Multi-damage Detection with Embedded Ultrasonic Structural Radar Algorithm using Piezoelectric Wafer Active Sensors through Advanced Signal Processing

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ABSTRACT
The embedded ultrasonic structural radar (EUSR) algorithm was developed by using piezoelectric wafer active sensor (PWAS) array to detect defects within a large area of a thin-plate specimen. EUSR has been verified to be effective for detecting a single crack either at a broadside or at an offside position. In this research, advanced signal processing techniques were included to enhance inspection image quality and detect multiple damage. The signal processing methods include discrete wavelet transform for signal denoising, short-time Fourier transform and continuous wavelet transform for time-frequency analysis, continuous wavelet transform for frequency filtering, and Hilbert transform for envelope extraction. All these signal processing modules were implemented by developing a graphical user-friendly interface program in LabVIEW.

The paper starts with an introduction of embedded ultrasonic structural radar algorithm, followed with the theoretical aspect of the phased array signal processing method. Then, the mathematical algorithms for advanced signal processing are introduced. In the end, laboratory experimental results are presented to show how efficiently the improved EUSR works. The results are analyzed and EUSR is concluded to have been improved by using the advanced signal processing techniques. The improvements include: 1) EUSR is able to provide better image of the specimen under monitoring; 2) it is able to detect multi-damage such as several cracks; 3) it is able to identify different damage types.

Keywords: embedded ultrasonics structural radar, piezoelectric wafer active sensor, signal processing, de-noising, Continuous Wavelet transform, Discrete Wavelet transform, Hilbert transform, envelope extraction, nondestructive evaluation, structural health monitoring, piezoelectric, multi-damage detection, cracks, ultrasonic, Lamb waves, SHM, PWAS, NDE, CWT, DWT

1. INTRODUCTION

Embedded nondestructive evaluation (NDE) is an emerging technology that will allow transitioning the methods of conventional ultrasonic to embedded systems for structural health monitoring (SHM). SHM requires the development of small, lightweight, inexpensive, unobtrusive, minimally invasive sensors to be embedded in the structure with minimum weight penalty and at affordable costs. Such sensors should be able to scan the structure and identify the presence of defects and incipient damage.

Current ultrasonic inspection of thin wall structures (e.g., aircraft shells, storage tanks, large pipes, etc.) is a time consuming operation that requires meticulous through-the-thickness C-scans over large areas. One method to increase the efficiency of thin-wall structures inspection is to utilize guided waves (e.g., Lamb waves) instead of the conventional pressure and shear waves. Guided waves propagate along the surface of thin-wall plates and shallow shells. They can travel at relatively large distances with very little amplitude loss and offer the advantage of large-area coverage with a minimum of installed sensors. Guided Lamb waves have opened new opportunities for cost-effective detection of damage in aircraft structures. Traditionally, guided waves have been generated by impinging the plate obliquely with a tone-burst from a relatively large ultrasonic transducer. Snell’s law ensures mode conversion at the interface, hence a combination of pressure and shear waves are simultaneously generated into the thin plate. However, conventional Lamb-wave probes (wedge and comb transducers) are relatively too heavy and expensive to be considered for widespread deployment on an aircraft structure as part of a SHM system. Hence,
different type of sensors than the conventional ultrasonic transducers is required for the SHM systems.

The phased arrays are a method of creating a virtual beam that sweeps the horizon through “electronic steering”, i.e. without mechanical motion. The beam steering effect is attained through controlled delays of the signals going to the various array sensors. In 1979, a method for dynamic delays without changing delay lines became available [13]. A comprehensive review of using time-delay techniques in ultrasonic imaging was given in [5]. Images obtained from real fatigue cracks and discussions of the optimum-imaging algorithm are reported by [9]. A self-focusing phased-array methodology was presented to generate Lamb waves for defect detection in [4]. The advantages of using a phased-array set of transducers in ultrasonic testing have been realized at an early stage and published in [10]. A phased-array system consisting of an integrated array system using piezoelectric film was used for the NDE of bonded lap joints [12]. A method was described which implemented oversampling in beamforming architecture and used digital recording technique to dynamically obtain beamforming without degrading the image quality [6]. A model was developed to compute the 3-D far-field acoustic pressure distribution of the wave radiated from an ultrasonic linear phased array with finite dimensions of the array elements [16]. A phase array transducer and a multi-channel time-delay system were used to achieve the controlled excitation of various guided-wave modes [11].

2. EMBEDDED ULTRASONIC STRUCTURAL RADAR ALGORITHM

The ultrasonics-based active SHM method uses piezoelectric wafer active sensors (PWAS) to transmit and receive Lamb waves in a thin-wall structure (Figure 1). The principle of operation of the embedded ultrasonic structural radar (EUSR) is derived from two general principles: (1) The principle of guided Lamb wave generation with PWAS; (2) The principles of conventional phased-array radar.

Figure 1  Piezoelectric wafer active sensors (PWAS) attached to a thin-wall structure

The guided Lamb waves generated by PWAS have the important property that they stay confined inside the walls of a thin-wall structure, and hence can travel over large distances. In addition, the guided wave can also travel inside curved walls, which makes them ideal for applications in the ultrasonic inspection of aircraft, missiles, pressure vessel, oil tanks, pipelines, etc. This has been proved by our curvature experiment [8]. Lamb waves can exist in a number of dispersive modes. However, through smoothed tone-burst excitation and frequency tuning, it is possible to confine the excitation to a particular Lamb wave mode, of carrier frequency $f_c$, wave speed $c$, and wave length $\lambda = c/f_c$. Hence, the smoothed tone-burst signal generated by one PWAS is of the form

$$s_x(t) = s_0(t) \cos 2\pi f_c t$$

where $s_0(t)$ is a short-duration smoothing window that is applied to the carrier signal of frequency $f_c$ between times 0 and $t_p$.

The principle of conventional phased-array radar is applied to the PWAS-generated guided waves, assuming a uniform linear array of M sensors (PWAS), with each PWAS acting as a pointwise omni-directional transmitter and receiver. The PWAS in the array are spaced at the distance d, which is assumed much smaller than the distance r to a generic, far-distance point, P. Since $d << r$, the rays joining the sensors with the point P can be assimilated with a parallel fascicle, of $\phi$. Therefore, for the $m^{th}$ PWAS, the distance will be shorter by $m(d \cos \phi)$. If all the PWAS are fired simultaneously, the signal from the $m^{th}$ PWAS will arrive at P quicker by $\Delta_m(\phi) = m(d \cos \phi) / c$. Yet, if the PWAS are not fired simultaneously, but with some individual delays, $\Delta_m, m = 0,1,\ldots,M-1$, then the total signal received at point P will be
where $1/\sqrt{r}$ represents the decrease in the wave amplitude due to the omni-directional 2-D radiation, and $r/c$ is the delay due to the travel distance between the reference PWAS ($m = 0$) and the point P. (Here wave-energy conservation, i.e., no dissipation, is assumed.)

Transmitter beamforming: If we have $\delta_m = m\Delta\phi$, then Equation (2) becomes

$$s_p(t) = \frac{1}{\sqrt{r}} \sum_{m=0}^{M-1} s_t\left(t - \frac{r}{c} + \Delta_m(\phi) - \delta_m\right)$$

(2)

There is an $M$ times increase in the signal strength with respect to a single PWAS. This leads directly to the beamforming principle that if $\delta_m = md\cos(\phi_m)/c$, and since $\Delta_m = md\cos(\phi)/c$, then constructive interference (beamforming) takes place when $\cos(\phi) = \cos(\phi_m)$, i.e. at angles $\phi = \phi_m$ and $\phi = -\phi_m$. Thus, the forming of a beam at angles $\phi_m$ and $-\phi_m$ is achieved through delays in the firing of the sensors in the array.

Receiver beamforming: if the point P is an omni-directional source at azimuth $\phi_m$, then the signals received at the $m^{th}$ sensor will arrive quicker by $md\cos(\phi_m)/c$. Hence, we can synchronize the signals received at all the sensors by delaying them by

$$\delta_m(\phi_m) = \frac{md}{c}\cos(\phi_m)$$

(4)

Pulse-echo method: Assume that a target exists at azimuth $\phi_0$ and distance R. The transmitter beamformer is sweeping the range in increasing angles $\phi$ and receives an echo when $\phi = \phi_0$. The echo will be received on all sensors, but the signals will not be synchronized. To synchronize the sensors signals, the delays $\delta_m(\phi_0) = md\cos(\phi_0)/c$ need to be applied. The original signal is

$$s_p(t) = \frac{M}{\sqrt{R}} s_t\left(t - \frac{2R}{c}\right)$$

(5)

At the target, the signal is backscattered with a backscatter coefficient, A. Hence, the signal received at each sensor will be

$$\frac{A \cdot M}{R} s_t\left(t - \frac{2R}{c} + \Delta_m(\phi)\right)$$

(6)

The receiver beamformer assembles the signals from all the sensors with the appropriate time delays

$$s_R(t) = \frac{A \cdot M}{R} \sum_{m=0}^{M-1} s_t\left(t - \frac{2R}{c} + \Delta_m(\phi) - \delta_m\right)$$

(7)

Constructive interference between the received signals is achieved when $\delta_m = md\cos(\phi_0)/c$. Thus, the assembled receive signal will be again boosted $M$ times, with respect to the individual sensors

$$s_R(t) = \frac{A \cdot M^2}{R} \sum_{m=0}^{M-1} s_t\left(t - \frac{2R}{c}\right)$$

(8)

Then the target range can be calculated as

$$R = \frac{ct\phi}{2}$$

(9)

Therefore, what we can determine the location of the damage by measuring the time delay between the receive signal, $s_R(t)$ and the transmit signal $s_t(t)$.

### 3. MATHEMATICS OF THE ADVANCED SIGNAL PROCESSING APPROACHES

#### 3.1. Short-time Fourier Transform (STFT)

Fourier transform is a dominant analytical tool for frequency analysis. However, it uses infinite sinusoidal waves as the base for frequency analysis to decompose signal into harmonics and will produce amplitude vs. frequency and phase vs. frequency spectra. The assumption of infinite sinusoidal waves results in the loss of time information when...
transforming from the time domain to the frequency domain. In the same time, Fourier transform assumes that the
signals are stationary and can only provide spectrum changing with respect to time while most practical signals are
nonstationary. To overcome this deficiency, the short-time Fourier transform (STFT) was developed. STFT allows
the representation of signals in both time and frequency domains through the used of a time windowing function [1].
By using windowing technique, STFT modifies Fourier transform by making it analyze only a small section of the
signal at a time. STFT employs a time-limited window to break up the signal into small time segments and assumes
that signal is stationary over the analyzed window. As the window function is shifted in time to incrementally cover
the whole signal length, continuously overlapped Fourier transforms are performed. Hence a spectrum of the
evolution of the signal with time and frequency is achieved. A set of windows are available for STFT windowing
processing. Suppose we have a signal $x(t)$ and a general window function $w(t)$. The spectrogram of the signal is

$$X(t, \omega) = |X_\omega(t)|^2 = \frac{1}{2\pi} \int e^{-j\omega t} x(\tau) w(t-\tau) d\tau \tag{10}$$

This type of spectrum is named spectrogram since it contains both time and frequency information. In order to get
more detailed information of the signal, we want the window size to be as short as possible. However, window size
can not be shortened unlimitedly due to the Heisenberg uncertainty principle

$$\Delta \omega \cdot \Delta t \geq \frac{1}{2} \tag{11}$$

In addition, if we cut the signal into too small parts, these parts will lose the connection to the original signal and
therefore cannot indicate the original signal’s properties. Another parameter affecting STFT is the step size. When
sliding the window along the time axis, the moving step needs to be small enough to eliminate the sidelobe effect.
The shortcoming of STFT method is that it uses a fixed length window for carving up the signal. For the high
frequency part of a nonstationary signal, a short window is preferred while for the low frequency part, a longer
window is preferred. Such adaptable windowing cannot be achieved with STFT. However, it can be achieved with
other methods, such as the wavelet transform (WT).

### 3.2. Wavelet transform

Wavelet analysis is introduced due to its ability to analyze time signals which contain non-stationary features at
many different frequencies. Generally, wavelet transform is a windowing technique with variable-size windows. It
can detect the trends, breakdown points, discontinuities in higher derivatives, self-similarity, etc. [2]. Similar to
Fourier transform, wavelet transform provides a tool for decomposing signals into elementary building blocks,
which are called ‘wavelets’. The difference between WT and FT is that the wavelets used in WT are aperiodic
signals while FT uses periodic sinusoidal signals. In addition, the WT decomposition is localized in both time and
frequency domains because the wavelets are built up from the dilation and shifting of a mother wavelet. This
characteristic makes WT especially useful for the analysis of nonstationary or aperiodic signals. Figure 2 lists
several often used wavelet signals.

The potential advantages of WT are: (a) provides different resolution according to the wavelet scales; (b) removes
redundancy associated with the STFT; (c) has better concentrated signal energy than Fourier transform. In addition,
wavelet based filtering by means of discrete wavelet decomposition can extract features which could be related to
structural damage.

#### 3.2.1. Continuous wavelet transform (CWT)

Continuous wavelet transform (CWT) is defined in a way similar to STFT, except that instead of a basis of infinite
sines and cosines of different frequencies, the CWT uses a basis of dilated and shifted versions of a single basis
function called mother wavelet [2]. The CWT of signal $s(t)$ is constructed by using a dilated and shifted version of
the mother wavelet, $\psi(t)$, in the form

$$CWT(a, \tau) = \frac{1}{\sqrt{a}} \int s(t) \psi\left(\frac{t-\tau}{a}\right) dt \tag{12}$$

where $a$ is the dilation of the mother wavelet and $\tau$ is the shift of the mother wavelet with respect to the examined
signal. The mother wavelet $\psi(t)$ should meet the zero-bias requirement

$$\int \psi(t) dt = 0 \tag{13}$$
If $\psi(t)$ is considered as the impulse response of a bandpass filter, the CWT can be understood through bandpass analysis [2]. As scale $a$ increases, the center frequency and the bandwidth of the bandpass filter also increases. The CWT resolutions depend on the scale. At low scale (high frequency), the time resolution is good, but the frequency resolution is bad due to the fact that the wavelet is localized well in time but poorly in frequency. The magnitude squared $|CWT(a,\tau)|^2$ is defined as the scalogram.

![Several often used wavelets](image)

Figure 2 Several often used wavelets: (a) Daubechies wavelet; (b) Haar wavelet; (c) Coiflet wavelet; (d) Symlet wavelet

A GUI LabVIEW program has been developed to allow us to select the most satisfactory mother wavelets, wavelet analysis levels, and scales. CWT automatically produces a spectrum of time-scale vs. amplitude. Corresponding spectrum of time-frequency vs. amplitude is generated according to the quasi-relationship between the scale and the corresponding frequency

$$f = \frac{\text{center frequency of the wavelet}}{\text{scale} \cdot \text{sampling interval}}$$

(14)

Considering that a particular frequency may need special attention, the coefficients at a certain scale (frequency) were also generated.

3.2.2. Discrete wavelet transform (DWT)

Discrete wavelet transform (DWT) is based on the algorithm of filter banks which are a cascade of filters used for signal processing. DWT decomposes a signal into different levels which represent different frequency bands. At each level, the input signal is filtered into two parts: the high-pass frequency components and the low-pass frequency components. At each level, different scale is achieved. Wavelets approximate the signal using only a few non-zero coefficients. This makes wavelet analysis good for compression, denoising, classification, and solving of inverse problems. Our research mainly focused on the denoising issue. In DWT, dilations and translations of the mother wavelet $\psi(t)$ define our orthogonal basis, the wavelet basis

$$\psi_{s,l}(t) = 2^{-s/2} \psi(2^{-s} t - l)$$

(15)

The variables $s$ and $l$ are integers that scale and dilate the mother wavelet $\psi(t)$ to generate wavelets, such as the Daubechies wavelet family. The scale index $s$ indicates the wavelet’s width, while the location index $l$ gives its position. To span our data domain at different resolutions, the analyzing wavelet is used in the scaling equation

$$W(x) = \sum_{k=-\infty}^{\infty} (-1)^k c_k \psi(2x + k)$$

(16)

where $W(x)$ is the scaling function for the mother wavelet $\psi(t)$, and $c_k$ are the wavelet coefficients. The wavelet coefficients must satisfy linear and quadratic constraints of the form
\[
\sum_{k=0}^{N-1} c_k = 2, \quad \sum_{k=0}^{N-1} c_k c_m = 2\delta_{m,0}
\]

where \( \delta \) is the delta function and \( m \) is the location index.

The coefficients \( \{c_0, \ldots, c_{N-1}\} \) are usually thought as filter coefficients. These coefficients, or the filter, are placed in a transformation matrix, which is applied to the raw data. The coefficients are ordered using two dominant patterns, one that works as a smoothing filter (like a moving average), and one pattern that works to bring out the data’s detail information. The coefficients matrix is applied in a hierarchical algorithm. In the matrix, the odd rows contain an ordering of wavelet coefficients that act as the smoothing filter, and the even rows contain an ordering of wavelet coefficients with different signs that act to bring out the data’s detail. The matrix is first applied to the original, full-length vector. Then the vector is smoothed and “decimated” in half and the matrix is applied again. Then the smoothed, halved vector is smoothed and halved again by applying the matrix once more. This process continues until only a few data points remain within the user-defined allowable error range. That is, each matrix application brings out a higher resolution of the data while at the same time smoothing the remaining data. The output of the DWT consists of the remaining smooth components and all of the accumulated detail components.

The special feature of the wavelet basis is that all functions \( w_{jk}(t) \) are constructed from a single mother wavelet \( w(t) \). This wavelet is a small wave (a pulse), normally starting at time \( t = 0 \) and ending at time \( t = N \). The shifted wavelets \( w_{0k} \) start at time \( t = k \) and end at time \( t = k + N \). The scaled wavelets \( w_{j0} \) start at time \( t = 0 \) and end at time \( t = N/2^j \). Their graphs are compressed by the factor \( 2^j \), where the graphs of \( w_{0k} \) are translated (shifted to the right) by \( k \). A typical wavelet \( w_{jk}(t) \) is compressed \( j \) times and shifted \( k \) times the mother wavelet \( w(t) \)

\[
w_{jk}(t) = 2^{-j} w(2^j t - k)
\]

Hence, the definition of DWT is

\[
\text{DWT}_{w_{j0}} \{ f(t) \} = \int_{-\infty}^{\infty} f(t) w_{j0}(t) dt
\]

### 3.3. Hilbert transform

The envelope is a curve or surface that is tangent to every one of a family of curves or surfaces. Envelope extracts the amplitude of a periodic signal. It can be used to simplify the process of detecting the time of arrival for the wave packets. We apply the envelope extraction of the signal before the cross correlation process for time of flight determination. The Hilbert transform is defined as

\[
H(x(t)) = \frac{1}{\pi} \int_{-\infty}^{\infty} \frac{x(\tau)}{t-\tau} d\tau
\]

Hilbert transform is often used to construct a complex analytical signal

\[
\tilde{x}(t) = \tilde{x}_{\text{re}}(t) + i \cdot \tilde{x}_{\text{im}}(t)
\]

where

\[
\tilde{x}_{\text{re}}(t) = x(t) \quad \text{and} \quad \tilde{x}_{\text{im}}(t) = H(x(t))
\]

For example, suppose we have a harmonic signal \( u_c(t) = A \cos(2\pi f_c t + \phi_0) \), where \( f_c \) is the carrier frequency and \( \phi_0 \) is the initial phase. We will have the Hilbert transform according to the Hilbert transform property that \( H(\cos(\omega t)) = \sin(\omega t) \)

\[
H(u_c(t)) = A \sin(2\pi f_c t + \phi_0) = A \cos(2\pi f_c t + \phi_0 - \frac{\pi}{2})
\]

Then, we construct the analytical signal shown in Equation (21). The real part of the constructed signal, \( \tilde{x}_{\text{re}}(t) \), is the original data \( x(t) \), while the imaginary part \( \tilde{x}_{\text{im}}(t) \) is the Hilbert transform of \( x(t) \). Actually, the imaginary part is a version of the original signal \( x(t) \) after a 90° phase shift. Thus, the Hilbert transformed signal has the same amplitude and frequency content as the original signal and includes phase information that depends on the phase of
the original signal. The magnitude of each complex value $\tilde{x}(t)$ has the same amplitude as the original signal. Therefore, we can say that the magnitude of the analytical signal $\tilde{x}(t)$ is the envelope of the original signal. Just by observing the envelope signal, the peaks of wave packages can be easily recognized.

One aspect of Hilbert transform for envelope detection is that the result may differ from the theoretical envelope if the frequency contents are relatively complicated. We have found out that for the receiving signal with original 3 counts tone burst and added noise and disturbance has an envelope far from the smooth envelope we expect to see. Hence, we concluded that, when the signal has contains more than one frequency components, the Hilbert transform for envelope extraction may have aliasing.

4. EUSR EXPERIMENTATION AND PREVIOUS RESULTS

An EUSR proof-of-concept system was built in the Laboratory of Active Materials and Smart Structures (LAMSS) of the University of South Carolina (Figure 3). Several specimens with different crack layouts were used. These specimens were 1220-mm (4-ft) square panel of 1-mm (0.040-in) thick 2024-T3 Al-clad aircraft grade sheet metal stock. The size of the simulated cracks is 19-mm (0.750-in) long, 0.127-mm (0.005-in) wide. Figure 3b shows the setup of the experiment. DAQ module uses a computer (laptop) to control and collect data from a multi-channel pulser/receiver, which consists of: (i) a HP33120A arbitrary signal generator; (ii) a Tektronix TDS210 digital oscilloscope; and (iii) a digital controlled auto-switch unit. The HP33120A was used to generate a 343 kHz Hanning windowed tone-burst excitation with a 10 Hz repetition rate. The Tektronix TDS210 digital oscilloscope, synchronized with the digital generator, was used to collect the response signals from the PWAS array. One of the oscilloscope channels was switched among the remaining elements in the PWAS array by the digitally controlled auto-switching unit.

![Figure 3](image)

(a) EUSR experimentation: (a) EUSR experiment setup; (b) EUSR LabVIEW program flowchart

A LabVIEW program was developed to process the collected raw data files. After EUSR algorithm, the resulting data is saved in a EUSR data file on the computer for later retrieval. It also enables other programs to access the EUSR data. Based on the EUSR algorithm, the resulting data file is a collection of signals that represent the structure response at different angles, $\phi$, from 0° to 180°. With advanced signal processing techniques, these data was transformed to a 2-D plane domain. In the end, a 3-D surface image is generated to represent the intensity of the reflections.

The preliminary results of using EUSR inspection on a specimen with a single broadside crack and on a specimen with a single offside crack are shown in Figure 4a and Figure 4b, respectively. (Broadside is defined as the position perpendicular to the center of the phased array, while offside position is a position somewhere else.) In Figure 4b, the offside position is at the angle 137°.

5. ADVANCED SIGNAL PROCESSING IMPLEMENTATION IN EUSR

5.1. DWT denoising

The DWT denoising efficiency is exemplified by comparing with the statistical denoising results of Demirli and Saniie (2001) (Figure 5a). We simulated an ideal wave-packet signal with a 100 MHz sampling frequency over a
2µs duration. Gaussian white noise (GWN) was then added at certain signal to noise ratios (SNR). Original DWT denoising result is shown in Figure 5b. We have found out that the efficiency of DWT denoising is affected by two factors: SNR and sampling frequency. The higher the SNR and/or the sampling frequency are, the more efficient is the DWT denoising. By using the densification technique [17], the DWT denoising is greatly improved (Figure 5c) and approximates the ideal signal with imperceptible difference. Figure 5d plots the error index (logarithm scale) for different densifications of $m = 8$ and $m = 50$. We see a higher densification factor gives a smaller error. Notice that increasing the DWT denoising level reduces the error in a log-lin manner up to a certain value, but the denoising process breaks down beyond certain level. A critical DWT level exists at which the denoising is optimal. This critical denoising level needs to be determined through adjustments made during the calibration trials.

![Figure 4](image)

**Figure 4** EUSR inspection images of broadside and offside cracks, (a) broadside crack inspection image; (b) offside crack inspection image

![Figure 5](image)

**Figure 5** DWT denoising: a) original noised signal with SNR = 5; b) low quality denoising with $m = 8$, level =1; c) high quality denoising with $m = 50$, level = 5; d) variations of error index at different level of $m = 8$ and $m = 50$

### 5.2. Spectrum analysis

Figure 6 presents the results of the STFT analysis using a Hanning window. The signal was collected using a PWAS transducer at 343 kHz excitation frequency. Figure 6a is the original signal, which has two close wave packets with large amplitudes. Compared to them, the echo from the crack shown in the middle of the plot at around $1.3 \times 10^{-4}$ ms is much smaller. Figure 6b shows the STFT spectrogram. The horizontal axis is time axis and the vertical axis is the frequency axis. In this time-frequency plane, the magnitude of each point is represented by contour. It can be seen that, in the time-frequency plane, strong signals appear mostly at the frequency around 330 kHz and close to the time when the wave packets in Figure 6a reach their peaks (local maxima). This further confirms that STFT is good representation of non-stationary signal due to its ability to indicate both time and frequency information.
Then, time-scale/frequency spectra were generated with the CWT method. Optimal results were obtained by selecting the best set of mother wavelet and scale range. An example of the CWT analysis is shown in Figure 7. The time-frequency coordinates were used because they provide a more conventional way of interpreting the data. It can be seen that most of the energy of our signal is concentrated in the frequency band around 343 kHz. The small echo at around $1.3 \times 10^{-4}$ ms is observed at scale 23, which corresponds to a frequency around 343 kHz.

Here we see that the common characteristics of STFT and CWT are that both give two-dimensional spectra for time-frequency analysis. Due to the fixed window length limitation, STFT cannot get the best results for signals having large frequency changes. In CWT, the window length is adjusted automatically by the CWT algorithm according to the local frequency scale.

![Figure 6 Short-time Fourier transform analysis: (a) original signal; (b) STFT contour plot.](image)

![Figure 7 Continuous wavelet transform on received signal: (a) original signal; (b) CWT spectrum in scale; (c) CWT filtering of the 343 kHz frequency component](image)

**5.3. Envelope extraction and CWT filtering**

The plots of Figure 4 indicate the general existence and location of the damage, but they are rather vague and do not define the damage location very well. Hence, we searched for ways to improve the quality and precision of the
EUSR image. One thing to be noticed is that the echoes from the damage do not have single peaks, because the wave packet suffered some dispersion. Therefore, Hilbert transform was employed to extract the envelope of wave packet so as to make it display a single peak. In addition, a thresholding technique was applied to eliminate the small having amplitudes are below the noise threshold.

However, as explained in previous section, Hilbert transform cannot correctly extract the signal’s envelope if it has a complicated frequency contents. Consider, for example, the first wave packet in Figure 8a. Due to the interference introduced during the measurement, the received signal has more frequencies than the ideal single excitation frequency of 343 kHz. The extracted envelope shows up with spikes rather than the expected smooth one. This deficiency was corrected by applying the narrow-band CWT filtering. Figure 8b shows the envelope extraction obtained after applying CWT filtering at scale 23 which has an equivalent frequency of about 343 kHz that closely corresponds to the excitation frequency of 330 kHz. The improvement is obvious. We concluded that Hilbert transform works very well for extracting the envelope of non-dispersive guided waves with simple frequency contents. For multi-frequency signals, this condition is achieved through narrow band filtering, such as done here with the CWT method. Figure 9 presents the new EUSR images obtained with the improved signal processing algorithm. The new EUSR images have a much better resolution and the shade indicating the crack is much closer to the actual crack size.

![Figure 8 Hilbert transform for envelope extraction comparison](image)

(a) Hilbert transform for envelope extraction on original received signal; (b) Hilbert transform for envelope extraction on CWT filtered signal

![Figure 9 EUSR inspection images of broadside and offside cracks with using Hilbert transform](image)

(a) broadside crack inspection image; (b) offside crack inspection image

5.4. **Experimental results with other specimens**

More experiments were designed to verify that the improved EUSR algorithm can also detect multiple cracks and pin-holes. Figure 10 shows a specimen which a broadside crack having a 30° slope. Figure 10b is the EUSR inspection image. It can be seen that it roughly indicates the slope. In the future, we will do further experimentation to find out the minimum slope that EUSR is sensitive and able to indicate.

Another specimen is shown in Figure 11a. It has two symmetrical offside cracks placed at 63° and 117°,
respectively. Figure 11b shows the resulting EUSR mapped image.

A different type of through-plate damage, the pin-hole damage, has also been considered in our experimental studies (Figure 12a). We wanted to verify the EUSR ability to detect small pin-holes and find out the minimum detectable pin-hole size. The experiment went through increasing diameters of 0.5 mm, 1 mm, 1.57 mm and 2 mm. The EUSR algorithm started detecting the pin hole at 1.57 mm diameter. EUSR image shows in Figure 12b. The tiny dot at the broadside position is the mapped image of the pin hole in the 2D specimen.

![Image](image1.png)

Figure 10  Detection of a broadside crack having 30° slope: (a) schematic; (b) EUSR GUI mapped image

![Image](image2.png)

Figure 11  Two symmetrical offside: (a) schematic; (b) EUSR GUI mapped image

![Image](image3.png)

Figure 12 EUSR detection of pin-holes: (a) schematic of the experimental specimen; (b) EUSR GUI mapped image of the minimum detectable pin-hole with 1.57 mm diameter

### 6. CONCLUSIONS

In this paper, we presented the applications of advanced signal processing techniques to the EUSR method using PWAS for constructing the phased array. After introducing briefly the general principles of EUSR algorithm, mathematical fundamentals of the advanced signal processing approaches being employed in our research, and the results from previous work, we discussed how we use the discrete wavelet transform for denoising, short-time Fourier transform and continuous wavelet transform for time-frequency spectrum analysis, Hilbert transform for
envelope detection, and continuous wavelet transform for signal frequency component extraction. These were followed by experimental results to verify the improvements of EUSR’s efficiency and reliability. We finally concluded that EUSR is proved to have the ability to detect different types of damage including: (a) single crack at either broadside or offside locations; (b) broadside crack with certain slope; (c) two horizontal aligned cracks; (d) pin-holes.

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