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Application of Hilbert-Huang Transform for Ultrasonic Nondestructive Evaluation

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***Abstract*—In this investigation, the Hilbert-Huang transform (HHT) has been evaluated to characterize the ultrasonic backscattered echoes from materials with different grain sizes and defects. The HHT is a combination of empirical mode decomposition and Hilbert spectrum analysis. First, the ultrasonic signal is decomposed into a series of intrinsic mode functions. Then, based on the Hilbert spectrum of these intrinsic mode functions, a time-frequency representation of the ultrasonic signal is obtained. Furthermore, to demonstrate the application of HHT in ultrasonic signal processing, the performance of HHT has been compared with the results from other time-frequency techniques such as chirplet signal decomposition. Numerical and analytical results indicate that HHT is a unique and effective tool for ultrasonic signal analysis accounting for narrow-band, broad-band, and dispersive echoes. This algorithm can be utilized in the analysis of ultrasonic signals often encountered in flaw detection, signal classification, and pattern recognition.**

Keywords- Hilbert-Huang Transform, Chirplet, Ultrasonic NDE

I. INTRODUCTION

In ultrasonic nondestructive evaluation (NDE) system, the patterns of detected echoes correspond to important physical information along the propagation path. These echoes often interfere with each other due to closed locations, boundaries, orientations, and size of random reflectors and they also may be contaminated by noise. Hence, it becomes challenging to unravel the desired information necessary for material characterization. Therefore, signal processing methods capable of characterizing the non-stationary and nonlinear behavior of ultrasonic signals for NDE applications are highly sought-after.

In an ultrasonic NDE system, it is common that the signal is non-stationary and/or nonlinear. Different time-frequency analysis methods, such as short-time Fourier transform, Wigner-Ville distribution, and wavelet transform, etc. have been utilized to deal with this situation by examining the signal in joint time-frequency domain. However, it is still a very significant problem to obtain a general basis which is adaptive to all signals, transient or stable, stationary or non-stationary, linear or nonlinear. Recently, the Hilbert-Huang transform (HHT) was proposed by Huang et al. [1] for signal analysis. This method consists of empirical mode decomposition and Hilbert spectrum analysis. HHT decomposes the signal into a series of intrinsic mode functions (IMF) by using the local characteristic information of the signal itself, such as the location of the local extreme points, and cross-zero points for data analysis. Therefore, these IMFs are oscillatory functions, which is inherently determined by the signal and adaptive to the signal itself. Moreover, unlike Fourier transform, these IMFs are not harmonic functions with constant frequency and constant amplitude. Their frequency is a function of time. The time-frequency representation of the signal, HHT, can be obtained from the Hilbert spectrum of these IMFs.

The HHT has been explored in the applications of structural heath monitoring, medical imaging, radar, speech, under-water acoustic feature extraction and climate variation analysis. It has been shown that HHT can be successfully utilized in many application areas, although there are still some critical mathematical problems to be solved [2-8]. In this paper, the HHT is introduced to characterize ultrasonic backscattered echoes and its performance has been compared to the estimation results obtained from chirplet signal decomposition algorithm [9-11].

The chirplet is a type of signal often encountered in ultrasonic applications. The six parameters of a chirplet [8], i.e., time-of-arrival, center frequency, amplitude, bandwidth factor, chirp rate and phase, can be used to represent a broad range of ultrasonic echo shapes. It has been successfully applied to analyze ultrasonic backscattered signals and obtain the parameters of the chirplets. In this work, these estimated parameters are used to confirm and verify the results and performance of HHT.

This paper is organized as follows: Section II briefly reviews the HHT. Section III discusses the link between HHT and chirplet signal decomposition and presents experimental results. Section IV summarizes the importance and application of HHT for ultrasonic NDE applications.

II. HILBERT-HUANG TRANSFORM

The HHT includes two processing components: empirical mode decomposition (EMD) and Hilbert spectrum processing. The objective of the EMD is to decompose a highly convoluted ultrasonic signal, $s(t)$, into a series of IMFs.

$$s(t) = \sum_{j=1}^{N} IMF_j(t) + r_1(t) \qquad (1)$$

where $r_1(t)$ denotes the residue of signal reconstruction; and $IMF_j(t)$ denotes the jth IMF function.

To check if a signal is an IMF or not, it should satisfy the following conditions:

1) $\left| Num_{extreme} - Num_{zero-crossing} \right| \le 1$

where

$Num_{extreme}$: The number of local extreme points (includes local maxima and local minima)

$Num_{zero-crossing}$: The number of cross-zero points.

2) $|m(t)| = \left| \frac{h_{\max}(t) + h_{\min}(t)}{2} \right| = 0$

where

$h_{\max}(t)$: The envelope interpolated by all the local maxima.

$h_{\min}(t)$: The envelope interpolated by all the local minima.

$m(t)$: The mean sequence of local maxima and minima envelops.

The process to obtain these IMFs is also called sifting process [1]. Figure 1 shows the flowchart of EMD (i.e., sifting process). The steps involved in the sifting process of signal $s(t)$ are outlined as following:

1. Prepare signal $x(t)$ for sifting process, where $x(t) = s(t)$, set the iteration index $j = 1$
2. Find all the local maxima and local minima of $x(t)$.
3. Interpolate the local maxima to form the maxima envelop, $h_{\max}(t)$. Similarly, the minima envelop, $h_{\min}(t)$, is obtained. Hence, the mean sequence, $m(t)$, can be obtained from $h_{\max}(t)$ and $h_{\min}(t)$.

$$m(t) = \frac{h_{\max}(t) + h_{\min}(t)}{2}$$

4. Subtract the mean envelop, $m(t)$, from the signal, $x(t)$ such that $h(t) = x(t) - m(t)$. Check if $h(t)$ is an IMF; If $h(t)$ is an IMF, go to Step 5; otherwise, go to Step 2 and update $x(t) = h(t)$, repeat Step 2 - 4. Otherwise, go to Step 5.
5. Save the IMF result: $IMF_j(t) = h(t)$, update the iteration index $j = j+1$, subtract the estimated IMF from signal $s(t)$ and obtain

$$x(t) = s(t) - \sum_{j=1}^{N} IMF_j(t) \cdot$$

6. Check the residue $x(t)$ from Step 5. If $x(t)$ is a constant or monotonic function, Save all IMFs and complete the sifting process; otherwise, update the $x(t)$ in Step 1 and repeat Step 2- 6.

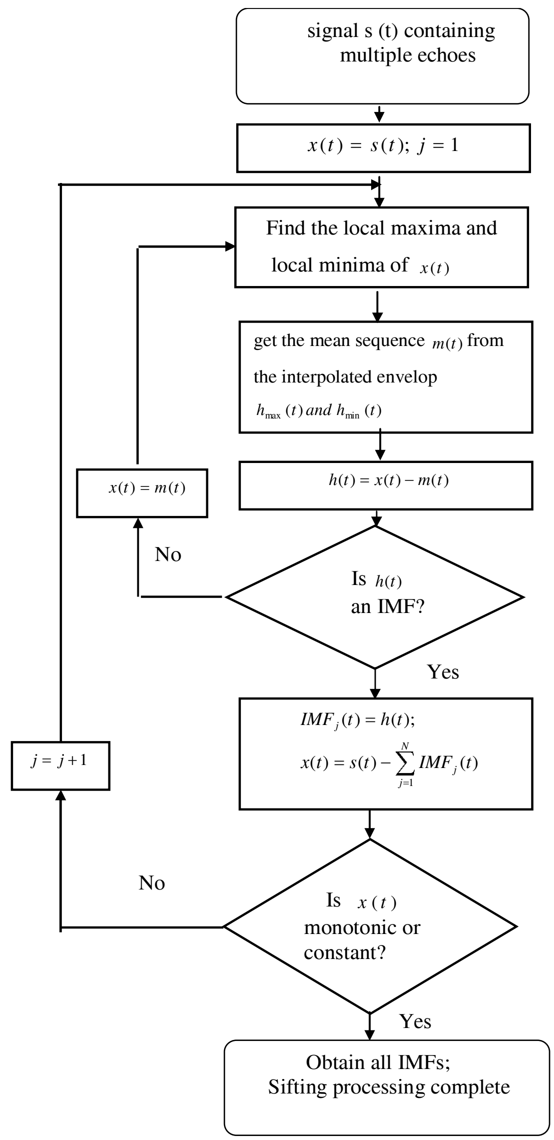

Figure 1. The flowchart of the sifting process

From the flowchart of the sifting process, it can be seen that the sifting process is a process to eliminate the asymmetric behavior of the signal and obtain the intrinsic oscillation.

To analyze the time-frequency property of signal, $s(t)$, Hilbert transform is applied to the signal. Therefore, the analytic signal, $z(t)$, can be defined as

$$\begin{aligned} z(t) &= s(t) + i\,H[s(t)] \\ &= a(t)\, e^{i\int \omega(t)dt} \end{aligned} \qquad (2)$$

where $H[\ ]$ denotes the Hilbert transform and

$a(t) = \sqrt{[s(t)]^2 + [H[s(t)]]^2}$,

$\omega(t) = \dfrac{d\theta(t)}{dt}$ and $\theta(t) = \tan^{-1}\left\{\dfrac{H[s(t)]}{s(t)}\right\}$.

Furthermore, Let $HT(t,\omega)$ denote the Hilbert time-frequency representation of the signal, $s(t)$, which is the combination of the amplitude $a(t)$ and the instantaneous frequency, $\omega(t)$.

Similarly, once all the IMF components are extracted from the signal, $s(t)$, the Hilbert time-frequency representation for each IMF and the reconstructed signal can be obtained through the Hilbert-transform process.

III. Chirplet Signal Decomposition

To quantify the performance of the HHT in the processing of ultrasonic backscattered signal, chirplet signal decomposition (CSD) is incorporated into this study for the comparison purpose.

The CSD algorithm is utilized to decompose the ultrasonic signal, $s(t)$, into a linear expansion of chirp echoes and efficiently estimate the parameter vectors of these echoes [9].

$$s(t) = \sum_{j=0}^{M-1} f_{\Theta_j}(t) + r_2(t) \qquad (3)$$

where, $r_2(t)$ denotes the residue of signal reconstruction,

$f_{\Theta}(t) = \beta \exp\left(-\alpha_1 (t-\tau)^2 + i2\pi f_c (t-\tau) + i\phi + i\alpha_2 (t-\tau)^2\right)$ denotes a single ultrasonic chirp echo.

$\Theta_j = [\tau, f_c, \beta, \alpha_2, \phi, \alpha_1]$ denotes the parameter vector, τ is the time-of-arrival, f_c is the center frequency, β is the amplitude, α_2 is the chirp rate, ϕ is the phase, and α_1 is the bandwidth factor of the ultrasonic echo.

IV. Experimental Analysis

An ultrasonic testing experiment is conducted to acquire ultrasonic backscattered signal from a steel block with a flat-bottom hole (i.e., target) using a 5 MHz transducer and sampling rate of 100MHz. Figure 2 shows the experimental data overlapped with the reconstructed signal using CSD algorithm, compared with the experimental data overlapped with the reconstructed signal using HHT. It can be seen that both methods can successfully reconstruct the experimental data. Moreover, the Wigner-Ville distribution (WVD) of the original signal and the reconstructed signal are shown in Figure 3. It can be seen that the target has been detected using CSD algorithm. Furthermore, the parameters of the target are shown in the first row of Table I, which lists the estimated parameters of chirplets.

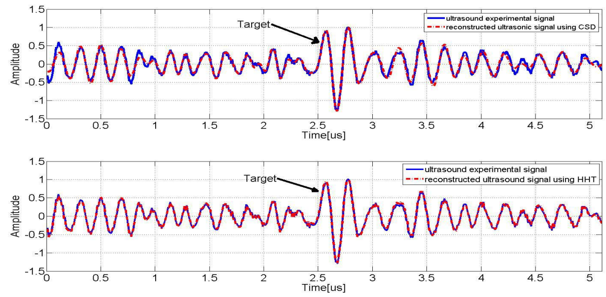

Figure 2. Ultrasonic experimental data superimposed with the reconstucted signal using CSD algorithm(top) and HHT(bottom)

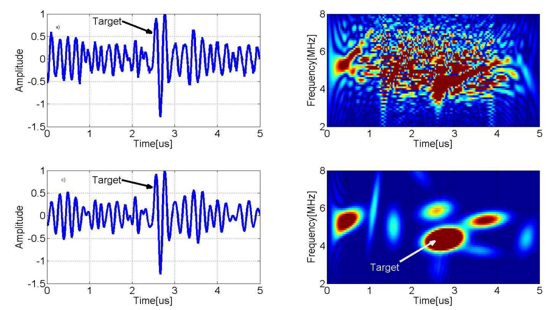

Figure 3. a) Ultrasonic backscattered signal
b) WVD of ultrasonic backscattered signal in (a)
c) Reconstructed signal using CSD
d) WVD of the reconstructed signal in (c)

The HHT has been applied to the same experimental data set. The EMD results are shown in Figure 4, where the ultrasonic experimental data, IMF #1, IMF #2, IMF#3 and residue function are listed from top to down. It can be seen that the echo location in IMF #1 is around 2.76 us, which is close to the time of arrival, τ, of the target in Table I.

Furthermore, unlike the WVD of the original signal (refer to Figure 3b), the Hilbert time-frequency representation of the ultrasonic signal (see Figure 5b) shows that the target is emphasized in the Hilbert time-frequency domain. As a comparison, the Hilbert time-frequency representation of the reconstructed signal (i.e., the summation of IMF#1, IMF#2 and IMF#3) is shown in Figure 5d. It can be seen that the information of the target is smeared and embedded in the time-frequency domain. However, by further examining the Hilbert time-frequency representation of the IMF #1, the useful information of the target, such as center frequency and time-of-arrival, is clearly shown in Figure 6b). The center frequency of the target is around 4.4 MHz and the time-of-arrival of the target is around 2.76 μs, which is in agreement with the estimated parameters using CSD algorithm.

V. Conclusion

In this study, the HHT has been introduced to analyze ultrasonic backscattered signals. Numerical and analytical results indicate that the HHT is a unique and effective tool for ultrasonic signal analysis according to the frequency content of the signal examined. This algorithm can be utilized in the analysis of ultrasonic signals often encountered in flaw detection.

Table I. Estimated parameters of chirplets

α_1 [MHz]^2	α_2 [MHz]^2	τ [µs]	f_c [MHz]	ϕ [rad]	β
4.0471	0.9305	2.7618	4.3513	-0.3515	0.6344
4.7087	2.7232	0.4432	5.3029	-1.6410	0.4160
2.6697	0.9354	3.7730	5.3614	2.9950	0.3057
4.0741	1.3073	2.5763	5.8642	-0.1821	0.2689
16.187	0.2435	1.5719	5.0293	3.7906	0.3002
10.316	3.7598	4.7039	4.4164	-1.0643	0.2400

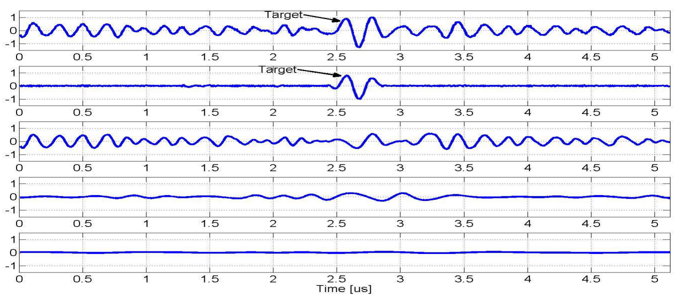

Figure 4. Empirical mode decomposition results (From top to down) Ultrasonic data, IMF #1, IMF #2, IMF #3 and the residue

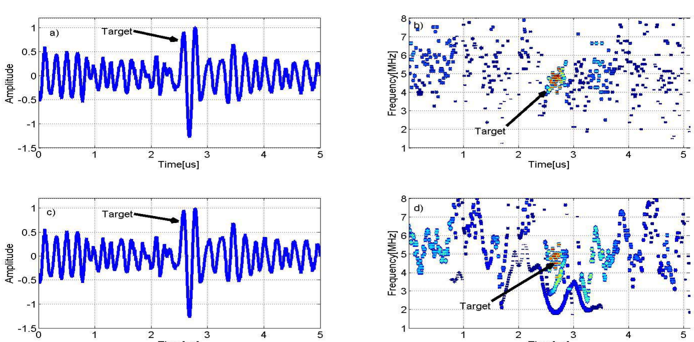

Figure 5. a) Ultrasonic backscattered signal
b) Hilbert time-frequency representation of ultrasonic backscattered signal in (a)
c) Reconstructed signal using IMF#1, IMF#2 and IMF#3
d) Hilbert time-frequency representation of the reconstructed signal in (c)

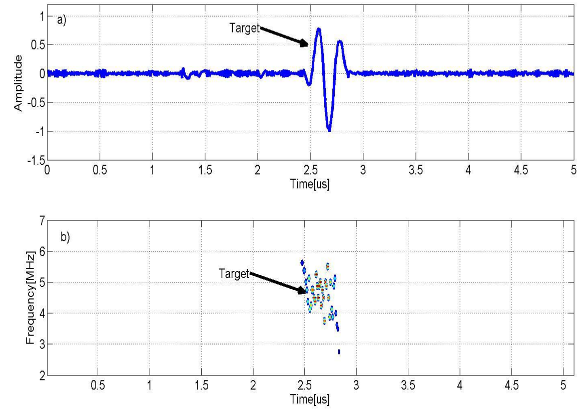

Figure 6. a) The IMF #1 from EMD results b) Hilbert time-frequency representation of the IMF #1 in (a)

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