The Application of Empirical Mode Decomposition Method on Detecting Underwater Sound

Fu-Tai Wang*, **Shun-Hsyung Chang**[†] , **Jenny Chih-Yu Lee**[†],**Haw-Jyi Lin***

* Dept. of Electrical Engineering, Hwa Hsia Institute of Technology
111 Gong Jhuan Rd., Chung Ho, Taipei, Taiwan
E-mail: wft@cc.hwh.edu.tw
[†] Dept. of Microelectronic Engineering, National Kaohsiung Marine University
142 Haichuan Rd., Nantzu, Kaohsiung, Taiwan

Abstract- **This paper proposes the use of Hilbert-Huang transform (HHT) empirical noise model (EMD) to the problem of non-stationary signals detection in underwater sound. The design procedures for an adaptive model of the background noise, using recursive density estimation of the joint distribution of the multivariate vectors of its Hilbert-Huang transform are described. Based on the HHT, any input data can be decomposed into a small number of intrinsic mode functions (IMFs) that can serve as the basis of non-stationary data for they are complete, almost orthogonal, local and adaptive. Discrete wavelet transform (DWT) is another tool for processing transient signals. From the computer simulation, based on the receiver operating characteristics (ROC), it shows that this proposed EMD-based detector is better than the DWT-based method.**

I INTRODUCTION

The wavelet transform is an adjustable window Fourier spectral analysis. Modifying the global representation of the Fourier analysis enables wavelet to analyze the non-stationary data. Based on a limited time window-width, various time-frequency approaches have been developed to detect signal underwater [1], [2], [3], [4], [5]. The necessary conditions for the basis to represent a non-stationary signal are: complete, orthogonal, local, and adaptive [6]. The locality and adaptive condition are the most decisive criteria for non-stationary data. By adapting to the local alteration of data, the processes of the decomposition can fully explain the hidden physics of the signals. The authors of [6] and [7] developed a new data analytical method HHT, based on the empirical mode decomposition (EMD), that a collection of intrinsic mode functions (IMFs) can be generated. In a broadband stochastic situation such as fractional Gaussian noise, the built-in adaptivity of EMD of HHT acting as a 'wavelet-like' dyadic filter bank was examined in [8]. An application of the EMD to identify the components of the wave spectra was investigated by Veltcheva [9]. By noting that each IMF is a zero-mean AM-FM signal, the Teager energy operator (TEO) can be used to track the energy of each IMF to estimate the IF [10] and [11].

In this article, these IMFs decomposed by the HHT of the non-stationary data are applied to an empirical model [2] to identify transient signals underwater. The summary features of these IMFs of underwater sounds appeared to exhibit distinctive multivariate behavior when signals occurred. A period of noise-only data is used to build an adaptive noise model of the background continuum by density estimation of these IMFs decomposed by the HHT. Observations considered to be outliers from this noise model at any time are then flagged as potential signals. In this paper, a comparison of the performance between the HHT-based model and the DWT-based method is illustrated.

II HILBERT-HUANG TRANSFORM AND INTRINSIC MODE FUNCTIONS

The Hilbert transform can make the data analytical and can provide a unique way for defining the instantaneous frequency. When $x(t) = \cos 2t$ with frequency $f = 1/\pi \approx 0.318$Hz, $x(t)$ has a zero mean and it is symmetric with respect to the zero mean. Its Hilbert transform is $\sin(2t)$ as in Fig. 1. Hilbert-Huang transform (HHT) is a new method for analyzing non-stationary signal [6]. Functions that satisfy the following two conditions are called intrinsic mode functions: (1) the number of zero crossings and the number of extrema must either equal or differ by one in the whole data set at most; and (2) the mean value of the envelope defined by the local minima and defined by the local maxima is zero at any point [6]. The local mean of the envelopes defined by the local minima and the local maxima is used to force the local symmetry instead. With the definition of the zero crossings, the IMF involves only one oscillation mode, excluding complex riding waves. With this definition, an IMF can be either a narrow band signal or non-stationary.

In most of the input data $X(t)$, more than one oscillatory mode is involved, and $X(t)$ are not IMFs. The process to reduce the data into IMF components is designated as the empirical mode decomposition (EMD) of the HHT [6]. This EMD is illustrated in Fig. 2. All the local minima are linked by a cubic spline as the lower envelope. For the local maxima, the upper envelope is produced. m_1 is denoted as the mean of these

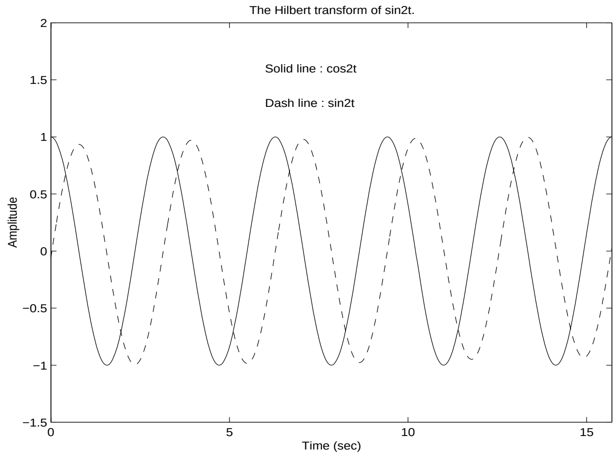

Figure 1: The Hilbert transform of cos2t is sin2t.

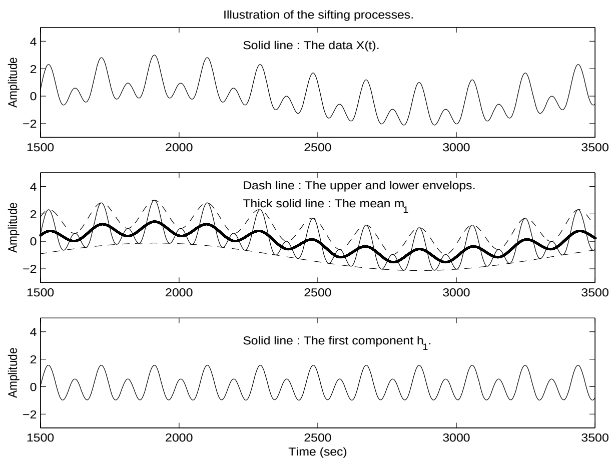

Figure 2: Illustration of the sifting process.

two envelopes. Two purposes of the sifting process are: (1) to eliminate riding waves; and (2) to make the wave-profiles more symmetrical [6].

As shown in Fig. 2, the wave h_1 is still asymmetric and it needs to be treated as the data and then take the the sifting process until h_{1k} is IMF. This IMF h_{1k} is then designated as the first IMF component of the data. The stopping criteria are provided in [7], [9]. The shortest period content of the data should be contained in c_1. Separating c_1 from the rest of the data, we have the residue r_1. By repeating the sifting process on r_1 and all the following r_js, the EMD of the HHT get

$$X(t) = \sum_{i=1}^{n} c_i + r_n. \tag{1}$$

Then a decomposition of the input data into n IMFs and one residue is achieved. The detail of the decomposition process is presented in [6]. Let us examine the linear sum of three cosine waves

$$x(t) = \cos\frac{2}{10}\pi t + \cos\frac{2}{20}\pi t + \cos\frac{2}{200}\pi t, \tag{2}$$

with the wave form in Fig. 3. The EMD of HHT has to be used for the asymmetric wave form. The three IMF components after applying the EMD are shown in Fig. 4.

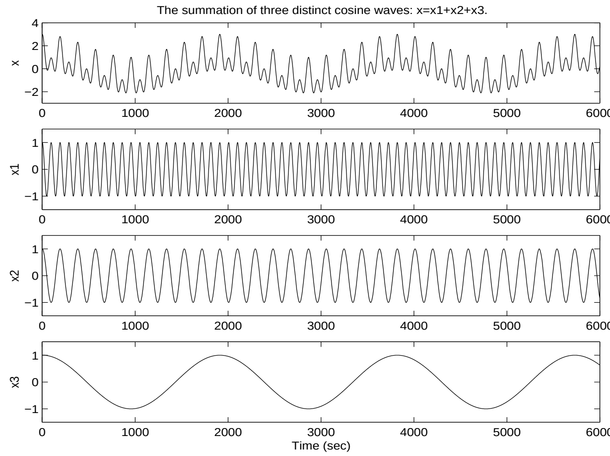

Figure 3: The summation of three distinct cosine waves: x=x1+x2+x3.

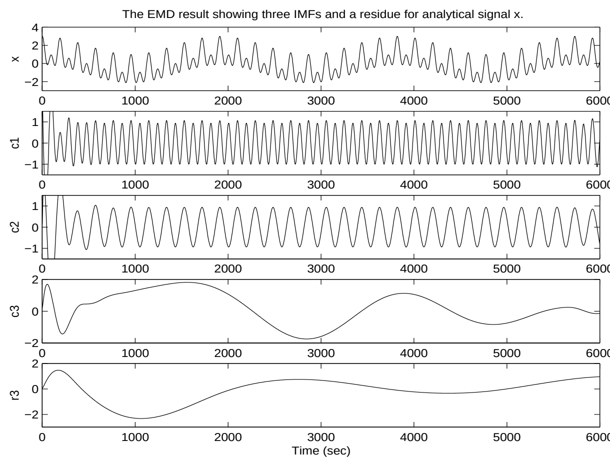

Figure 4: The EMD result showing three IMFs and a residue for analytical signal x.

By applying the Hilbert transform to the IMFs which sifted from the EMD of HHT, the instantaneous frequency of each component can be computed. That the amplitude and the instantaneous frequency are functions of time enable us to represent the data in a three-dimensional plot designated as the Hilbert spectrum [6]. Considering an isolated sine wave and treat it by the Hilbert spectral analysis. From the Hilbert spectrum as in Fig. 5, the energy of the calibration signal is highly localized in both time and frequency domains.

III EMPIRICAL MODE DECOMPOSITION AND SIGNAL DETECTION

Hilbert-Huang transform is a new method for analyzing nonstationary signal [6]. Any input data can be decomposed into a small number of intrinsic mode functions by using the empirical mode decomposition (EMD). From the Hilbert transform of the IMF, the instantaneous frequencies of the signal can be given. Finally, the input data is presented by the Hilbert spectrum in an energy-frequency-time distribution. Because the Hilbert transform can make the data analytical, it can provide

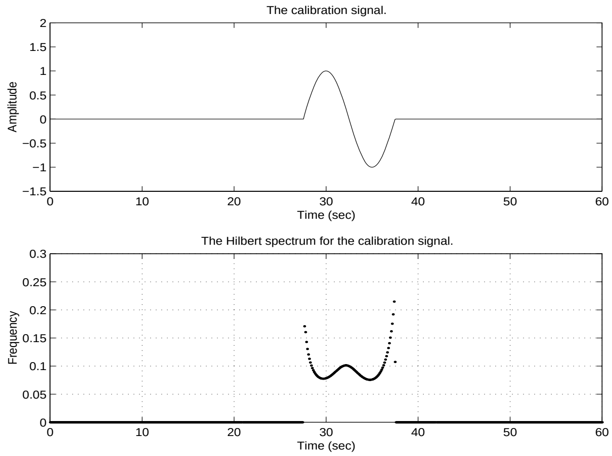

Figure 5: A calibration of time localization of the Hilbert spectrum analysis.

a unique way for defining the instantaneous frequency. In order to obtain a meaningful instantaneous frequency, some limitations should be adopted on the data. Functions that satisfy those restrictions are called intrinsic mode functions [6]: (1) the number of zero crossings and the number of extrema must either equal or differ by one in the whole data set at most; and (2) the mean value of the envelope defined by the local minima and defined by the local maxima is zero at any point.

At any given time, the input data $X(t)$ are not IMF's. More than one oscillatory mode is involved in most of them. The process to reduce the data into IMF components is designated as the empirical mode decomposition (EMD) [6]. The decomposition process starts with the envelopes constructed by the local minima and maxima separately. Once the extrema are found, all the local minima are linked by a cubic spline as the lower envelope. For the local maxima, repeat the procedure to produce the upper envelope. Then, all the data is covered by the lower and upper envelopes. The mean of these two envelopes is denoted as m_1. The first component h_1 is the difference between the data and m_1. Two purposes of the sifting process are: (1) to eliminate riding waves; and (2) to made the wave-profiles more symmetrical [6]. Ideally, h_1 should be an intrinsic mode function. Although all the local minima are negative and all the local maxima are positive, but wave h_1 is still asymmetric. Now h_1 is treated as the data and then take the the second sifting process: The sifting procedure has to be repeated k times, until h_{1k} is IMF. This IMF h_{1k} is then designated as the first IMF component of the data. The stop of the sifting process is determined by the size of the standard deviation SD:

$$\text{SD} = \sum_{t=0}^{T} \left[\frac{|h_{1(k-1)}(t) - h_{1k}(t)|^2}{h_{1(k-1)}^2(t)} \right], \qquad (3)$$

which computed from the two successive sifting results. Other stopping criterions are provided in [7], [9]. The shortest period content of the data should be contained in c_1. Separated c_1 from the rest of the data, we have the residue r_1. The sifting process then can be reprated on r_1 and all the following r_js and get

$$X(t) = \sum_{i=1}^{n} c_i + r_n. \qquad (4)$$

Then a decomposition of the input data into n IMF's and one residue is achieved. The detail of the decomposition process is presented in [6]. The EMD is adaptive and highly efficient, because it extracts IMF directly from the signal which associated with intrinsic time scales. For based on the local properties of the data, the EMD decomposition is applicable to non-stationary processes.

The authors of [2] used an empirical model of the noise for signal detection and found that summary features of discrete wavelet transform (DWT) decompositions of underwater sounds appeared to exhibit distinctive multivariate behavior when signals occurred. According to [2], underwater sound recordings are divided into appropriate time "window". Subdividing any given input data into periods of 0.743 second (with each period containing $2^{15} = 32768$ data points). Each of these 0.743 second segments split into 256 time windows with a length of 128 samples is subjected to the DWT analysis. The reconstructing details $d_1, ..., d_5$ of DWT in level 1 to level 5 covering the frequency ranges that are of interest in this case (i.e. 1–20 kHz) are summarized in terms of four mean sums of squares, $(v_{t,1}\ , \cdots\ , v_{t,5})$ for each time window t, so that

$$v_{t,j} = \frac{\sum_{k=1}^{128} d_{j,k}^2}{128}, \qquad j = 1, \cdots, 5$$

where $d_{j,k}^2$ are taken from time window t. Focusing on three mean sums of squares and forming a vector of multivariate observation $\mathbf{v}_t$=$(v_{t,3}\ , v_{t,4}\ , v_{t,5})$ in time window t. The behavior of these observations $\mathbf{v}_t, t = 1, \cdots, 256$ cover the range 1–5KHz. The joint behavior of these mean sums of squares of noise is significantly different from that of signals. This result suggests the usage of density estimates to establish the initial density estimate of noise and then to detect the signal.

Inspired by this application and by noting that IMF's can serve as the basis of non-stationary data and this basis is complete, almost orthogonal, local and adaptive, in this article, these IMF's of underwater sounds that are decomposed by the EMD is applied to this method. IMF's c_1, c_2, c_3 of underwater sounds are summarized in terms of three mean sums of squares, $(v_{t,1}\ , v_{t,2}\ , v_{t,3})$ for each time window t, so that

$$v_{t,j} = \frac{\sum_{k=1}^{128} c_{j,k}^2}{128}, \qquad j = 1, 2, 3,$$

where $c_{j,k}^2$ are taken from time window t. Focusing on these mean sums of squares and forming a vector of multivariate observation $\mathbf{v}_t$=$(v_{t,1}\ , v_{t,2}\ , v_{t,3})$ in time window t. The joint behavior of these mean sums of squares of noise is significantly different from that of signals. Based on the receiver operating characteristics (ROC), the following section will show that these vectors of multivariate observations $\mathbf{v}_t$ produced by EMD can establish the initial density estimate of noise and get a better detection performance then that proposed by DWT.

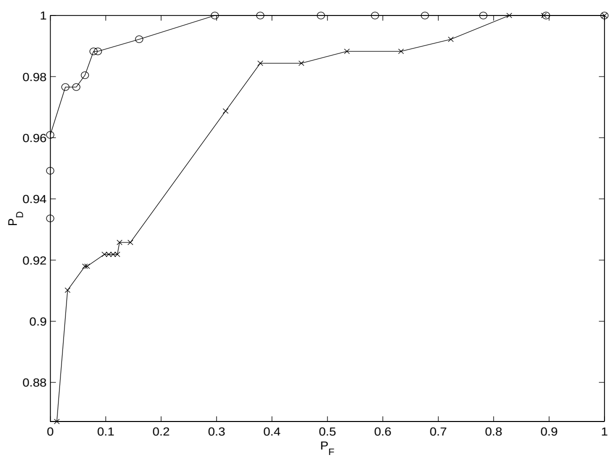

Figure 6: ROCs for the EMD-based detector 'o' and that of the DWT-based detector 'x'.

IV EMPIRICAL MODEL AND COMPUTER ANALYSIS

The authors of [2] suggested the usage of density estimates [12] to establish the initial density estimate of noise and then to detect the signal. The performance of the proposed EMD-based detector is compared to the DWT-based method by using the ROC curves in the following experiment. The empirical mode decomposition (EMD) is first applied to an initial sample ($32,768$ data points) taken from a sound recording consisting of pure background noise without signals of interest. The intrinsic mode functions (IMF's) c_1, c_2, c_3 decomposed by the EMD are summarized in terms of three mean sums of squares. Each one has 256 time windows. Density estimation of the joint distribution of these summaries is used to obtain an adaptive noise model of the background continuum and to choose a threshold value η.

For every threshold value η, with the experiment repeated 256 times, the $\mathsf{P_D}$ and the $\mathsf{P_F}$ for that particular threshold value can be evaluated. This experiment is run for several values of the threshold value η, and the ROC of the EMD-based detector by representing the $\mathsf{P_D}$ as a function of the $\mathsf{P_F}$ can be obtained and is plotted in Fig. 6. A comparison of the ROC between the EMD-based detector and the DWT-based method illustrated in Fig. 6 shows that the proposed method is better than the DWT-based detector if the $\mathsf{P_F}$ is lower than 0.83.

V CONCLUSION

The empirical mode decomposition (EMD) is introduced to the problem of signal detection in underwater sound. Based on the EMD, any input data can be decomposed into a small number of intrinsic mode functions (IMF's) which can serve as the basis of non-stationary data for they are complete, almost orthogonal, local and adaptive. Based on the receiver operating characteristics (ROC), it shows that this proposed EMD-based detector is better than the DWT-based method.

Acknowledgments

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REFERENCES

[1] S. A. Benno and J. M. F. Moura, "On translation invariant subspaces and critically sampled wavelet transforms," *Multidimensional Systems and Signal Process.,* vol. 8, pp. 89-110, Jan. 1997.

[2] T. C. Bailey, T. Sapatinas, K. J. Powell, and W. J. Krzanowski, "Signal detection in underwater sound using wavelets," *Journal of the American Statistical Association*, vol. 93, no. 441, pp. 73-83, March 1998.

[3] S. R. Massel, "Wavelet analysis for processing of ocean surface wave records," *Ocean Engineering*, no. 28, pp. 957–987, 2001.

[4] S. H. Chang and F. T. Wang, "Application of the robust discrete wavelet transform to signal detection in underwater sound," *INT. J. ELECTRONICS*, vol. 90, No. 6, pp. 361-371, 2003.

[5] F. T. Wang and S. H. Chang, "Signal Detection with Shift Invariant Noise Model Based on Wavelet," *in proc. OCEANS 2004 MTS/IEEE Conference and Exhibition*, Kobe, Japan, pp. 735-739, 2004

[6] N. E. Huang, Z. Shen, S. R. Long, M. C. Wu, H. H. Shih, Q. Zheng, N. C. Yen, C. C. Tung and H. H. Liu, "The empirical decomposition and the Hilbert spectrum for nonlinear and non-stationary time series analysis," *Proc. R. Soc. Lond. A.*, no. 454, pp. 903–995, 1998.

[7] N. E. Huang, M. L. Wu, S. R. Long, S. P. Shen, W. Q. Per, P. Gloersen, K. L. Fan, "A confidence limit for the empirical mode decomposition and the Hilbert spectral analysis," *Proc. R. Soc. Lond.*, no. 459, pp. 2317–2345, 2003.

[8] P. Flandrin, G. Rilling, and P. Goncalves, "Empirical mode decomposition as a filter bank," *IEEE Signal Processing Letters*, vol 11, no. 2, pp. 112–114, Feb. 2004.

[9] A. D. Veltcheva, C. G. Soares, "Identification of the components of wave spectra by the Hilbert Huang transform method," *Applied Ocean Research* , no. 26, pp. 1–12, 2004.

[10] A.-O. Boudraa, J.-C. Cexus, F. Salzenstein, L. Guillon, "IF estimation using empirical mode decomposition and nonlinear Teager energy operator," *Symp. on Control, Communications and Signal Processing*, pp. 45–48, 2004.

[11] F. T. Wang, S. H. Chang, and Jenny C. Y. Lee, "Hybrid wavelet- Hilbert-Huang spectrum analysis," *proc. OCEANS 2005 Europe IEEE Conference and Exhibition*, Brest, France, pp. 902–905, 2005.

[12] B. W. Silverman, *Density Estimation for Statistics and Data Analysis,* London: Chapman and Hall, 1986, pp. 78.