Indian Journal of Science and Technology, Vol 8(13), DOI: 10.17485/ijst/2015/v8i13/56303, July 2015
ISSN (Print) : 0974-6846
ISSN (Online) : 0974-5645

Application of Hilbert Transform for Flaw Characterization in Ultrasonic Signals

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Abstract

Ultrasonic Testing is the highly reliable Non Destructive Testing (NDT) technique for flaw detection in steel weldments. Ultrasonic test signals are analyzes to identify the nature of the defect. In this paper, Hilbert transform is used for decomposing the ultrasonic test signals into high and low frequency components (namely Intrinsic Mode Function). These components are characterised in terms of Power Spectral Density (PSD). An attempt has been successfully made to classify the flaws based on PSD. It is found that power spectral density of planar defects is higher than volumetric defects for the fourth Intrinsic Mode Function.

Keywords: Flaw Characterisation, Hilbert Transform, Lack of Fusion, Power Spectral Density, Ultrasonic Signals

1. Introduction

In spite of technological advances in welding, defects do occur in welds. It is because welding is dependent on many physical parameters[1,2]. Hence it necessitates a quality assessment technique to characterize the welds. Radiographic Testing, Ultrasonic Testing, Infrared Thermography are the most commonly used NDT techniques for weld quality assessment. Of the above techniques, Ultrasonic testing is used for the assessment of weld defects in thick walled weldments. It uses high frequency sound energy to detect flaws to make dimensional measurements and material characterization. It is of three types namely pulse echo technique, Time of Flight Diffraction (ToFD) and Phased Array technique[3]. In Pulse echo technique[4], a transducer sends out a pulse of energy and the same or a second transducer receives the reflected energy. This reflected wave is diagnosed and analysed to identify the types of defects through Cathode Ray Oscilloscope (CRO). Features are extracted from these signals to identify and characterise the defects. As these signals are non-stationary in nature, non-stationary tools such as DWT, Stockwell transform and EMD can be used for the analysis of these signals. In this paper, EMD is used for analysing the signals and characterize the flaw through Hilbert Transform. Hilbert transform pioneered by Huang et al.[5,7] is used for analysing the non-stationary signals in two methods: 1. Decomposing the signal into Intrinsic Mode Function using Empirical Mode Decomposition and 2. Performing spectral analysis using Hilbert spectral analysis. Empirical Mode Decomposition[6] decomposes the signal into finite set of function called IMF. These Intrinsic mode function is obtained by iterative sifting process which successively subtracts the local mean from a signal. This sifting process is performed until a signal with a zero mean and whose number of extrema and zero crossing differ by at most one. Then spectral analysis is obtained by HT.

Hilbert transform gives out instantaneous amplitude and frequencies that describe signal more locally. Hilbert transform, $\hat{y}(t)$ for any function x(t) is given as. The PV is the Cauchy's principle value integral[7,8].

$$H[x(t) = \hat{y}(t) = \frac{1}{\pi} PV \int_{-\infty}^{\infty} \frac{x(\tau)}{t-\tau} d\tau \quad (1)$$

The analytic function is obtained by Hilbert transform pair as shown in equation (2). $z(t) = x(t) + i\hat{y}(t) = A(t)e^{i\theta(t)}$

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Where,

$$A(t) = (x^2 + \hat{y}^2)^{1/2}, \theta(t) = tan^{-1}\left(\frac{\hat{y}}{x}\right) \& \, i = \sqrt{-1} \qquad (2)$$

A(t) and $\theta(t)$ are the instantaneous amplitudes and phase functions, respectively.

This paper is organized as follows: Section 2 describes the related work. Proposed methodology is detailed in Section 3. Results and discussions are given in section 4 and section 5 concludes the work.

2. Related Work

In[9] they gave an algorithm for ultrasonic flaw classification of Carbon Fiber Reinforced Polymer (CFRP) using Wavelet Packet Transform (WPT) and Discrete Wavelet Transform (DWT). A scan signals of 100 samples are used for classification Feature extraction was obtained at 3rd level of decomposition using DB5 and PCA. The flaw signal was categorised with WPT_Egy and the other three were classified based on WPT coefficients and DWT statistical features and coefficients are performed to differentiate based on signal energy. The feature vectors selected by PCA method were taken as inputs to train ANN and SVM classifiers. It was concluded that WPT Energy values gave more information about the flaw. In[10] they proposed an algorithm to detect the flaw signal in composite materials using SSP and MPSD. The SSP algorithm improves the SNR. Signal feature is detected by using constant Q decomposition. The echoes were decomposed in to linear. The MPSD algorithm is used to decompose backscattered signals into a linear chirplet function and are verified using three specimens of Carbon Fiber Reinforced Polymer (CFRP) multi-layered composite materials. In[11] suggested a method for surface cracks sizing through frequency analysis. Depths ranging from 1mm to 8mm were fabricated and are analyzed with pulse-echo technique frequencies of 2.25 MHz, 5 MHz and 10 MHz. In[12], developed an algorithm using artificial bee colony intelligent optimization to detect flaw in metal machinery. Feature extraction was done using wavelet packet decomposition. Flaw signal identification was done using ABC-SVM algorithm. In[13] have modeled and classified the signal flaw using EMD and neural network. The original signal is decomposed into IMFs. Eigen vectors were built both time domain and Fourier domain to identify flaws. Then the flaw type was decided using neural networks. Yu Wang et al.[14] had developed an algorithm to classify the ultrasonic flaw signal using EMD and RSAR. Initially the statistical parameters were extracted using EMD. The feature selection was performed using rough set attribute reduction. Using BP neural network the flaws were identified. In[15] had proposed an algorithm to quantify porosity based on spectral analysis and phase statistics. The evaluation of porosity in CFRP component was done using Linear Predictive Coding Approach independent of material thickness and shape. In[16] proposed an algorithm, where the defects lack of fusion and longitudinal cracks are classified using Multilayer Perceptron, Radial Basis Function and Self-organizing Maps. Feature extraction was performed using PCA. 91% of success rate was obtained. In[17] they performed feature extraction using wavelet analysis. The features that recognize the defect of the metal thin composite plate is obtained by decomposing the signal into frequency bands for which the energy torque is calculated. From the related work it shows that the ultrasonic flaw signal were created manually and analyzed using experimental analysis for flaws like lack of fusion, crack and feature extraction was done but only 91% accuracy. Feature selection was done using EMD and then flaws were identified using neural network BP algorithm.

3. Proposed Methodology

In order to characterize the flaws from ultrasonic signals, it is necessary to acquire the ultrasonic signals by deliberately introducing defects in the weld pieces both Stainless Steel and Carbon Steel weldments are considered. Ultrasonic test signals of the weldments are acquired to depict lack of fusion, root, sidewall crack, and transverse crack. These signals are acquired with both 2MHZ and 4MHZ probe.

From the time domain analysis of the signals it is found that frequency is different for volumetric and planar defect hence it is necessary to obtain the frequency spectrum of the signals in order to analyze the flaws. Next step is to identify an appropriate transform for converting the time domain into frequency domain. From the literature, Fourier transform is the highly reliable tool for converting a time domain signal into frequency domain. However as the ultrasonic test signals are non-stationary in nature, frequency transform could not provide the desired results. Hence Hilbert Transform is chosen for the analysis. Hilbert Transform performs the decomposition of the input signal by removing the high frequency components. These high frequency components are called Intrinsic Mode Function. This process is repeated

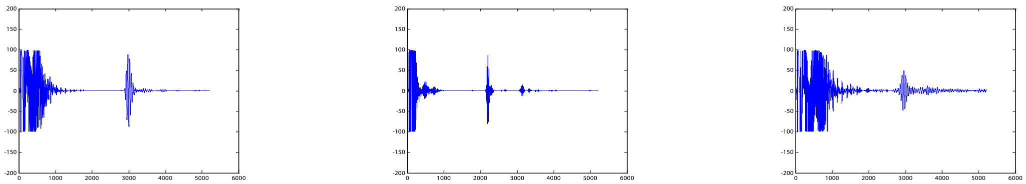


Figure 1. Input ultrasonic signal of Lack of Fusion, Rootcrack, SLAG for Carbon Steel #1 using 2MHZ.

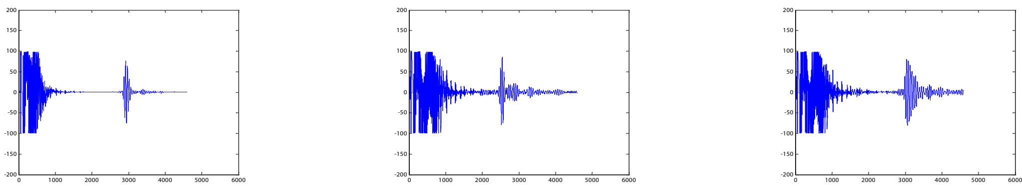


Figure 2. Input ultrasonic signal of Lack of Fusion, Rootcrack, SLAG for Stainless Steel #1 using 2 MHZ.

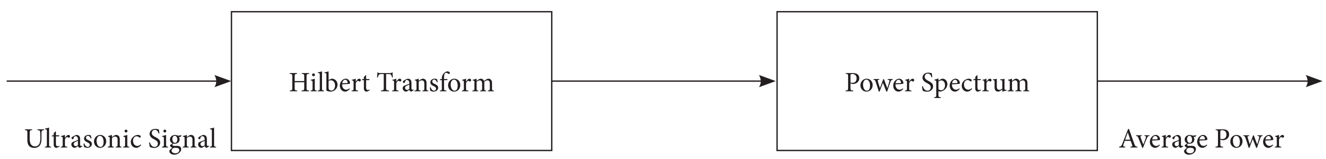


Figure 3. Block Diagram for Proposed Methodology.

till the below condition is satisfied. 1. The number of local extrema of and the number of its zero-crossings must either be equal or differ at most by one. 2. At any time t, the mean value of the "upper envelope" (determined by the local maxima) and the "lower envelope" (determined by the local minima) is zero. The block diagram depicting the proposed methodology is shown in Figure3.

4. Results and Discussion

Ultrasonic signals are obtained for five different flaws namely lack of fusion, root, sidewall crack, and transverse crack. Power Spectrum Density (PSD) is calculated on the time domain signals and on the Intrinsic Mode Functions (IMF) of the Hilbert transformed input signals. Average power is calculated on the Power Spectrum Density of both time and frequency transform domain signals. Power Spectrum Density of the above cases are tabulated in Tables 1 and 2. The input signal and the corresponding PSD's are shown from Figures 1 and 2.

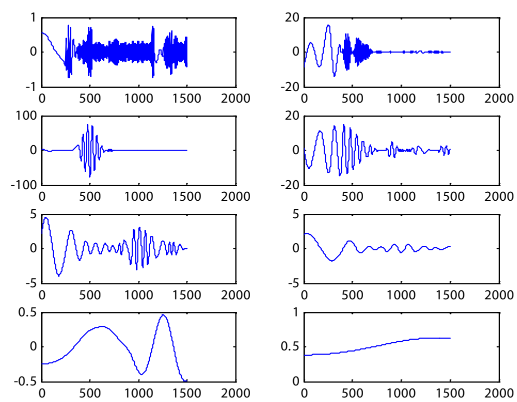
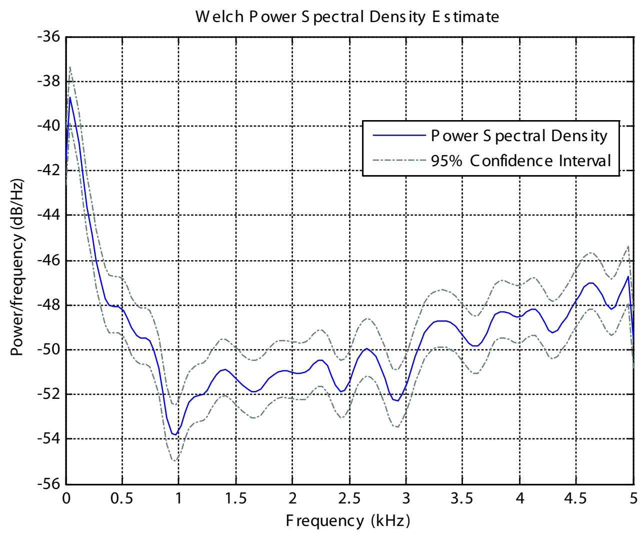
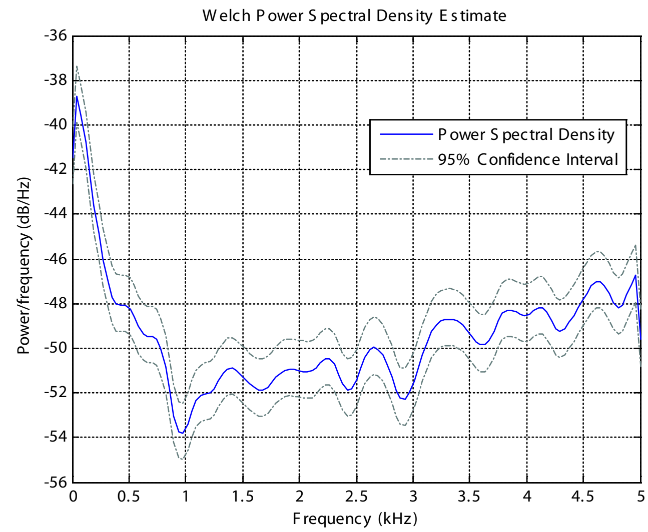


Figure 4. Intrinsic Mode Function of Lack of Fusion in Carbon Steel #1 using 2 MHz probe.

In order to facilitate better analysis, EMD was performed on the signals and the average power is calculated on the power spectral density of each Intrinsic Mode Function (IMFs). The IMFs and the corresponding PSDs are shown in Figures 4 and 5 respectively. Average power


Welch Power Spectral Density Estimate
Power Spectral Density
95% Confidence Interval
Power/frequency (dB/Hz)
Frequency (kHz)


Welch Power Spectral Density Estimate
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Power/frequency (dB/Hz)
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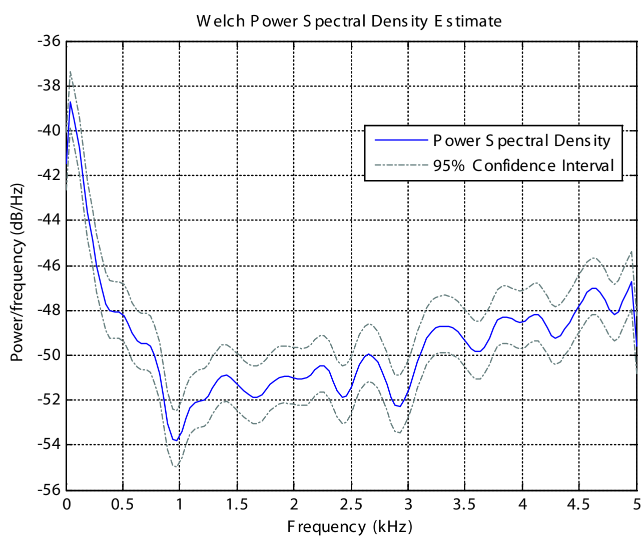
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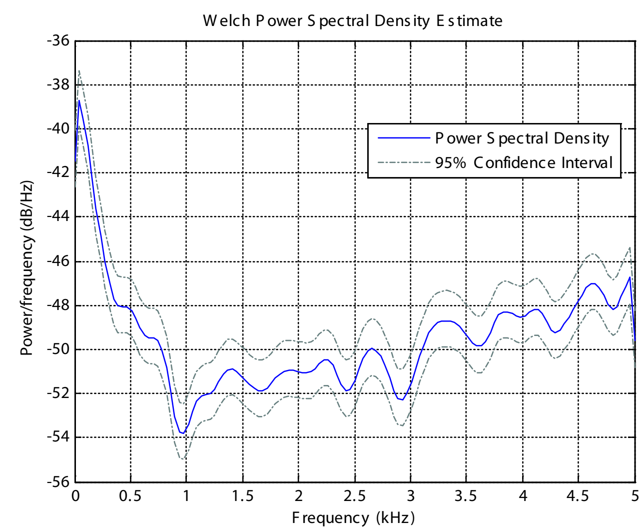
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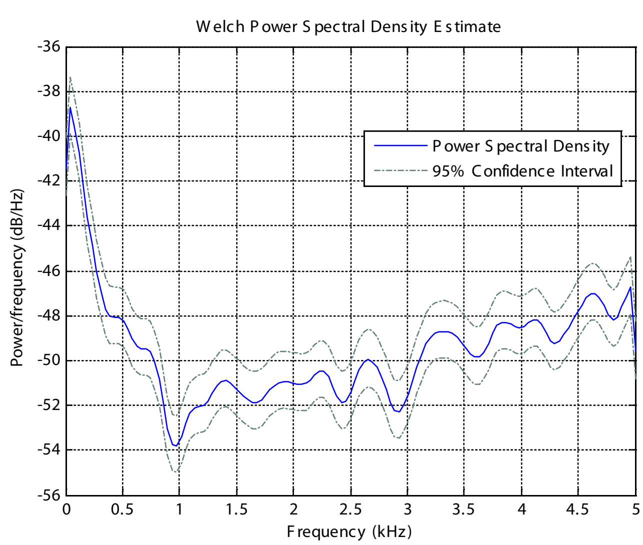
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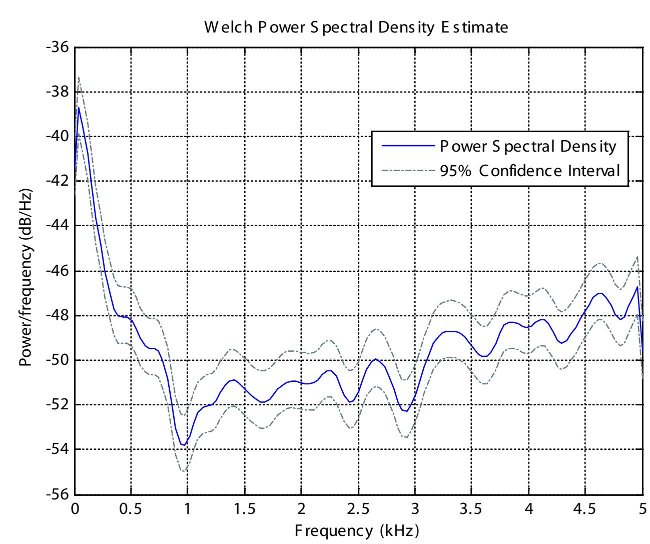
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Frequency (kHz)

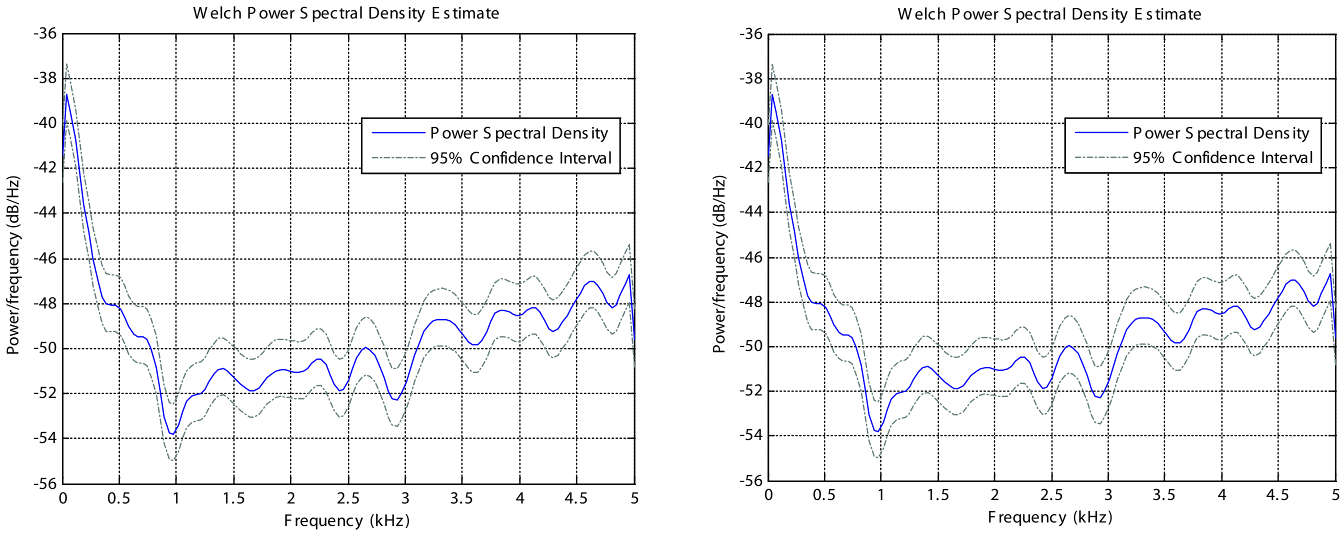

Figure 5. PSD for the corresponding Intrinsic Mode Function of LOF for CS1 using 2MHZ.

Table 1. Average power on PSDs of IMFs of planar defects using 2MHZ

Intrinsic Mode Functions	Average Power						
	LOF_CS1	LOF_CS2	LOF_SS1	ROOT_SS1	SWC_CS2	SWC_SS2	TRSC_SS2
IMF #1	0.0734	23.7093	0.1680	0.3559	0.3214	4.3867	0.2292
IMF #2	18.5590	273.9208	191.4487	197.3626	187.9195	346.8253	0.2330
IMF #3	245.8806	2.8046	3.3556	36.7039	64.8681	87.4495	15.4095
IMF #4	29.7964	48.4455	0.4830	15.4212	29.2681	24.7382	3.9164
IMF #5	2.5937	3.1569	0.0225	1.2536	0.9986	3.7163	0.5448
IMF #6	0.6020	0.3255	0.0480	0.1028	0.0553	0.6024	0.753
INF #7	0.0656	0.1189	0.0067	0.0675	0.2096	0.1696	0.0403
IMF #8	0.0054	.00094	0.0040	0.0204	0.0335	0.1065	0.0099
IMF #9	NA	NA	0.0012	0.0482	0.0312	0.0649	0.0300
IMF #10	NA	NA	NA	NA	NA	NA	NA

Table 2. Average power on PSDs of IMFs of volumetric defects using 2 MHZ

Intrinsic Mode Functions	Average Power		
	PO_CS2	PO_SS2	SL_CS1
IMF #1	0.2412	0.1366	0.1490
IMF #2	36.5698	93.2754	97.2450
IMF #3	20.1991	61.0104	16.7722
IMF #4	1.5470	16.1119	4.5169
IMF #5	0.4824	0.4547	0.0928
IMF #6	0.0410	0.1764	0.0170
INF #7	0.0609	0.1654	0.0040
IMF #8	0.0430	0.0740	0.0027
IMF #9	0.0400	0.00072	0.00019

is calculated on the Power Spectrum Density of each IMF and is tabulated as shown in Table 1 and Table 2 for planar and volumetric defects. From Table 1, it is inferred that the slope of the average power variation between Intrinsic Mode Function 2 and Intrinsic Mode Function 3 is greater for planar defects than that of volumetric defects.

5. Conclusion and Future Work

In this paper, Hilbert Transform is applied on the Intrinsic Mode Function of the Empirical Mode Decomposition decomposed ultrasonic signals. It is found that the slope between the average powers of IMF#2 and IMF#3 is greater for planar defects than for volumetric defects. Average power for the IMF#4 is much higher for planar defects than volumetric defects. However there are outliers for the above interpretation. Also generalisation of classification rules cannot be made within the planar and volumetric defects. In order to develop classification strategies it is necessary to determine a set of statistical parameters that describe the IMF's.

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