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Algorithm for Denoising of Underwater Acoustic Signal using Ensemble Empirical Mode Decomposition

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***Abstract*— The main focus of this paper is denoising of underwater acoustic signal to improve the performance of underwater acoustic instruments. The major sources of underwater ambient noises are distant shipping, wind, rain and biological activities. In this paper we have considered wind driven noise, which occupies wide bandwidth,as ambient noise source. A lot of research work has been done on denoising and most of the researchers have used wavelet as the denoising tool. In this paper we have proposed a novel denoising algorithm based on EEMD (Ensemble Empirical Mode Decomposition) , which is mainly suitable for non-linear and non-stationary signals. The results presented here will give an insight on the performance of this adaptive algorithm.**

Key words: ambient noise, denoising, Ensemble Empirical Mode Decomposition, Instrinsic Mode Functions (IMF), wind noise.

I. INTRODUCTION

A. Ambient Noise

Ambient noise is the prevailing, sustained unwanted background of sound at some location in the ocean and it excludes all forms of self noise [1].The four major classes of ambient noise are biological activity, ocean traffic, seismic and hydrodynamic. Each class of ambient noise is caused by a particular ambient noise source. Hydrodynamics is caused by the movement of water, which includes tides, storms, wind, current, rain, etc.In this paper we have considered only the wind driven noise, which is one of the dominant source of the ambient noise. Ambient noise is highly variable in shallow water due to high variability of ship traffic, wave guide nature of shallow water environment, reflection of noise from the bottom and surface and then by the biological activities. Sound speed in shallow water, where ocean depth is less than 200 meter, varies substantially [1].

B. Wind Generated Noise

In the absence of sound from ships and marine life, underwater ambient noise levels were dependent mainly on wind speeds at frequencies between 100 Hz and 25 KHz. The process by which the wind causes the ambient noise in the sea has been speculated by many theoreticians. Different processes are dominant in different portions of the overall frequency band from 1 to 50 KHz. In shallow water, in the absence of local shipping and biological noise, wind noise dominates the noise of distant shipping, over the entire frequency. At low wind speeds the average noise level was independent of windspeed but that at high windspeeds the noise level was linearly correlated with the logarithm of the wind speed [1]. In the absence of sound from ships and marine life, underwater ambient noise levels were dependent mainly on wind speeds at frequencies between 100 Hz and 25 KHz. C.L.Piggot (1964) took measurements on the Scotian shelf on sea noise data and analysed the spectral energy distribution for a number of wind speeds. He observed that noise was wind dependent in the high frequency band. A seasonal variation of noise level that was independent of frequency was also observed. The noise levels at the same wind speeds were higher during winter months [2][3].

C. Denoising

Underwater ambient noise consists of many noise signals ,which were generated by both natural and man-made sources. The removal of the noise from noisy data to obtain an unknown signal is referred as denoising. Extracting the desired signal, which is buried in to noise, is an essential step in the underwater communication to improve the performance of the acoustic instruments. There are many linear denoising methods available and those methods were not suitable for nonstationary signals. There has been a reasonable amount of research work has been done one denoising of nonstationary signals, most of which were based on wavelets. The main drawback of wavelet analysis is that it is non-adaptive in nature. Once the basic wavelet was selected, the same has to be used to analyse all the data. Since the most commonly used Morlet wavelet is Fourier based, it also suffers the many shortcomings of Fourier spectral analysis.EMD method was proposed for analysing nonlinear and nonstationary data [4] .Using EMD any complicated data can be decomposed in to finite number of IMFs. This decomposition method is adaptive and therefore highly efficient. The EMD also has one drawback called mode mixing, which makes the decomposition unstable. So in this paper we have used EEMD base denoising algorithm.

II. EMPIRICAL MODE DECOMPOSITION

Empirical Mode Decomposition (EMD) has been proposed (Huang, et al. 1998, Huang et al. 1999) as an adaptive time-frequency data analysis method. It has proven to be quite versatile in a broad range of applications, for extracting the desired signal from noisy signal[4].Using EMD any complicated data can be decomposed in to set of IMF.This method is adaptive and highly efficient,so it is used for analysing nonlinear and nonstationary data..

In the EMD approach, the data $x(t)$ is decomposed in terms of IMFs, c_j, i.e.,

$$x(t) = \sum_{j=1}^{n} c_j + r_n \qquad (1)$$

Where r_n is the residue of data $x(t)$, after n- number of IMFs are extracted.IMFs are simple oscillatory functions with varying amplitude and frequency, and hence have the following properties [4]:

1. Throughout the whole length of a single IMF, the number of extrema and the number of zero-crossings must either be equal or differ at most by one (although these numbers could be differ significantly for the original data set).
2. At any data location, the mean value of the envelope defined by the local maxima and the envelope defined by the local minima is zero.

The EMD algorithm is given as [4]

I. Given an input signal $x(t)$, identify its local extrema.

II. Interpolate between local maxima to construct an upper envelope $emax(n)$ and between local minima to construct a lower envelope $emin(n)$.

III. Compute the mean of the envelopes

$$m(n) = \left(emax(n) + emin(n)\right)/2$$

IV. Obtain $h_1 = x(t) - m_1$ and inspect whether the number of extrema and the number of zero crossings must either be equal or differ at most by one. Plus, inspect whether all the local maxima are positive and all the local minima are negative.

V. If not, repeat the sifting process and obtain

$h_1 - m_{11} = h_{11}$ and repeat to obtain

$h_{1(k-1)} - m_{1k} = h_{1k}$

VI. If h_{1k} constitutes an IMF, then designate it as $c_1 = h_{1(k)}$

VII. Now we obtain the first residual r_1 via $x(t) - c_1 = r_1$

VIII. Treat r_1 as a new data set, and perform the sifting process to obtain c_2.

IX. Continuing the sifting process we obtain

$$r_2 = r_1 - c_2, \ldots\ldots, r_{n-1} - c_n = r_n$$

X. The signal can be obtained from the IMF's as follows

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

III. THE ENSEMBLE EMPIRICAL MODE DECOMPOSITION

To overcome the scale separation problem without introducing a subjective intermittence test, a new noise-assisted data analysis (NADA) method was proposed, the Ensemble EMD (EEMD) [5], which defines the true IMF components as the mean of an ensemble of trials, each consisting of the signal plus a white noise of finite amplitude. With this ensemble approach, we can clearly separate the scale naturally without any priori subjective criterion selection.

The EEMD algorithm is given as follows[5]:

1. Add a white noise series to the targeted data.
2. Decompose the data with added white noise into IMFs.
3. Repeat step 1 and step 2 again and again, but with different white noise series each time.
4. Obtain the (ensemble) means of corresponding IMFs of the decompositions as the final result.

The effects of the decomposition using the EEMD are that the added white noise series cancel each other, and the mean IMFs stays within the natural dyadic filter windows, significantly reducing the chance of mode mixing and preserving the dyadic property. In fact, if the added noise amplitude is too small, then it may not introduce the change of extrema that the EMD relies on. However, by increasing the ensemble members, the effect of the added white noise will always be able to be reduced to a negligibly small level.

IV. DENOISING ALGORITHM

A. *Existing time domain thresholding algorithm*

In this algorithm Energy of each IMF has calculated, and then threshold value was calculated. The IMFs were shrunken using non negative threshold function and then added to get the denoised output [6]. We have considered a chirp signal, which is explained in the next section, as the input signal and a real time wind driven ambient noise signal as a source of noise. The noise signal, which was collected at the wind speed of 5.06 m/s, was added with the input signal to obtain the noisy signal. Then EEMD was applied to the noisy signal,then the noisy signal was decomposed in to set of IMFs.The energy of each IMF was defined as[7][8].

$$energy(count) = \frac{energy(1)}{0.719} * 2.01^{-count} \qquad (2)$$

Where $energy(1)$ is the energy of the first IMF which can be calculated by

$$energy(1) = \left(\frac{(median(|mode(1)|)}{0.6745}\right)^2 \qquad (3)$$

Where $mode(1)$ is the first IMF.

The threshold value of each IMF can be calculated by

$$threshold(count) = \sqrt{\left(\frac{energy(count)}{xsize}\right) * 2 * \log(xsize)} \qquad (4)$$

The first IMF can be discarded as it captures most of the noise and for other IMFs the adaptive threshold can be calculated using Eq. (4).

Then the coefficients of each IMF was shrunken using non negative Garrote threshold function which is given by [9][10]

$$mode(count) = mode(count) - \left(\frac{threshold(count)^{count}}{mode(count)^{(count-1)}}\right) \qquad (5),$$

For values of IMF greater than or equal to the threshold value. and

$$mode(count) = 0 \qquad (6),$$

For values of IMF less than the threshold value. Finally the shrunken IMFs were added to obtain the denoised signal.

B. *Proposed algorithm using frequency domain thresholding*

All the denoising methods have been done using time domain thresholding.In this paper we have proposed a novel denoising algorithm based on frequency domain thresholding. The algorithm is given as follows:

1. Input signal is assumed as a chirp signal.
2. A real time wind noise signal at a particular wind speed was

added with the input signal, which is called as noisy signal.

3. Then EEMD was applied to the noisy signal to obtain a set of IMFs.
4. Fourier transform was applied to each IMF.
5. Then threshold value has been applied to each IMF.i.e.signal amplitude, which are less than the threshold value are assigned zero.
6. Inverse Fourier transform was applied to each IMF.
7. Then all the thresholded IMFs were added together to get the denoised signal.

In this algorithm different threshold values from 10% to 90% of signal power were used. The mean square error (MSE) value was calculated for each threshold value. We have selected the threshold value, which was having minimum MSE value, as the desired threshold value.

V. RESULT AND CONCLUSION

In this paper we have considered chirp signal as input signal.The chirp signal is an oscillatory burst that starts at a low frequency and changes to a high frequency as time progresses. A chirp pulse is a frequency modulated pulse. Its duration is T, within this time the frequency is changing in a monotonic manner from a lower value to a higher one or reverse. The difference between these two frequencies is a good approximation for the bandwidth B of the chirp pulse. The wind driven noise signal was collected using sensitive hydrophones. It was ensured that other noises were absent during the measurement. The output of hydrophone is a voltage signal, which was converted into acoustic pressure based on the sensitivity of the hydrophone. The input chirp signal was added with noise signal to produce noisy signal, then EEMD was applied to decompose the noisy signal into set of IMFs.Then time domain denoising algorithm was applied to perform denoising.

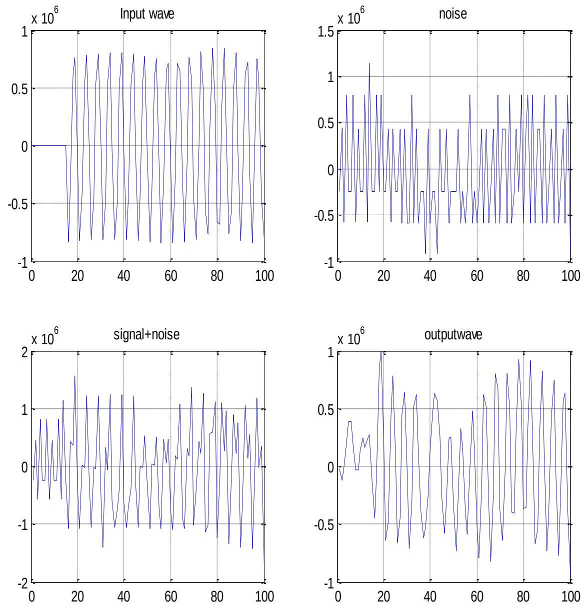

Figure 1 Results of time domain approach

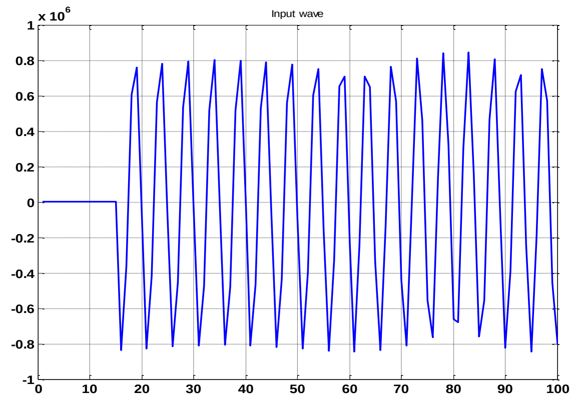

Figure 2 Chirp input signal

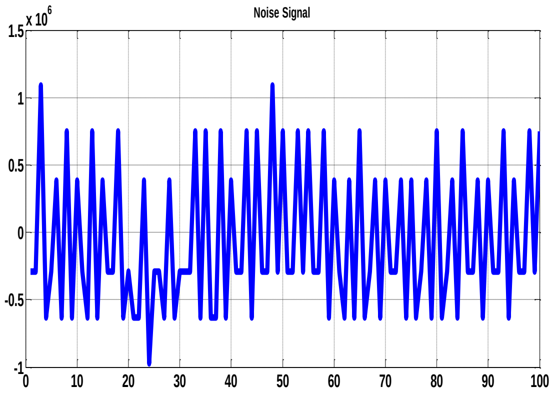

Figure 3 Noise signal

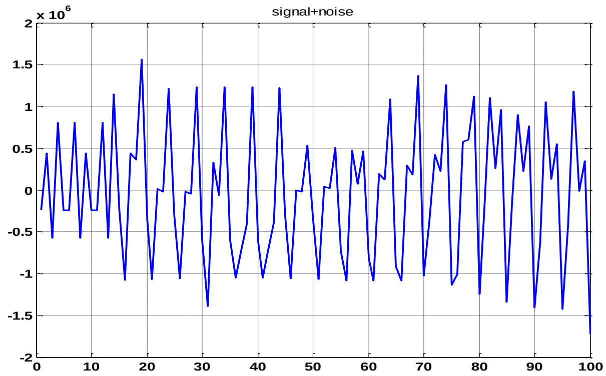

Figure 4 Noisy signal

The result of time domain algorithm is presented in Fig.1 and it is clear from the figure that the output signal was contained more noise. The time domain approach was not suitable for this noise, So we have applied threshold in frequency domain .The input chirp signal, which was used in this algorithm is shown in Fig.2 and it was also converted in sound pressure, which is measured in micropascal, based on the sensitivity of the hydrophone [11].Fig.3 shows the real time wind driven underwater ambient noise signal, which was measured at the wind speed of 5.06 m/s.The input signal was added with noise signal to produce noisy signal, which is presented in Fig.4. The noisy signal was decomposed in to set of IMFs using EEMD and the IMFs are shown in Fig.5.Then FFT was applied to each IMF, which is shown in Fig.6. The figure clearly shows that all IMFs are having maximum power at same point. Because signal component has more power than noise component at signal frequency. So different threshold values were chosen between 20% to 90% of the maximum power. Threshold was applied to each IMF and then IFFT has applied to IMFs.Then all the IMFs were added together to obtain the denoised output signal.

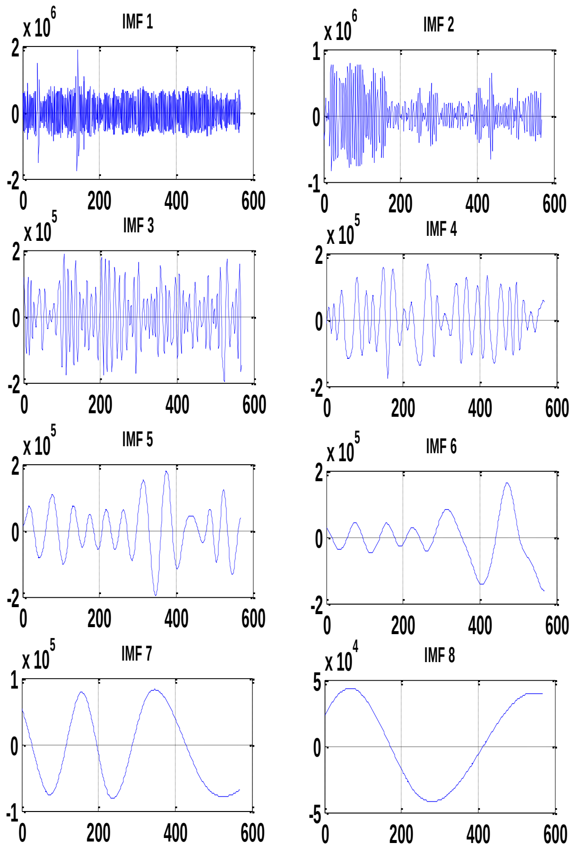

Figure 5 IMFs of noisy signal

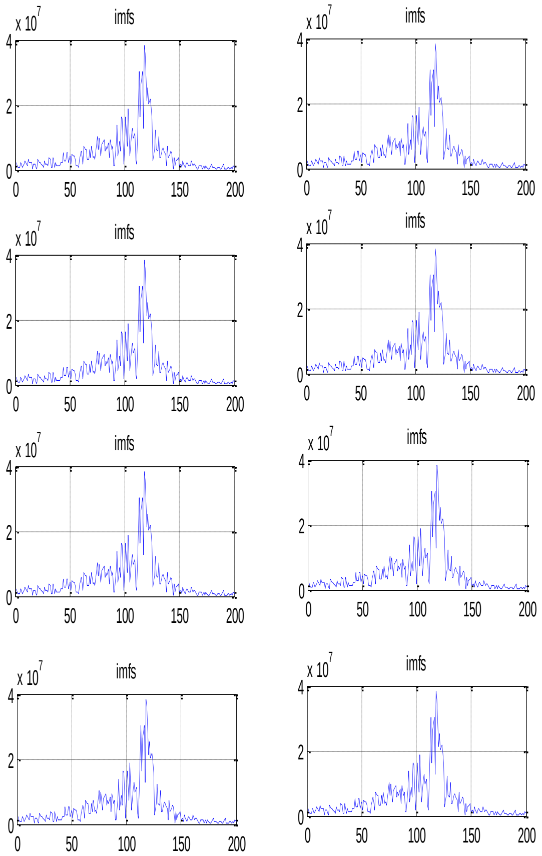

Figure 6 FFT of IMFs

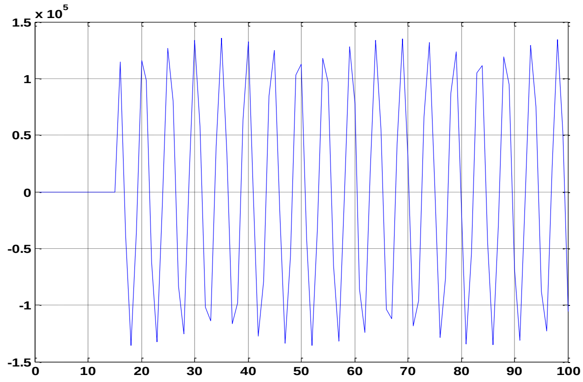

Figure 7 Denoised ouput signal

The Mean Square Error (MSE) was calculated for each threshold value using the following equation.

$$\text{Mean Square Error (MSE)} = \frac{1}{N}\sum_{n=1}^{N}(Z(n) - \hat{Z}(n))^2 \quad (7)$$

Where N is the length of data, $Z(n)$ is actual input signal and $\hat{Z}(n)$ is the denoised signal.Table 1. Shows the threshold values and their corresponding MSE values,till 60% threshold there was no change in MSE and above 60% the MSE value start decreasing.It has very less MSE at 90% threshold,so that was taken as desired threshold value.This algorithm was tested for different wind noise signal and the output is good all the time.

TABLE 1

Threshold value in %	**MSE Value**
20	0.0027
40	0.0027
50	0.0027
60	0.0027
70	0.0026
80	0.0023
90	0.0018

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