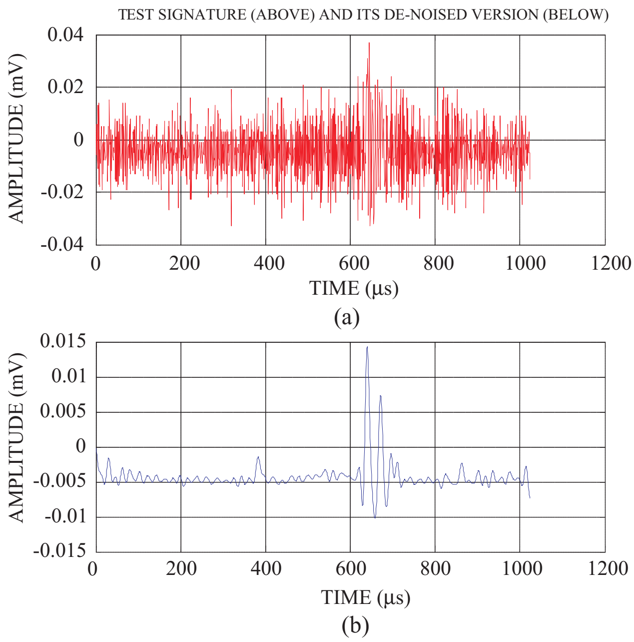

Figure 6. (a) Test-2 data and (b) de-noised data showing signal from a crack.

The de-noised signal was also analysed to identify the signature of the phenomenon during pressure testing. Data has been analysed for the phenomena related to hydraulic noise, crack, and rubbing of fasteners. Further, these signals were also classified employing CWT and CFE methods. A good correlation was seen between the reference signatures of the phenomenon and the actual test data.

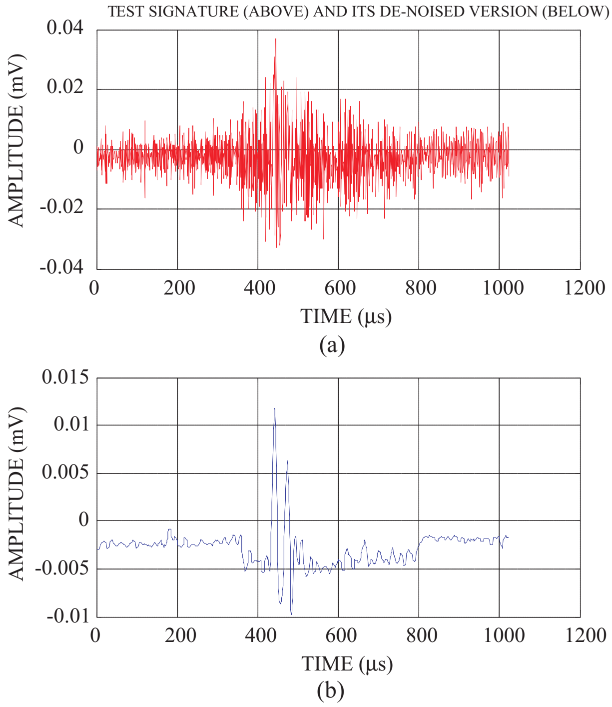

Figure 7. (a) Test-3 data and (b) de-noised data showing signal from rubbing of fasteners.

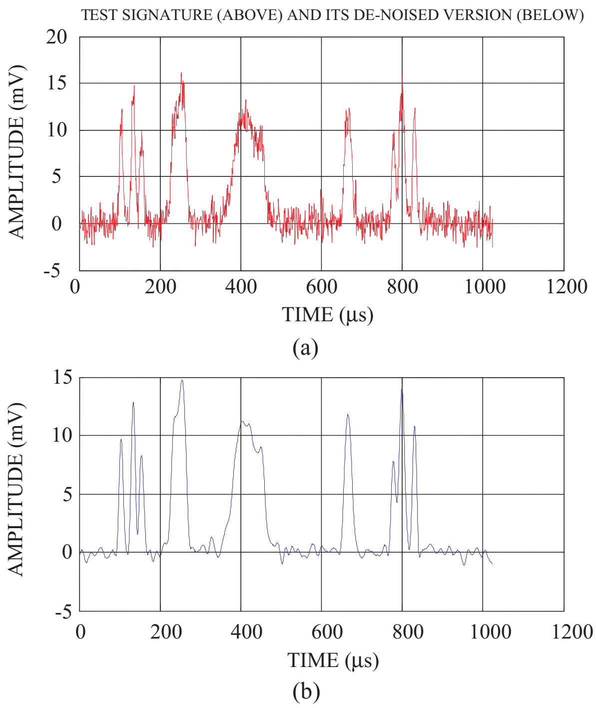

Figure 8. (a) Sample signal and (b) de-noised data.

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