Comparative study of noise reduction in ultrasonic inspection system

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Abstract: The effective noise reduction schemes in ultrasonic inspection have shown significant role for detection of flaws in materials. This paper presents the comparative result of noise reducing schemes based on Hilbert-Huang transform and Wavelet transform. The basic principle of HHT scheme includes two parts which are empirical mode decomposition (EMD) algorithm and a sum of intrinsic mode functions (IMF). By doing EMD process, the valuable information out of individual IMF can be maintained with reduced noise level for feature vectors. In the Wavelet transform, the signals are decomposed into low and high information and the feature vectors can be selected by Wavelet coefficients. In order to compare the performance of the two distinct schemes, this paper utilizes the soft and hard thresholding criterion on WT and HHT.

Key-Words: Ultrasonic inspection, Automatic signal processing, Hilbert-Huang Transform, Wavelet Transform, Denoising scheme, Nondestructive evaluation.

1 Introduction

Ultrasonic inspection techniques are commonly used to characterize welds in a variety of applications such as chemical and nuclear plants, and gas transmission. Due to the imperfections introduced into the material during the welding process, welding regions are often susceptible to various kinds of defects. In ultrasonic inspection of submarine hull welding, the detection of flaws is often rendered difficult by the clutter introduced due to the grain structure of the material. The scattering of ultrasonic waves from grain boundaries can interfere and introduce artifacts in the received signal that can sometimes mask indications of a small flaw. Hence, denoising the signal will enhance the ability of the automatic signal processing (ASP) system to detect flaws. In order to reduce noise in the detected signal, researchers provided many different kinds of signal processing methods, such as Short Time Fourier transform (STFT), two-dimensional fast Fourier transform, Wavelet transform and Wigner-Ville Transform [1,2]. Time-frequency distribution method is one of popular approaches in various applications for non-stationary and nonlinear signals [3]. Since STFT only analyzes stationary signals, the window width must be restricted in time and frequency domain. Wavelet transform has advantages such as being able to change adaptively to the time and frequency resolution according to the different frequency band, but the performance depends on the selection of wavelet basis.

Hilbert-Huang Transform (HHT) is a time-frequency analysis technique introduced by Huang et al, to process non-stationary signals. It combines the Hilbert transform and the Empirical Mode Decomposition (EMD). According to time scale characteristics, a signal is decomposed into a sum of monotonic function called Intrinsic Mode Function (IMF), which emphasizes local feature. [4] has been applied to EEG signals using the characteristics of IMF, instantaneous frequency (IF), marginal frequency (MF), and the Hilbert spectrum. In [5], Qin et al, introduced the instantaneous frequency estimation with iterated Hilbert transformation for multi-component demodulation. Through the decomposition, these IMF coefficients are transformed and processed by Hilbert transform. The HHT has two advantages: First, the signals with variable amplitudes and frequencies are obtained based on the EMD process. This process shows the advantage of breaking down the restriction of the Fourier transform with fixed amplitudes and frequencies. Second, EMD belongs to adaptive decomposition whose basis functions are sine and cosine functions, which has a series of variable amplitudes and frequencies. For non-stationary signals, this paper applied to the HHT method for reducing the noise. HHT can be applied to vector controller in control system [6].

In this paper, we describe the introductory ultrasonic welding inspection system in section 2. Wavelet transform and Hilbert-Huang transform will be explained in section 3 and 4 including the experimental results. Conclusions are drawn in section 5.

2 Ultrasonic inspection system

Welding is the most efficient way to join metals. It is also the only way to join two or more pieces of metal to make them act as one piece. Welding is widely used to manufacture or repair all products made of metal. Welds are encountered in many structures such as gas transmission pipelines, nuclear power reactors, aircrafts, automobiles, and ships.

Weld defects are produced by material stress, fatigue, and environmental changes as well as the manufacturing process. During weld inspection, the commonly occurring defects in welded joints are porosity, slag, lack of fusion, and cracks in Figure 1.

These defects can be categorized into two major types of discontinuities, namely volumetric and planar. Volumetric discontinuities include porosity and slag. Lack of fusion and cracks in the joints are referred to as planar flaws.

Test welds were fabricated with induced discontinuities. The welded test plates were 24 x 24 x 1 ½ - inch thick HY-80 steel as shown in Figure 2. A gas metal arc welding (GMAW) process was used to fabricate the plates. Figure 3 shows a general scanning procedure and geometry for a test plate. The transducer was moved along the longitudinal axis of the weld. In order to ensure coverage of the defect area, the test sample plate was scanned from either sides of the weld, referred to as north and south views.

Signals using an automated scanning system were generated using a 5 MHz transducer, 60 degree angle beam, and a sampling frequency of 25 MHz. Figure 4 shows the measured signal and corresponding frequency spectrum.

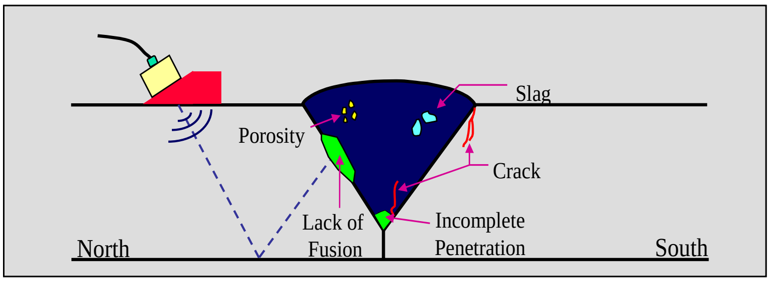


Fig. 1. Description of flaw types.

Fig. 2. Test sample of weld inspection.

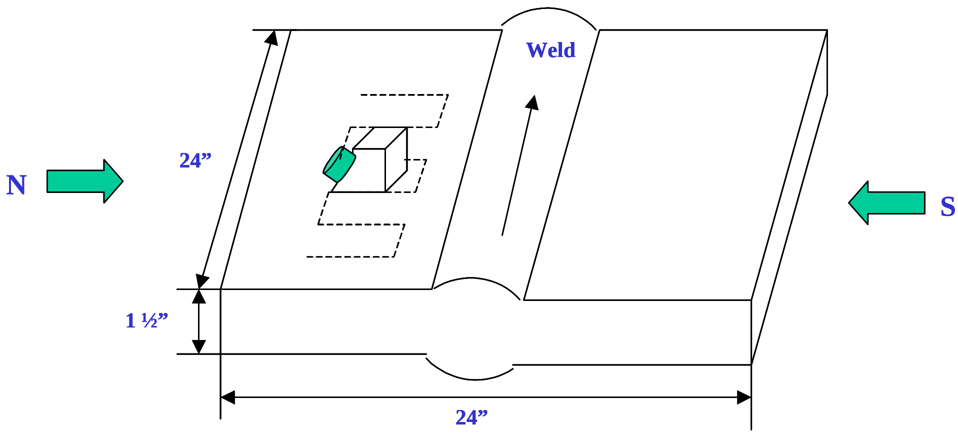


Fig. 3. Weld inspection geometry.

3 Wavelet transformation

3.1 General

Wavelet transform [7-9] is a recent analysis technique that is becoming increasing popular in many signal processing applications. The main characteristic of the wavelet transform is its multi-resolution decomposition of the information contained in a function or signal at different scales. In other words, wavelet analysis allows the use of longer time intervals where we want more precise low frequency information and shorter time intervals at high frequency information to get a good time resolution.

In the time-frequency plane, the basis functions of wavelet transform are localized in both frequency (scale) and time, in contrast to Fourier basis functions that are localized only in frequency. This multi-scale or multi-resolution analysis (MRA) is based on the following properties. First, the spanned signal spaces are nested from the null space to the full space, which can be written as

$$\{0\} = V_{-\infty} \subset \cdots \subset V_{-2} \subset V_{-1} \subset V_0 \subset V_1 \subset V_2 \subset \cdots \subset V_{\infty} = L^2(\mathbf{R}) \tag{1}$$

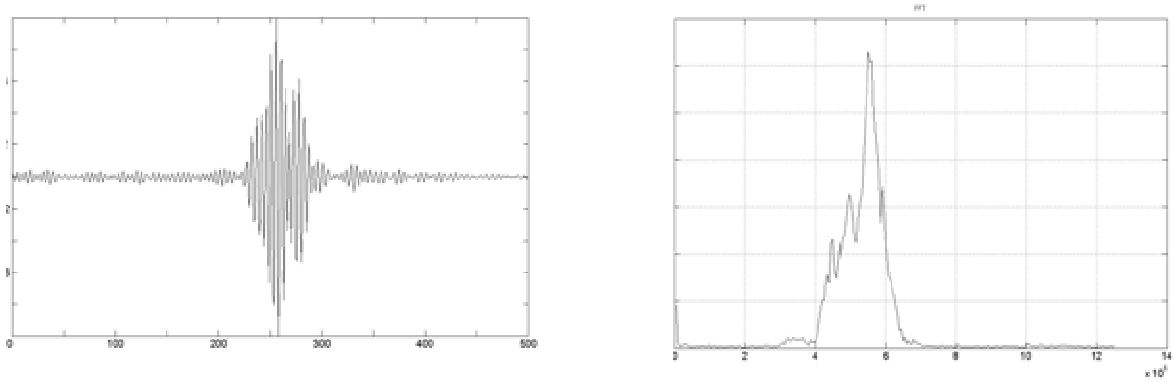
The above equation implies that V_1 consists exactly of all the functions in V_0 compressed by a factor of 2, V_2 consists of the functions in V_0 compressed by a factor of $2^2 = 4$, V_{-1} consists of the functions in V_0 dilated by a factor 2, and so on. For every pair of spaces $\{V_j, V_{j+1}\}$, we can define an orthogonal complement W_j from which the higher space can be recovered. This relation can be expressed as

$$V_j \oplus W_j = V_{j+1}, \quad j \in Z. \tag{2}$$

The symbol ‘⊕’ in Eq. (2) implies that the vectors in W_j plus the vectors in V_j can generate all vectors in V_{j+1}. V_j and W_j are orthogonal. The basis for each nested subspace V_j are derived from a scaling function $\phi(t)$. This scaling function $\phi(t)$ and its translation $\phi_k(t) = \phi(t-k)$ form an orthonormal basis for V_0 and can be written as $V_0 = \underset{k}{span}\{\phi_k(t)\}$. Hence, any function $f(t) \in V_0$ can be expressed as $f(t) = \sum_k a_k \psi_k(t)$. A two dimensional family of functions is generated from the dyadic scaling function according to $\varphi_{j,k}(t) = 2^{j/2}\varphi(2^j(t-k))$ so that $V_j = \underset{k}{span}\{\varphi_{j,k}(t)\}$. The details in the signal reside in the subspaces W_j which are spanned by dilates and translates of the wavelet function $\psi_{j,k}(t)$. Furthermore, it is required that the scaling functions and wavelets be orthogonal.

3.2 Denoising scheme

The original wavelet shrinkage algorithm of Donoho and Johnstone [10][11] has found many applications



(a) (b)

Fig. 4. The original signal and its spectrum.

in data de-noising. Noise cancellation using wavelet shrinkage is one possible approach for ultrasonic nondestructive evaluation. The main idea underlying wavelet shrinkage de-noising relies on wavelet coefficient thresholding. A standard model of noise in signals is additive Gaussian white noise that can be modeled as

$$y_i = f_i + z_i, \quad i = 0,1,...,n-1. \qquad (3)$$

where f_i are samples of f and z_i are independent and identically distributed (iid) N(0,1) random variables. For this model, Donoho and Johnstone showed in [12] that orthogonal wavelet transforms provide a powerful tool in recovering the original samples f_i by applying a simple thresholding rule to the noisy wavelet coefficients. The wavelet shrinkage de-noising procedures can be summarized as follows:

1. Decomposition.

Apply the discrete wavelet transform to a signal in Equation (3.19) and get the wavelet coefficients that can be defined as

$$WT(y_i) = WT(f_i) + WT(z_i) \qquad (4)$$

where WT stands for discrete wavelet transform, which is a linear operation. Hence, $WT(z_i) \overset{iid}{\sim} N(0,1)$ is also a Gaussian.

2. Threshold detail coefficients.

The main part of wavelet based de-noising is thresholding, which simply assigns wavelet coefficients with amplitudes less than a certain threshold to zero. In order to choose the threshold value, it is defined by $\lambda = \sigma\sqrt{2\log n}$ where n is a signal length and σ is the noise variance of the wavelet coefficients at the finest level [13][14]. In this research investigation, the level-independent estimates [15] of λ, i.e., one common estimate for all the multi-resolution levels in the wavelet decomposition, is obtained by including all the detail coefficients.

The threshold calculation method involves selecting the threshold as a quantile of the empirical distribution of the wavelet coefficients. In order to perform the thresholding operation, a nonlinear soft thresholding operation [16] may be applied as

$$\hat{w}_i = \begin{cases} w_i - \lambda, & w_i \geq \lambda \\ 0 & |w_i| < \lambda \\ w_i + \lambda, & w_i < -\lambda \end{cases} \qquad (5)$$

3. Reconstruction.

Using the inverse DWT, the thresholded wavelet coefficients are transformed back to obtain the filtered estimate of function, $\hat{f}_i$ of f_i.

Figure 5 shows the denoised signal and decomposition process by the Daubechies Wavelet threshold method.

4 Hilbert-Huang Transformation

4.1 General

The Hilbert Huang Transform (HHT) consists of two processes. First, it performs the Empirical Mode Decomposition (EMD) of the signal. Second, it calculates the Hilbert Spectrum of the EMD output IMFs. From these spectrums, an amplitude and frequency-time representation of the signal can be determined. Figure 6 describes the general flow of HHT. EMD algorithm plays role in HHT method to remove the measurement noise. The main interest of the EMD is to consider the features of the analyzed signal, which are oscillations on determining the IMFs by using an iterative process. This explains that the time-scale of the decomposition will automatically be adapted to the dynamic of the analyzed signal. The individual IMF is the result of the sifting process, which attempts to satisfy the following two criteria [17-20].

(1) The number of zero crossings and the number of local extrema must be the same or off by at most one.

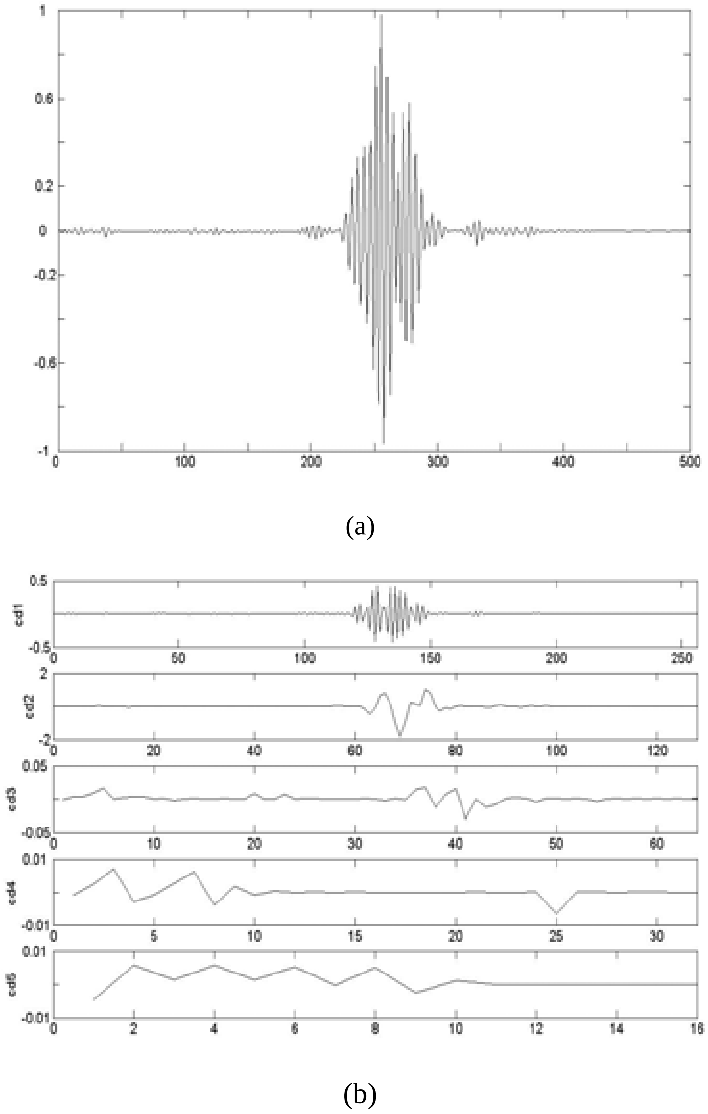


Fig. 5. The results from (a) a denoised signal and (b) its decomposition by Wavelet Transform

(2) The mean defined by the average of the local maxima envelop and local minimum envelop must be zero.

The following describes the general procedures for the sifting process of EMD.

Step 1: Calculate the upper and lower envelopes of the signal $x(t)$ and their mean value $m_1(t)$.
Step 2: Calculate $h_1(t)=x(t)-m_1(t)$
Step 3: Check if $h_1(t)$ satisfies the IMF properties.
Step 4: If not, use $h2(t)= h_1(t)-m_2(t)$ to obtain new h, where $m_2(t)$ is found from $h_1(t)$ as in Step 1.
Step 5: Continue until an $h_k(t)$ satisfies the IMF properties. When done, $c_1(t)=h_k(t)$ is the first IMF.
Step 6: Considering the $r(t)=x(t)-c_1(t)$ as the new signal, continue from Step 1 to get the higher IMFs, upto $c_n(t)$. The process is continued until the residue becomes a monotonous function.

Figure 7 shows the EMD decomposition and corresponding frequency spectrum on different scales with a signal,

$$x(t) = \sin(2*\pi*50*t) + \sin(2*\pi*100*t) + \sin(2*\pi*150*t) + 0.2*rand \quad (6)$$

From Figure 7, it can be seen that EMD is a new principal component analysis method, which extracts IMFs from high to low frequency, and those IMF coefficients focus on the most significant information of the original signal. Generally, noises are mainly concentrated on the first several scales. In Figure 7, IMF1 mainly includes high-frequency noise on the first scale, IMF2 on second scale of 150Hz, IMF3 of 100Hz, and IMF4 of 50Hz respectably. Through this process, the useful information can be extracted from EMD algorithm.

4.2 Denosing scheme

In Figure 5-(a), we can see that the denoising effect is not very well compared to that of the Wavelet transform. Figure 5-(b) shows the decomposition on different scales and the decomposition shows that measurement noise still exists on different scales. This paper uses the HHT method to remove the measurement noise. Figure 8 is the decomposed signal by HHT, which shows that noise and useful signal mainly focus on the first several scales (such as 1^{st},2^{nd}, 3^{rd}). In other words, the rest of IMFs can be ignored since the scales of the intrinsic mode amplitude are very small.

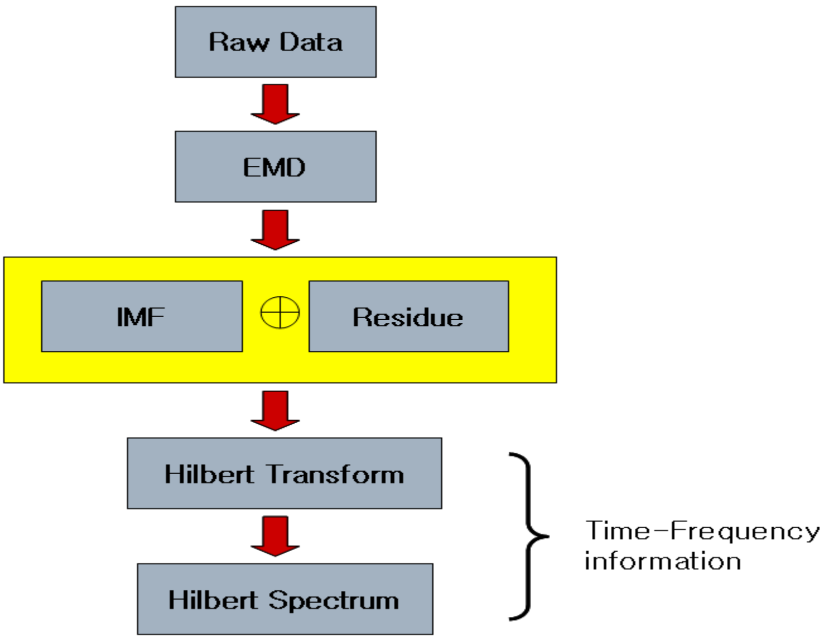
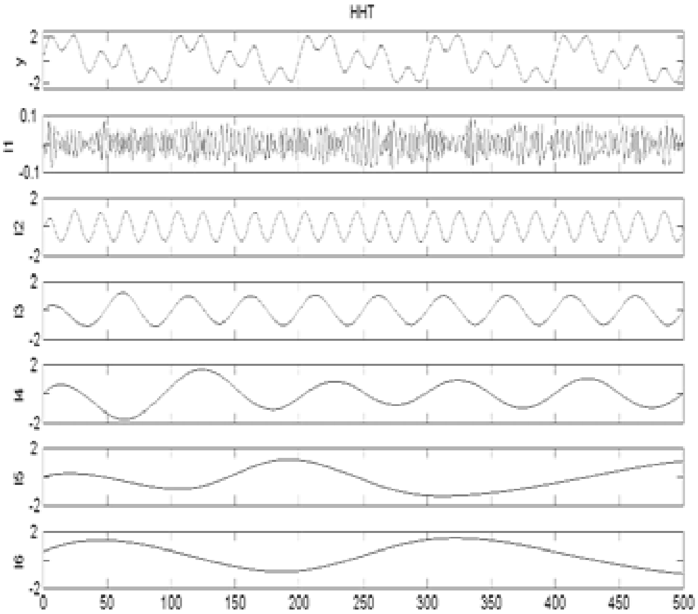
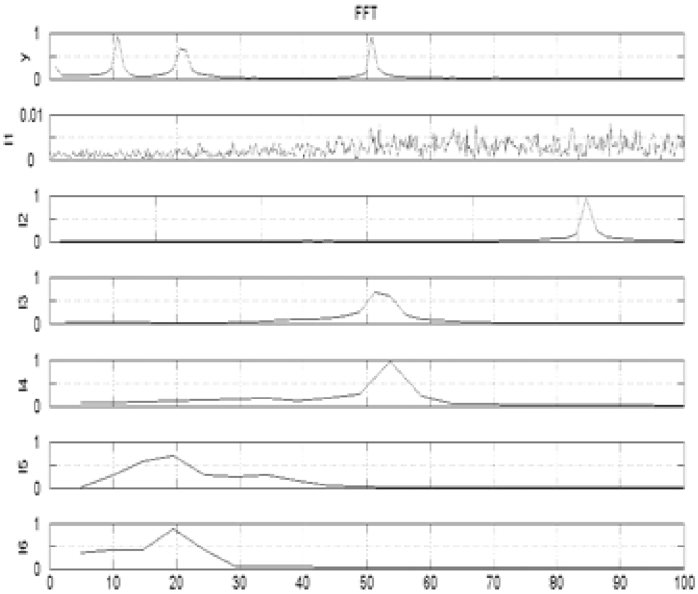


Fig. 6. The overall process of HHT



(a)



(b)

Fig. 7. EMD decomposition and frequency spectrum analysis: (a) EMD decomposition and (b) Frequency spectrum on different scales

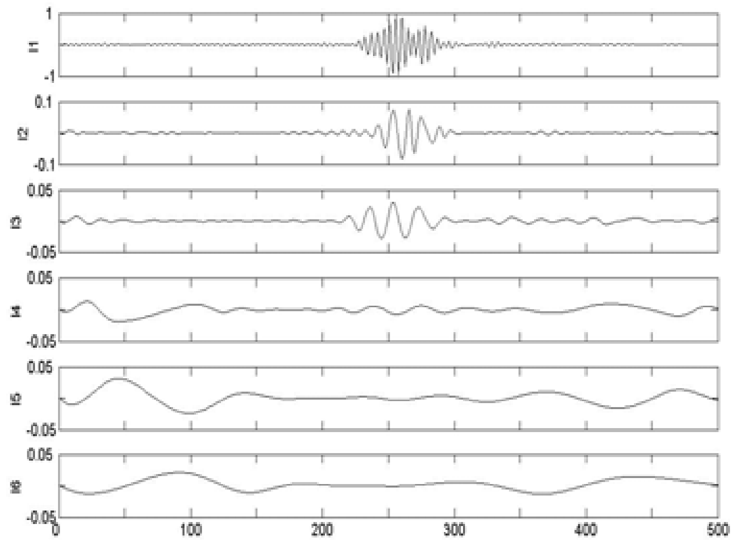
The denoising procedure by HHT is as follows:

(1) The signal with the noise is decomposed by EMD.

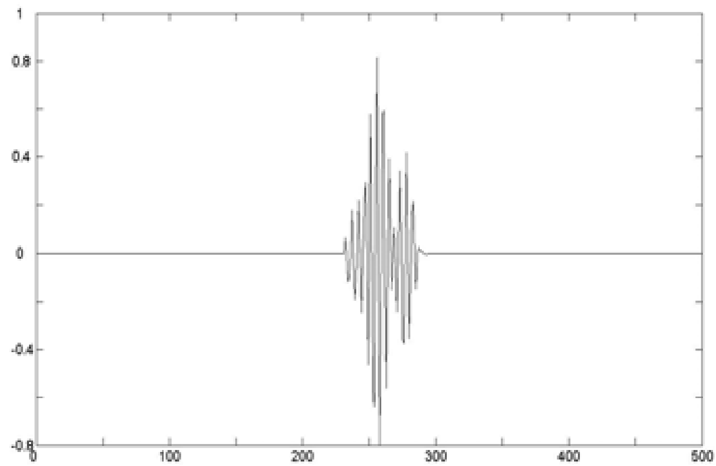
(2) From the scale with the valuable information, for example, 1^{st}, 2^{nd} or 3^{rd} scale, choose appropriate threshold at every scale [21] and remove high frequency noises using Eq. (7).

$$imf'(j,k) = \begin{cases} 0, & if\,|imf(j,k) < C_j| \\ \mathrm{sgn}(\mathrm{imf(j,k)})(|\mathrm{imf(j,k)}| - \mathrm{C_j}) & \mathrm{if}\,|imf(j,k) \geq C_j| \end{cases} \quad (7)$$

where $\{C_j\}$ are thresholds. The proceeded IMF coefficients from those scales (mainly the first 3 scales) are reconstructed and the filtered signal can be obtained from the reconstruction process. Fig.8-(b) shows the filtered signal by the method above. Comparing to Fig.5-(a), we could figure out that the result of the HHT method is better than that of the Wavelet transform.



(a)



(b)

Fig. 8. The results from (a) decomposition by HHT and (b) the denoised signal.

5 Conclusion

This paper introduced a method that is used to remove the measurement noise in welding by HHT. After analyzing its characteristics, the HHT method showed the capability to remove the measurement noise. The results showed that IMF coefficients by EMD include the local attribute information of the signal, which can reflect the signal's non-stationarity. Compared to the Wavelet transform, the HHT method has a better improvement.

Using the HHT method, several problems should be resolved for the future works. First, boundary treatment: Due to the limited length of the signal, both its two endpoints are not sure to be the extrema, therefore, the upper and lower envelop by cubic spline interpolation could be distorted seriously near the signal's each endpoint. Therefore the method of symmetric extension, endpoints value extension or a method selecting a starting point of the spline interpolation near the endpoint according to the change trends should be considered. Second, soft thresholding method: For the denoising purpose, it always comes up as a main issue for thresholding. We need to more study for the optimal thresholding value selection.

Acknolegement

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