1. Introduction

Non-destructive testing (NDT) for fault detection in structures has received more attention in recent years. Significant advances in instrumentation technology and digital signal processing have been made [16, 17, 19, 25, 30]. Signal processing methods together with structural health monitoring (SHM) permit the identification and diagnosis of faults and their location based on changes in static and dynamic behavior. The objective of this paper is to demonstrate a novel signal processing for detection, identification and flaw sizing of structural damage using ultrasonic testing with Electromagnetic Acoustic Transducers (EMATs). Damage detection involves the recognition of a defect within a structure. Damage location is the identification of the geometric position of the defect. Defect classification is the cluster of the damage type into multiple damage scenarios. In the absence of external interferences, a good measure of detectability of a flaw is its signal-to-noise ratio (SNR). Although the SNR depends on various parameters such as electronics used, material properties, e.g. homogeneity and damping, and flaw size, it can be improved using advanced signal processing. The main scientific novelties presented in this paper focus on filtering signal noise through advanced digital signal processing; incorporating wavelet transforms for image and signal representation enhancements; investigating multi-parametric analysis for noise identification and defect classification; studying attenuation curves properties for defect localisation improvement and flaw sizing and location algorithm development.

Keywords: fault detection and diagnosis, electromagnetic acoustic transducers (EMAT), wavelet transforms, non destructive tests, guided waves.

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A HEURISTIC METHOD FOR DETECTING AND LOCATING FAULTS EMPLOYING ELECTROMAGNETIC ACOUSTIC TRANSDUCERS

HEURYSTYCZNA METODA WYKRYWANIA I LOKALIZOWANIA USTEREK Z WYKORZYSTANIEM ELEKTROMAGNETYCZNYCH PRZETWORNIKÓW AKUSTYCZNYCH

The objective of this paper is to demonstrate a novel signal processing for detection, identification and flaw sizing of structural damage using ultrasonic testing with Electromagnetic Acoustic Transducers (EMATs). Damage detection involves the recognition of a defect within a structure. Damage location is the identification of the geometric position of the defect. Defect classification is the cluster of the damage type into multiple damage scenarios. In the absence of external interferences, a good measure of detectability of a flaw is its signal-to-noise ratio (SNR). Although the SNR depends on various parameters such as electronics used, material properties, e.g. homogeneity and damping, and flaw size, it can be improved using advanced signal processing. The main scientific novelties presented in this paper focus on filtering signal noise through advanced digital signal processing; incorporating wavelet transforms for image and signal representation enhancements; investigating multi-parametric analysis for noise identification and defect classification; studying attenuation curves properties for defect localisation improvement and flaw sizing and location algorithm development.

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Celem niniejszego artykułu jest omówienie nowatorskiego sposobu przetwarzania sygnałów w celu wykrywania, identyfikacji i oceny uszkodzeń strukturalnych przy użyciu ultrasonograficznych testów za pomocą elektromagnetycznych przetworników akustycznych (EMAT). Wykrywanie uszkodzeń polega na rozpoznawaniu istniejących defektów wewnątrz danej struktury. Lokalizacja uszkodzeń sprowadza się do identyfikacji geometrycznego położenia defektu. Klasyfikacja defektu to klaster typu uszkodzenia w wielu scenariuszach uszkodzeń. W przypadku braku zewnętrznych zakłóceń, dobrym wskaźnikiem wykrywalności błędu jest stosunek sygnału do szumu (SNR). Pomimo tego, że SNR zależy od różnych parametrów, takich jak użycia elektronika, właściwości materiału, np. jednorodność i tłumienie, a także wielkość wady; wskaźnik ten można poprawić przy użyciu zaawansowanego przetwarzania sygnałów. Główne nowe zagadnienia naukowe przedstawione w niniejszym artykule skupiają się na filtrowaniu szumu wykorzystując transformaty falkowe w celu ulepszenia obrazu i sygnału; badanie analizy wieloparametrycznej w celu identyfikacji szumów i klasyfikacji defektów; badanie właściwości krzywych osłabiania w celu sprawnego wykrywania i oceny wad oraz rozwoju algorytmu lokalizacji.

Słowa kluczowe: wykrywanie i diagnozowanie wad, elektromagnetyczne przetworniki akustyczne, EMAT, transformaty falkowe, badania nieniszczące, fale prowadzone.
dynamic structural features [14, 22, 23]. In addition, these techniques can be remotely controlled and they should work online, resulting in a reduction of costs associated to manual inspections, downtimes, etc. [11, 20, 28].

Guided waves are a common technique employed for SHM within the NDT field, being particularly useful for structural components based on plate or tube geometries. The technique is based on the excitation of low frequency ultrasonic waves propagating along a structure such as a pipeline over long distances, allowing inspection of large areas without any relocation of the transducers.

The purpose of this paper is to demonstrate a novel fault detection and diagnosis (FDD) approach using ultrasound inputs in conjunction with advanced signal processing methods [4, 10, 21, 31] for monitoring the structural condition of a steel plate. The novel signal processing is based on system identification techniques in discrete time to estimate potential faults. The wavelet and Hilbert transforms are employed to work in conjunction with an automatic peak detection algorithm [5]. The algorithm detects which peaks correspond to echoes from the edges, and which correspond to potential defects. Once a potential crack is detected, the algorithm shows the exact location of the defect, and the crack size is compared with the attenuation curve.

2. Electromagnetic acoustic transducers for condition monitoring

The electromagnetic acoustic transducer (EMAT) is a transducer for non-contact sound generation and reception using magnetostrictive phenomena and the interaction of the Lorenz force with the crystal lattice of the material being inspected. EMATs have been widely used in non-destructive testing in the generation of Shear and Lamb waves [3, 33]. In this study EMATs manufactured by SONEMAT Limited in the UK (Figure 1) have been used to carry out the experiments of interests. The EMATs employed use a specific coil and magnet configuration appropriate for the tests carried out [27].

A 3 mm thickness plate of 316Ti stainless steel has been employed for the experiments. The EMATs incorporate a race track coil with periodic permanent magnet to generate shear waves (SH0 mode) in the plate. The dimension of each EMAT is 15 mm x 5 mm x 5 mm. The distance between the magnets is 1 mm and the magnetic strength of each magnet is 0.3 T. The diameter of the coil is 0.315 mm, the width 15 mm and length 35 mm, with a lift-off distance of 0.1 mm from the samples surface. The EMAT configuration is shown in the schematic of Figure 2.

This type of EMAT configuration is applicable for the detection of transverse defects, such as spiral cracking, blow-out holes, circumferential cracking, bell splitting, etc. Since 316Ti stainless steel has an austenitic microstructure it is paramagnetic and therefore, magnetostriction is not relevant. Ultrasonic waves are produced due to the Lorentz forces acting normal to the plate surface producing ultrasonic waves propagating along the longitudinal direction of the test plate.

3. Experimental Tests

An artificial defect has been induced in the plate using spark erosion to carry out automatic detection and location of defects. Figure 3 shows the experimental configuration employed. The EMAT is excited by a 256 kHz and six-cycle pulse. Shear waves are generated in both directions. The
EMAT (R) receives echoes from the edges and from the crack. Figure 4 shows the four first reflections produced by the boundaries.

Shear waves are non-dispersive signals, i.e. the propagation velocity of these waves is not frequency dependent. The propagation velocity of shear waves depends on the material properties [32]. For the 3 mm austenitic steel plate (316Ti) considered herewith the shear wave velocity is 3020 m/s.

4. Signal processing

This section presents a novel method based on a wavelet-based algorithm that has been applied to the signals from the EMATs to improve the SNR. A pre-filter has been implemented to extract the low frequency information of the EMAT signals, where it reduces the unexpected frequency components of signals. Then a denoising algorithm has been applied to improve the SNR without introducing time delay in the original signals [15].

4.1. Wavelet pre-filter and de-noising.

The wavelet transform is an analysis method which can be employed to identify the local characteristics of a signal in the time and frequency domain, e.g. with the use of a series of decomposition coefficients at different frequency bands [6, 10]. It is recommended for large time intervals where great accuracy is required at low frequencies and vice versa, e.g. small regions where precision details are required at higher frequencies [7]. The wavelet transform is also a useful method to characterise and identify signals with spectral features, unusual temporary files and other properties related to non-standing waves.

Wavelet transforms are an alternative to the fast Fourier transform (FFT), or to the short-time Fourier transform, to obtain results in the time domain [13] and [24]. The signal processing from the time domain to the frequency domain usually implies loss of information, being difficult to determine the appearance of specific frequencies [26].

Signals are divided therefore into low frequency approximations (A) and high frequency details (D), where the sum of A and D is always equal to the original signal. The division is done using low pass and high pass filters [2]. In order to reduce the computational and mathematical costs due to the data duplication, a sub-sampling is usually implemented, containing the half of the collected information from A and D without losing information.

In the case of the multi-level filters, they repeat the filtering process with the output signals from the previous level. This leads to the wavelet decomposition trees (Figure 5) [1, 9]. Additional information is obtained by filtering at each level. However more decompositions levels do not always mean more accurate results.

The objective of the signal pre-processing is to extract the most important information of the original signal before carrying out signal de-noising. It generates new signals adjusted for the application of filters, providing more robust results and greater similarity between signals obtained under different conditions.

The first filter used to prepare the signal has been employing a Daubechies wavelet transform. Daubechies wavelets were used because they handle with boundary problems for finite length signals, being their biggest advantage over other families [12, 29] and [34]. The decomposition five D5 contains more information of the original signal and a lower signal noise ratio without delay regarding to the original signal.
Effective filtering should not eliminate any information about the defects, e.g., the peaks with low amplitudes, because it is likely that any of these peaks can be due to a defect. This section describes the approach considered in order to remove noise without compromising the detection of a smaller defect.

The denoising of the signal is performed employing a multilevel 1-D wavelet analysis using Daubechies family. The wavelet decomposition structure of the signal to be de-noised is extracted. The threshold for the de-noising is obtained by a wavelet coefficients selection rule using a penalization method provided by Birgé-Massart. An overly aggressive filtering could eliminate data of interest, such as small echoes that come from defects. Figure 6 shows the original signal and the de-noised signal when it is applied the wavelet de-noised filter. In contrast to other digital filters, the Wavelet de-noising filter does not produce an unwanted signal delay.

It is observed that the filter removes noise significantly, and also does not eliminate information that is related to different structural features.

4.2. Finding events within the signal: Envelope and smooth

Hilbert Transform is employed to obtain the envelope of the filtered signal. It is necessary to smooth the envelope with the aim of finding events in the signal, which usually appear as peaks, i.e., it is desired not false alarms. An inadequate window size could produce distortions as “sawtooth” in the signal.

A good result is achieved by applying again a Wavelet de-noising filter and selecting the low frequency decompositions (approximations). This produces a smoothed function without significantly altering the signal (Figure 7).

4.3. Cracks detection and edges location

The approach identifies the events from the signals that are obtained from elements as boundaries or welds. This process consists of the following steps (see Figure 8):

• Peak search: It is important to select a proper threshold for this purpose.
• Identify echoes from the edges: The time of flight of each echo is obtained and compared with the distances of the sensor and actuator regard to the boundaries.
• Theoretical and experimental comparison for identification of the boundaries (Figure 9).

The obtained information allows the discarding of false cracks, and also provides information such as the attenuation of the ultrasonic wave propagation along the material. The algorithm uses the distance of the EMATs from the edges to perform a self-identification of signal events. The event is located theoretically when the two possible ways of propagation of ultrasound, forward and reverse, are analysed together, taking into account the time of flight (ToF) of each echo. Then the algorithm correlates the theoretical events with the potential events detected in the signal. Finally, the measurement accuracy is checked and validated or not, and each specific event is experimentally located, and obtaining the experimental propagation velocity.

Vector $X$ contains the position values of the peaks obtained experimentally, $Y$ the height of the peaks of $X$, and $X^*$ the position values of the peaks obtained theoretically.

$$X = [x_1, \ldots, x_i, \ldots, x_n]$$

$$Y = [y_1, \ldots, y_i, \ldots, y_n]$$

$$X^* = [x^*_1, \ldots, x^*_i, \ldots, x^*_m]$$

The matrix $C$, given by equation (1) contains the absolute difference between each value of $X$ and each value of $X^*$. 
The purpose of this approach is to select the real peaks having its homologous in the set of theoretical peaks. For each $x_i$, the most similar value $x^*_j$ is chosen if the difference between them is less than the tolerance $\theta$, where an alarm could notice that the similitude has not been found. The minimum value of the components of each column $C_j$ is given by a particular $x_i$. $X_{\text{edges}}$ is a subset of $X$ that contains the minimum values of each column $C_j$, i.e.:

$$X_{\text{edges}} = \left[ x_{\text{edges}1}, x_{\text{edges}2}, \ldots, x_{\text{edges}m} \right]$$

where $x_{\text{edges},j} = x_i, x_i \in X \forall r, j : c_{ij} = \min(C_j) \leftrightarrow c_{ij} < \theta, j = 1, \ldots, m$ (2)

This method allows the determination of the absolute and relative error between the values obtained and expected for each event. The differences between the experimental and theoretical values are shown in Figure 10.

The peaks that do not have their counterpart with the theoretical peaks are possible echoes that come from a defect ($X_{\text{cracks}}$).

$$X_{\text{cracks}} \subseteq X \cdot X_{\text{cracks}} \neq X \cap X_{\text{edges}} \quad (3)$$

where the heights of $X_{\text{cracks}}$ are:

$$X_{\text{cracks}} = \left[ x_{\text{cracks}1}, x_{\text{cracks}2}, \ldots, x_{\text{cracks},n-m} \right], \quad k = 1, 2, \ldots, n - m$$

The potential crack detection and location (see Figure 11) is based on the echoes that are coming from the same crack, where they could come from different paths due to the EMAT generate forward and reverse shear waves.

The algorithm considers that if the distance travelled is close, the defect is detected and therefore located. The scheme of this method is shown in Figure 12.

The pattern recognition approach is based on an automatic detection of cracks that compares the ToF employed by the same pulse to travel two different paths [18]. The two shortest paths for detecting a crack between the sensor and transmitter are the path “a” and path “b” shown in Figure 13. The distance travelled by an echo in the path “a”, for example $d_{\text{echo}_a}$, is used to determine the distance $d_{rc_a}$ between the crack and the receptor. Similarly, the distance travelled by an echo in the path “b” $d_{\text{echo}_b}$ is used to determine the distance $d_{rc_b}$. The distances $d_{rc_a}$ and $d_{rc_b}$ should be close.

The method performs a comparison between the distances obtained for each component of $X_{\text{cracks}}$.

The paths are:

Path a:

$$d_{\text{echo}_a,k} = dr + 2dr + 2d_{rc_a,k} \quad (4)$$
The distance \( d_{rc_{a,k}} \) is compared with all the echoes that come from the path 2 \((\text{bk}, \text{drc})\). Therefore, the pair of echoes that provide the most similar distances \( d_{rc_{a,1}} \) and \( d_{rc_{a,2}} \) have the greatest likelihood to come from the same defect.

\[
\text{Drc} = \left[ d_{rc_{a,1}}, \ldots, d_{rc_{a,k}}, \ldots, d_{rc_{a,n-m}} \right], k = 1, 2, \ldots, n-m
\]

Path b:

\[
d_{echo_{b,k}} = 3 dtc + 2 dt + dr_{c_{b,k}}
\]

\[
dtc = dtr - dr_{c_{b,k}}
\]

\[
d_{echo_{b,k}} = 3(dt - dc_{b,k}) + 2 dt + dr_{c_{b,k}}
\]

\[
dr_{c_{b,k}} = \frac{3 dt + 2 dt - d_{echo_{b,k}}}{2}
\]

The distance \( dr_{c_{a,k}} \) is compared with all the echoes that come from the path 2 \((\text{drc}_{a,k})\). Therefore, the pair of echoes that provide the most similar distances \( dr_{c_{a,1}} \) and \( dr_{c_{a,2}} \) have the greatest likelihood to come from the same defect.

\[
\text{D} = \begin{bmatrix}
    d_{r_{c_{a,1}} - r_{c_{b,1}}} & \cdots & d_{r_{c_{a,1}} - r_{c_{b,k}}} & \cdots & d_{r_{c_{a,1}} - r_{c_{b,n-m}}} \\
    \vdots & & \vdots & & \vdots \\
    d_{r_{c_{a,k}} - r_{c_{b,1}}} & \cdots & d_{r_{c_{a,k}} - r_{c_{b,k}}} & \cdots & d_{r_{c_{a,k}} - r_{c_{b,n-m}}} \\
    \vdots & & \vdots & & \vdots \\
    d_{r_{c_{a,n-m}} - r_{c_{b,1}}} & \cdots & d_{r_{c_{a,n-m}} - r_{c_{b,k}}} & \cdots & d_{r_{c_{a,n-m}} - r_{c_{b,n-m}}} 
\end{bmatrix}
\]

where \( k = 1, 2, \ldots, n-m \) and \( l = 1, 2, \ldots, n-m \). In some cases could appear superposition between two echoes that came from paths a and b, and therefore they would present in the signal as a single peak. The main diagonal provides the solution for these cases. The component \( e_{crack_{k,l}} \) is de minimum difference between both paths, given by:

\[
e_{crack_{k,l}} = d_{kl} : \quad d_{kl} = \min(D) \leftrightarrow d_{kl} < t, \quad \forall k,l.
\]

The solution to the problem of location is \( f_{crack,a} \), which is the distance of the crack from the sensor.

\[
f_{crack,a} = dr_{c_{a,k}}, \quad \forall k : \quad d_{kl} = \min(D) \leftrightarrow d_{kl} < t, \quad \forall k,l.
\]

The main diagonal is not taken into account for all other cases because it is assumed that there are no overlapping echoes. The difference between the \( dr_{c_{a,k}} \) and \( dr_{c_{b,l}} \) must be within the tolerance.

\[
e_{crack} = d_{kl} : \quad d_{kl} = \min(D) : k \neq l \leftrightarrow D_{kl} < t, \forall k,l.
\]

In some cases, there may be a need to consider the amplitude of each echo to perform the analysis. Theoretically an echo coming from a large transverse crack should have a greater amplitude than the echoes from smaller cracks, because more energy will be reflected. The equation (15) weights the more similar distances with the amplitude of the two echoes of each path.

\[
f_{crack,a}^{w} = dr_{c_{a,k}}, \quad \forall k : \quad d_{kl}^{w} = \min \left( \frac{d_{r_{c_{a,k}}^{w}} - d_{r_{c_{b,l}}^{w}}}{Y_{r_{c_{a,k}}^{w}} + Y_{r_{c_{b,l}}^{w}}} \right) ; k \neq l, \quad \forall k,l.
\]

In most cases the amplitude of the echoes is several orders of magnitude smaller than the ‘x’ axis.

The equation (16) is a heuristic expression which gives more weight to the amplitude and corrects this problem.

![Fig. 13. Two shortest paths from Tx and Rx detecting the defect. The distance is given in centimetres](image1)

![Fig. 14. Crack location relative to the left edge (meters)](image2)
Finally, when the location is determined the crack is shown in a schematic with the actual dimensions of the plate and the position of the sensors (Figure 14).

5. Conclusions

This paper presents a new SHM approach using EMATs and advanced signal processing to automatically identify, locate and determine the severity of a defect in a plate. The technique presented could be used to detect defects in pipes operating under relatively high temperature. The approach employed is based on pre-filtering and denoising using Wavelet methodologies and the Hilbert Transform to detect relevant peaks. The Time of Flight (ToF) of the echoes is calculated theoretically and then compared with the experimental times to determine which echoes come from the plate borders. Any other echo represents a potential crack. Echoes from the same defect travelling on different paths are compared and the defect is located by taking consideration of the amplitude.

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