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Ultrasonic NDE for Internal Defect Detection in Multi-layered Composite Materials by Multi-resolution Signal Decomposition

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Abstract: Ultrasonic NDE has been a well known approach to investigate material's microstructures, mechanical properties and structure integrity in industry. The internal structure of a material and position of anomalies can be recognised by the reactions of different materials to ultrasound. However, the interpretation of ultrasound signals is difficult in composite material inspection task due to the fact that the ultrasonic pulse is reflected not only by the defect occurred within the material but the microstructures and multiple lay ups of the material. This phenomenon causes the backscattering noise to hinder the real defect's signal during the inspection. Backscattering noise exists in multiple frequencies. The objective of this study was to develop a new noise reduction method to enhance the defect detectability in coarse-grained structure material such as composites materials. This method increases Signal-to-noise Ratio (SNR) by means of decomposing the original signal into multiresolution representations. To prevent the loss of information, the signal is processed in both temporal and frequency domain. The proposed method has been tested on simulated signal and Glass Fiber Reinforced Plastics (GFRP) laminates. Both simulation and experimental results showed that this method can significantly reduce grain noise while preserving the resolution of the original signal of the defect.

Key words: Ultrasound, signal-to-noise ratio, wavelets, composite materials, glass fiber reinforced plastics

INTRODUCTION

Non-destructive testing (NDT and E) is the application of technical methods to examine materials or components in terms of their macroscopic or microscopic compositions, integrity and mechanical properties without impairing their future usefulness (ASTM International, 1999). This technology has been widely applied in industrial and civil engineering for new and in-service health monitoring of materials. Major NDT and E techniques are X-radiography, thermography, eddy current, acoustic emission and ultrasonic testing. The adoption of these techniques in an application is highly dependent on the material properties of the test object and the nature of the flaws (Ng *et al*., 2011). Typically, NDT and E techniques are based on the analysis of the transmitted signals. Among these techniques, ultrasonic testing has always been prominent in NDE and T as it offers a great advantage in which it is applicable on all kinds of materials, having high penetration depth and flexible (Shull, 2002). Ultrasonic NDE works on the principal of detecting and interpreting the time delayed of the reflected ultrasound waves by boundaries (D'Orazio *et al*., 2008). The boundaries could be the back surface of the material or a discontinuity (e.g., crack, porosity or delamination). The maximal amplitude of ultrasound echoes is used as a means to characterize the nature, size and orientation of defects. For any kind of material, scattering of ultrasound waves occurs as ultrasound pulse is induced to the material during testing. In homogeneous material, the scattering is not apparent and can be neglected (Rubbers and Pritchard, 2003). However, in the case of coarse-grained structure such as composite materials, the scattering effect may annihilate the return echoes and obscure the defect visibility. This signal drowning problem arises when the wavelength of the reflected ultrasound signal by a defect and the scattering of the constituent particles in the propagating medium are at the same order of magnitude. These echoes are distributed randomly in time and known as backscattering noise. In the preliminary work, the technique of providing high SNR has been utilized to resolve the echoes associated with large grained and highly attenuated material (Bilgutay *et al*., 1981;

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Kraus and Goebbles, 1980). Basically, there are two ways to achieve high SNR in ultrasonic testing: (1) Optimum frequency selection of an acoustic wave for detecting specific discontinuity and (2) Increasing the ultrasound wavelength. The latter method also limits the detectability of small discontinuity.

By signal processing means, significant work to increase SNR includes Split-spectrum Processing (SSP) (Bosch and Vergara, 2008), Expectation-maximization (EM) algorithms (Benammar *et al*., 2008), Hilbert transform (Drai *et al*., 2000), Hilbert-Huang transform (Kazys *et al*., 2008) and Discrete Wavelet Transform (DWT) (Liang and Que, 2009). SSP works on the principal of frequency diversity to identify the actual defects from grain boundary. This method decomposes the received broadband signal into a number of smaller frequency bands by means of digital filtering. Later, each band is inversed Fourier transform to obtain the individual frequency shifted signals. These individual signals are then worked on amplitude minimization (SSP-AM) or polarity thresholding (SSP-PT) to improve SNR (Ericsson and Stepinski, 2002). The shortcoming of SSP is the application of single window for all frequencies in the Fourier transform. This yields the same resolution of the signal analysis at all locations in the time-frequency plane. Benammar *et al*. (2008) work showed that the performance of EM algorithm is comparable to SSP-PT for thickness measurement and defect localization but EM algorithm requires more computation work as deconvolution is carried out in time domain. Hilbert transform is very sensitive to signal drowned in noise especially experimental signals (Drai *et al*., 2000). Hilbert-Huang transform offers the adaptive time-frequency decomposition for the received signal but this method is highly dependent on the material and defects to be examined. In other words, different material or defects may require the selection of different sets of intrinsic modes. DWT gives a very good result to enhance the detectability of discontinuity in ultrasonic signal processing (Zhong and Oyadiji, 2007; Tang and Abeyratne, 2000). Wavelet transforms offer an infinite set of possible basic functions to approximate the measured signal. Dilation and shifting of mother wavelet enables the access of signal information in different scales. Thus, this technique offers a great flexibility to signal interpretation. Wavelet de-noising (Tokmakci and Erdogan, 2009) has been widely used as noise filtering and pattern recognition tool for image processing due to the advantage of wavelet transform. Many thresholding rules have been suggested by (Lazaro *et al*., 2002). The objective of this study is to develop a new wavelet-based multiresolution signal decomposition method. This method decomposes the received signal into multiresolutional means by a selected mother wavelet. In each state of scaling, minimization is implemented inside each frequency band to discard the noisy data. After a few repetitions, it can be observed that the amplitude of backscattering noise is averaged whilst the real defect's signal amplitude becomes apparent. The main advantage of the proposed method is that threshold rules of the ordinary wavelet de-noising are replaced by the minimization approach for wavelet shrinkage as an improvement to the more flexible detection algorithms.

DISCRETE WAVELET TRANSFORM

The fundamental principal of wavelet theory is to analyze according to scale (Graps, 1995). As a function of zero average (Mallat, 1998), a mother wavelet can be dilated with a scale parameter s and translated by *l*:

$$\forall s,l, s \wedge l \in Z : \left(\Phi_{s,l}(t) = 2^{-\frac{s}{2}} \Phi\left(2^{-s}t - l\right) \right) \tag{1}$$

Where, s is the wavelet's width and *l* is the wavelet's position. In DWT, a finite energy signal f can be decomposed over the wavelet orthogonal basis as Eq. 1 to become:

$$f = \sum_{s=-\infty}^{+\infty} \sum_{l=-\infty}^{+\infty} \left\langle f, \Phi_{s,l} \right\rangle \Phi_{s,l} \tag{2}$$

in which each partial sum of f:

$$d_s(t) = \sum_{l=-\infty}^{+\infty} \left\langle f, \Phi_{s,l} \right\rangle \Phi_{s,l} \tag{3}$$

brings out the detail variations at the scale of 2^s. Recursively applying Eq. 2 decomposes the signal f into a matrix of sequence coefficients $d_1, d_2, ..., d_M, a_M$. Figure 1 illustrates the wavelet decomposition of

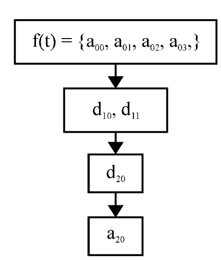

Fig. 1: Two-band wavelet transform for a four-sample signal f(t)

signal f. Vice versa, adding up these layers of computed coefficients following the sequence ultimately resembles the original signal f:

$$\|f\|^2 = \|a_M\|^2 + \sum_{m=1}^{M} \|d_M\|^2 \tag{4}$$

where, a_M and d_M are the approximation and the detail coefficients, respectively. D_M are representations of signal f at higher scale as m increases.

WAVELET-BASED MINIMIZATION

This section discusses a multiresolution signal decomposition method to improve the detection of actual defect's signal embedded in noise. The approach of minimization based on signal polarity is used to accentuate the actual defect's signal amplitude out of backscattering noise. Figure 2 illustrates the scheme of the proposed wavelet-based minimization signal processing. The method consists of three successive steps, namely (1) Signal decomposition by multiple scales and translations, (2) Grain noise averaging and (3) Signal reconstruction. Firstly, the input noisy signal is decomposed up to N levels of approximation and detailed coefficients using a selected mother wavelet. Minimization is then carried out to average the noise amplitude in each frequency band. Lastly, the altered coefficients are synthesised to resemble the original signal.

The algorithm shown in Fig. 3 summarizes the procedure of the proposed wavelet-based minimization for defect detection. DWT is applied to separates the input signal $X = x_0, x_1,..., x_n$ into two frequency bands. In this operation, the wavelet coefficients are halved to become approximations and details by a chosen two-channel symmetric filter banks (Abdelnour and Selesnick, 2005). Thus, Eq. 2 can be rewritten as:

$$r(n) = \sum_{k=-\infty}^{\infty} c_k \phi(n-k) + \sum_{k=-\infty}^{\infty} \sum_{j=0}^{\infty} d_{j,k} \psi(2^j n - k) \tag{5}$$

where, c_k and $d_{j,k}$ denotes the approximation and detailed coefficients, respectively. j is the scaling factor and k is the shifting factor. Given Eq. 5, two sets of coefficient series (high-pass and low-pass) are generated. It is noted that c_k depicts the high-pass coefficients and $d_{j,k}$ depicts the lowpass coefficients. To avoid the signal overflow, down sampling by two is implemented as stated in step 3 of the algorithm. Step 4-7 suppresses the small value coefficients that represent the noise content. The value of

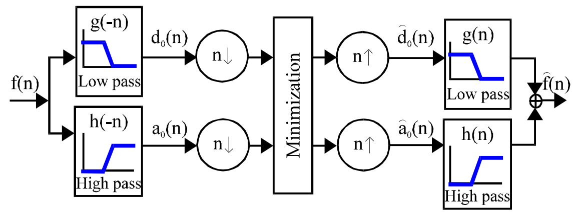

Fig. 2: Computation scheme of the proposed wavelet-based minimization signal processing for f(n)

Step 1:	Give j and k, define a mother wavelet as described in Eq. 1
Step 2:	Separate signal f into high and low frequency bands by a filter bank
Step 3:	Down sample c_k and $d_{j,k}$
Step 4:	Set $X_{hi} = c_k$ and $X_{lo} = d_{j,k}$
Step 5:	For each element pair in x_{hi} and X_{lo}, compare their value sign
Step 6:	If the element pair in X_{hi} and X_{lo} contains same value sign, set $A_i = \min(X_{lo,i}, X_{hi,i})$
Step 7:	Else set $A_i = 0$
Step 8:	Up sample the processed c_k and $d_{j,k}$
Step 9:	Inverse DWT of the processed c_k and $d_{j,k}$

Fig. 3: The wavelet-based minimization algorithm

the amplitude of the processed signal is set to zero when the data set exhibits polarity reversal in which the zero-mean valued presented by the backscattering noise signal. Step 9 recombines the processed approximation and detail coefficients back into the original signal by means of inverse DWT. To compensate the aliasing in step 3, up sampling is carried out by padding zeroes between the sample data. Step 4-7 repeats for each iteration of decomposition (step 2). This algorithm assumes Gaussian distribution, N(0,1) for the backscattering noise.

EXPERIMENTAL SETUP

To demonstrate the practical capability of the proposed method, the wavelet-based minimization is tested on simulated signals and actual signals from ultrasonic testing on coarse-grained structured material. The simulated signals are generated by Field II (Jensen, 1996; Jensen and Svendsen, 1992), an ultrasound field simulation program.

Simulated ultrasound data: The measured ultrasound signal s(t) can be expressed as the sum of two components (Song and Que, 2006):

$$s(t) = y(t)+n(t) \tag{6}$$

where, y(t) is the acoustic signal and n(t) is the embedded noise. Signal s(t) is the ultrasound data that is distorted by noise. A typical ultrasonic signal y(t) was generated using the simulated 1 MHz transducer. White Gaussian noise was then added to the waveform. Figure 4 shows the noisy received signal with SNR = 0.1 and 1024 sample length. To construct a full-range ultrasound signal in a pulse-echo testing setup, back wall echo and the simulated defect's echo were added to y(t).

Experimental system: A four- layered GFRP laminates ($[0^0]_4$) with the dimension of 200×200×3 mm were prepared. The test specimen has Mylar-induced delamination at the depth of 0.89 mm from the front surface of the specimen. A single transducer with 1 MHz centre frequency and diameter of 31.24 mm acted as transmitter and receiver of ultrasonic signals. The ultrasonic testing system worked as follows: The transducer, working on piezoelectric effect (Diamanti *et al*., 2005), transformed electrical pulses into mechanical vibrations to generate ultrasonic waves (pulse). The transducer was placed onto the GFRP specimen and the pulse generated was transmitted into the test object (GFRP). The pulse travelled through the test object and responded to the object's a boundary (i.e., voids, cracks or delamination). The returned signal (echo) was then transformed back into electrical pulses that can be observed on an oscilloscope. The depth of the defect (d) of the test object from the surface is measured by Eq. 6:

$$d = \frac{vt}{2} \tag{7}$$

where, v is the velocity of ultrasonic wave in the material and t is Time of Flight (TOF) measurement of the reflected echo. Figure 5 shows the response of the pristine specimen and the response of the damaged specimen. The time for the maximum peak of two successive pulses for both specimens was captured and compared. The presence of defects in the damaged specimen causes the difference of the duration between two pulses. A 2 kS sec^{-1} sampling rate was used to acquire the signals from the receiver.

EXPERIMENTAL RESULTS

The purpose of this study is to suppress n(t) (Eq. 6) as the effect of grain noise scattering in ultrasonic testing. The results of the proposed wavelet-based minimization method were compared to the related state-of-the-art methodology, namely SSP-AM and SSP-PT.

Results from simulated data: Figure 6 shows the outcomes of the proposed wavelet-based minimization algorithm, SSP-AM and SSP-PT, respectively on simulated signals. The filter bank in SSP algorithm was made up of ten 100 Hz-bandwidth Gaussian filters with 10% overlapping. It can be observed that wavelet-based minimization algorithm outperformed SSP-AM and SSP-PT to achieve 9.87 dB for SNR. It shows 79.8% improvement of SNR for the simulated noisy data. It is due to the multiresolutional scaling of the proposed algorithm to highlight the noise level during signal decomposition. Each iteration of signal decomposition scales the original data by 2^j where, j = 1, 2, 3,..., n. The original data is in other words zoomed out by the power of two in time domain before the minimization is carried out. This method

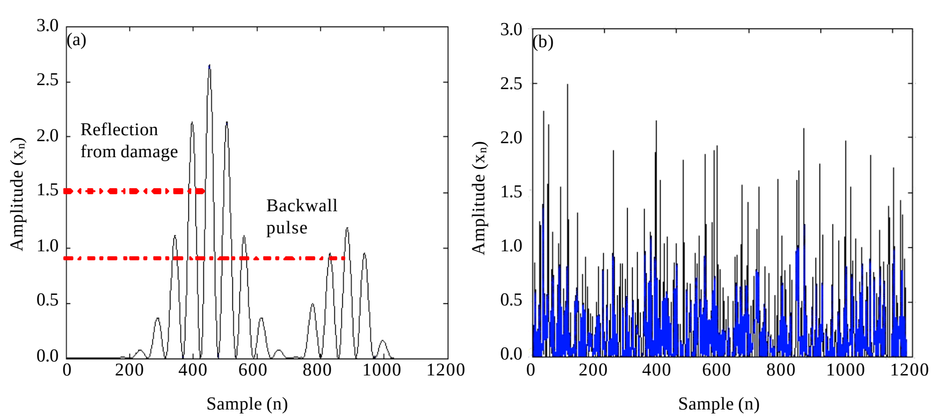

Fig. 4(a-b): (a) Noiseless signal with backwall and simulated defect's echoes separated by Δt = 4.5 µsec (equivalent to 3.46 mm) and (b) Noise signal with SNR = 0.1

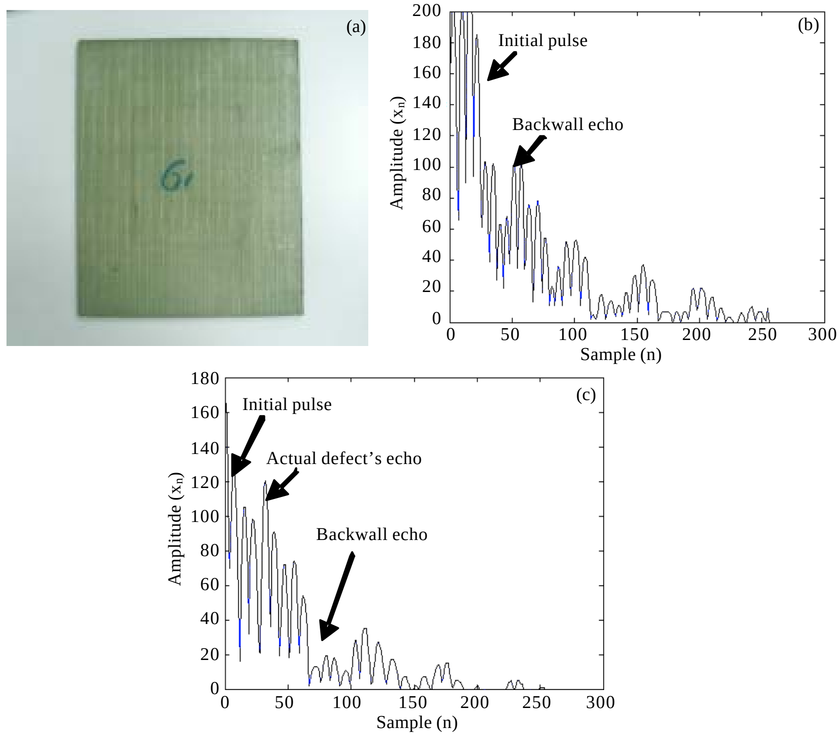

Fig. 5(a-c): (a) GFRP specimen with Mylar induced delamination, (b) Experimental signal from pristine specimen and (c) Experimental signal from damaged specimen

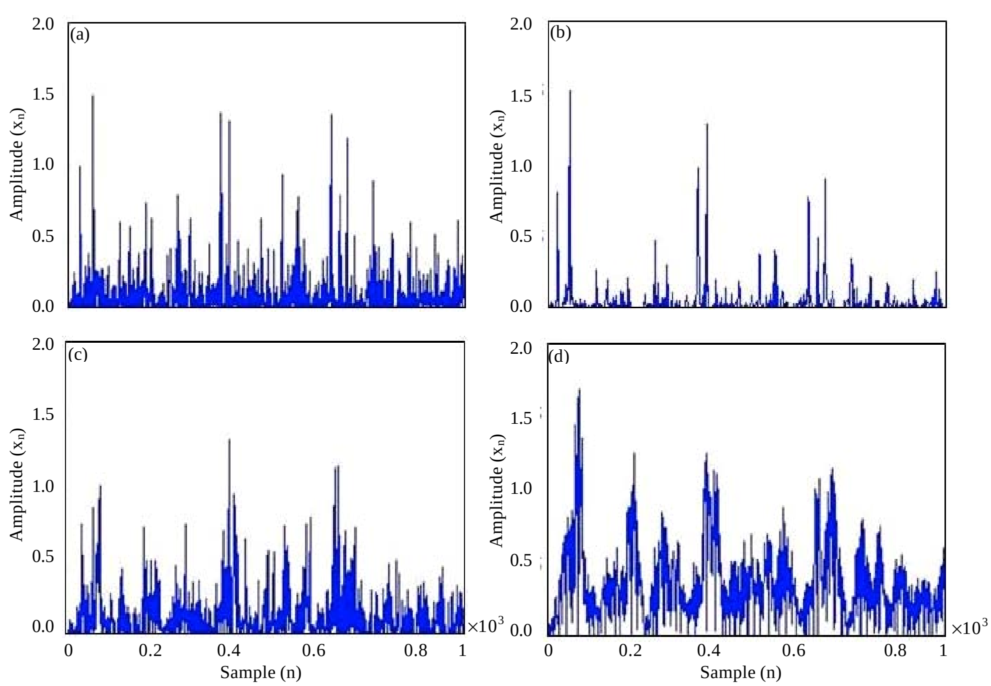

Fig. 6(a-d): (a) Simulated noisy signal, (b) Processed signal by wavelet-based minimization, (c) Processed signal by SSP-AM and (d) Processed signal by SSP-PT

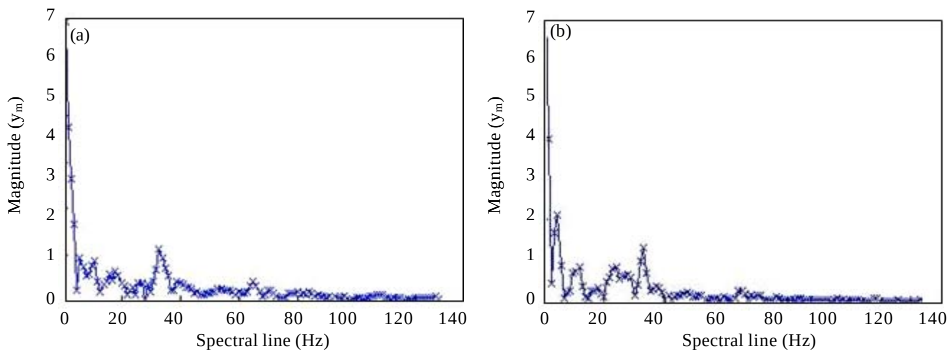

Fig. 7(a-b): Frequency domain of (a) Experimental signal and (b) Windowed experimental signal by Hanning window

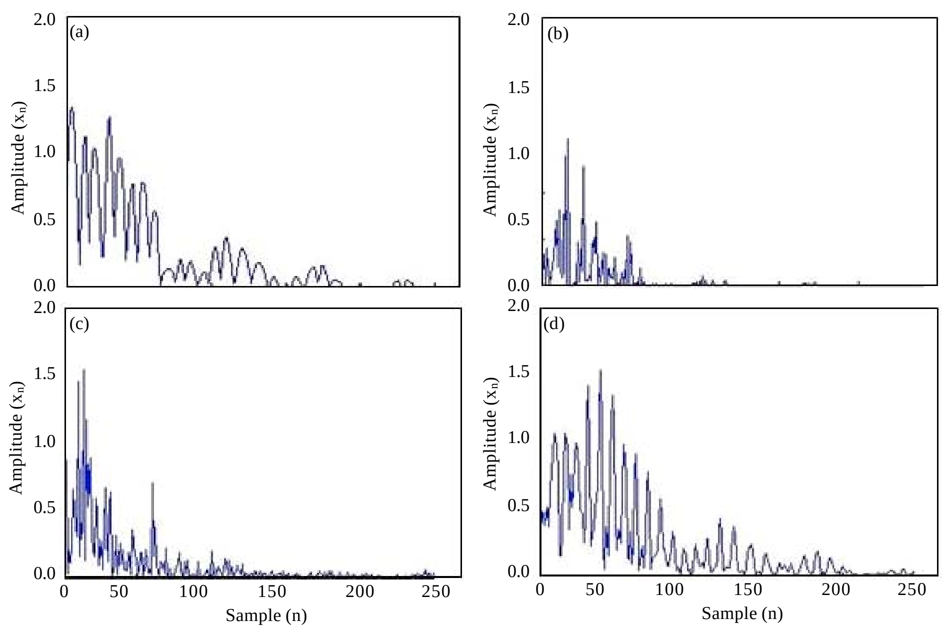

Fig. 8(a-d): (a) Experimental signal from damaged GFRP, (b) Processed signal by wavelet-based minimization, (c) Processed signal by SSP-AM and (d) Processed signal by SSP-PT

also works well on separating the close-spaced echoes that occurs especially on thin laminate examination. Figure 6d shows that SSP-PT outperformed SSP-AM to obtain higher SNR. SSP-PT captures the polarity reversal for the data in the presence of only grain noise and sets the corresponding amplitude value to zeroes at time instants. Otherwise, minimum amplitude value of the data set is depicted. SSP-AM is instead based on amplitude averaging to reduce grain noise.

Results from experimental data: Damage was introduced by inserting a piece of Mylar between the first and second layer of the GFRP pre-preg. The delamination was approximately 100 mm long and located 0.89 mm depth from the front surface of the specimen. A-scan data was obtained from the experimental system discussed. In practical ultrasonic testing, a range of frequency is generated during pulse excitation. To prevent dispersion that can cause spectral leakage in frequency spectrum analysis, a Hanning window was applied on the received data prior to the execution of the proposed algorithm. Figure 7 illustrated the frequency spectrum of the windowed signal. It can be observed that the frequency width was sharpened. This method separates two frequency components that are close to each other and have almost equal amplitude to prevent lose of information in spectrum analysis.

Figure 8 shows the outcomes of the proposed wavelet-based minimization algorithm, SSP-AM and SSP-PT on experimental data. The proposed

Table 1: Comparison of the SNR of different methods

	Defect's signal	Grain noise	Signal to noise ratio	SNR (dB)
Original data	1.220	0.520	2.346	7.407
Wavelet-based minimization	2.095	0.686	3.054	9.697
SSP-AM	3.158	1.310	2.411	7.644
SSP-PT	1.385	0.548	2.527	8.052

wavelet-based minimization algorithm shows 30.9% improvement of SNR for the experimental data. The performance of wavelet-based minimization algorithm, SSP-AM and SSP-PT towards SNR is shown in Table 1. The proposed method accomplished 9.70 dB for SNR. It can be noted that the SNR improvement from 7.41 to 9.70 dB for the measured signal is significant. The proposed method exhibited good performance to detect the defect's signal compared to SSP-AM and SSP-PT.

CONCLUSION

Defect detection in coarse-grain structured material has been a great challenge in ultrasonic NDE. The backscattered noise due to multi-centred pulse reflection from the grain boundary may hinder the actual defect's signal. A multi-resolution signal decomposition method based on wavelet principal has been developed to improve the detection of defect in coarse-grained materials. This algorithm splits the received signals into multiple frequency bands by varying the scales of a chosen mother wavelet. This principle works on the hypothesis that the signal data exhibits polarity reversal when the dataset contains only grain noise. Thus, for each band of the signal having the same polar direction, the minimum amplitude value is selected. Otherwise, zero value is chosen. The processed signals are then recombined to resemble the original signal. The proposed method has shown to improve SNR in simulated and experimental data. The experimental results showed that this method successfully resolved the close-spaced echoes in composite materials. This improvement has the benefit of more effective flaw detection within noise level in complex ultrasound NDE such as composite materials. As future work, the proposed method is applied on ultrasonic C-scan to enhance the flaw visibility.

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