ISSN (Online) : 2278-1021
ISSN (Print) : 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering
Vol. 3, Issue 5, May 2014

Comparison of denoising techniques for Underwater Acoustic Signals.

Aashish Sharma[1], Dr. Surbhi Sharma[2]

ME Student, Department of Electronics and Communication, Thapar University, Patiala[1]

Assistant Professor, Department of Electronics and Communication, Thapar University, Patiala[2]

***Abstract*:** Underwater communication (UWC) is a low frequency communication. Its main application is transfer of data in between underwater instruments such as hydrophones, radars etc. The use of low frequency signal comes from the fact that the electromagnetic signals get absorbed under the water due to their high frequency. UWC is very defiant to work with because of its low frequency and random noise present in its conduit. The main purpose of this paper is to detect and denoise the various underwater acoustic signals using two different techniques i.e. EMD (Empirical Mode Decomposition) and Wavelet Transform. These methods denoise the signal by taking into account the effect of AWGN noise. Different types of threshold techniques have been used to denoise the signals. The simulation results shows that there is significant improvement in SNR of the signal when wavelet-soft thresholding technique is used. It is also observed that with the help of thresholding techniques, noise has been downgraded to certain level.

Keywords- Denoising, Underwater, acoustics, audio, DWT, EMD, Thresholding.

I. INTRODUCTION

Underwater acoustics [1] describes about the proliferation of acoustics under water and the communication of the perfunctory influences that establish acoustics under the water and its confines. Classic regularities allied with underwater acoustics are amid 20 Hz and 500 Hz .The transmission of acoustics inside the depths at frequencies subordinate than 20 Hz is typically inconceivable rather than piercing profoundly under the bottom of marine environment, however regularities over 500Hz are infrequently castoff since they are dipped hastily. Sound voyages promptly via water many spells quicker in comparison to air. As in exposed space, reverberations are conveyed through underwater as a firm tendency. They can be garish or indulgent, in elevation- or near to the ground, persistent, and their ability descents with amassed aloofness from cradle. Underwater communication [2] is the conduction of information from end to end in water. From time immemorial to current trends, auditory movement is still the crucial intermediary of motion transference in the deep, subsequently the EM [3] sprays will be feast due to its high rate of recurrence.In demand to antedate in research the enactment of audile exchange arrangements in tangible inundated ambiences proliferation strait archetypes are vivacious. With basis upon their rating of comprehensiveness and exactitude, these archetypes can awfully upsurge the odds of actual consciousness and thus slacken the price tag of broad-spectrum [4] practice.

Channel tapping [5] is frequently confronted with the problem of seizing the maximum of true ocean vibrant developments while restraining the amount of response strictures. In the standpoint of techniques which are to be used here, the techniques used here have been implemented on noisy image viz. DFT[6], DWT[7], EMD[8] and other STFTs[9] like DCT[10] etc. and the results thus produced are very promising. Based upon the results of the techniques applied on the noisy image [11] these techniques have been applied on synthetic underwater acoustic signals and the results have been shown.

Generally for research purposes of rigorous motions Fourier transform [12] is applied. There is no doubt that this transform is highly profitable & expedient, but it fails in probing the short-range ephemeral sound enactment. The point at which Fourier Transform stops responding discrete wavelet transform comes into play. In multi-path configurations [13], an estimation of the channel impulse response [14] is beneficial for sinking or revoking detrimental multi-path effects. In this perspective, there are numerous denoising techniques. The DWT approach though a bit multifarious but better than other orthodox techniques because it takes into account the sharp features of signal while decomposing as well as reconstructing the signal. The empirical mode decomposition (EMD) practice is familiarized for distinguishing motions from nonlinear, Non-stationary developments [15]. The main advantage of this modus operandi is that the rudimentary utilities are formulated from the motion itself as contrasting to being restricted beforehand like in the DFT and DWT .The EMD procedure obliquely molders the novel signal into numerous extreme and squat intrinsic mode functions (IMFs). EMD has been used for research purposes because it does not require any preset root purposes. Thus the most important denoising techniques are based on empirical mode

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decomposition (EMD) & Discrete Wavelet transform (DWT).

II. SIGNAL DENOISING

The process of extracting a novel signal from a mixture of signal and noise is called denoising. With the help of denoising noise in the signal is either compressed or detached from signal. The general procedure of signal denoising is given as follows.

For denoising the signal we have used two important Techniques EMD (Empirical Mode Decomposition)& DWT (Discrete Wavelet Transform) After the decomposition of signal thresholding [16] technique (HARD, SOFT, WAVELET) is applied in order to suppress the noisy coefficients. After the suppression of noisy coefficients inverse transform is applied to the thresholded signal and it is reconstructed using inverse transform and clean output is obtained. The procedure is explained in flowchart given in Figure1

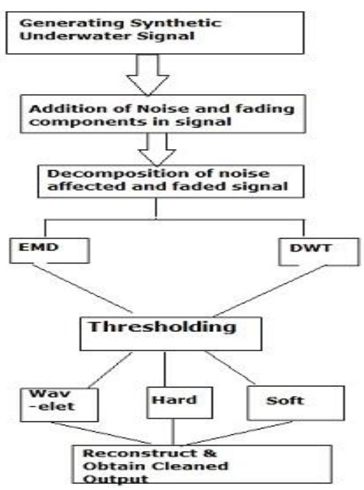


Figure 1 Flowchart of algorithm

III. EMPIRICAL MODE DECOMPOSITION

The EMD encompasses the flexible breakdown of known signal, Y (t) into a progressions of vacillating constituents which are also known as IMFs, by means of a disintegration practice termed as sifting protocol. The quintessence of this method is to ascertain the vacillating constituents at distinctive times, so that they can be elaborated in the vicinity via the stint amid dualistic extremes of a fluctuating manner or via the interval deferment concerning twofold zilch junctions. Mathematically:-

$$s(t) = \sum_{j=1}^{M} y_j(t) \cos\theta_j(t) \qquad (1)$$

Where y_j – amplitude

θ_j - phase

1) The disintegration Process

The route to get hold of the IMFs from the assumed gesture is called sifting. This method performs in the following manner. First of all the maxima and minima of Y_i is recognized. After that Utterance of the set of utmost and marginal points to attain a superior casing ($Y_{j_{up}}$) and an inferior casing ($Y_{j_{low}}$), respectively is done. After that Calculation of the value-by-value average of the superior casing and inferior casing is performed

$$m_j = (Y_{j_{up}} + Y_{j_{low}})/2. \qquad (2)$$

Where, m_j =average of upper casing and lower casing

After computation of average value detraction of the average from the novel signal to vintage is done as

$$d_j = Y_j - m_j. \qquad (3)$$

Where d_j = extracted signal

After that a Check is performed such that d_j satisfies the two situations for existence of IMF or not. If d_j is not found to be an IMF, aforementioned iterations remain continual by the time d_j mollifies the dual circumstances.

After an IMF is engendered, the lingering signal is

$$r_j = y_j - d_j \qquad (4)$$

Where r_j = residual signal after performing sifting is held as the novel signal, and stages preceding this are iterated to spawn for the next IMF, and so on. After completion of this process, the original signal

$$y_j = \sum_{i=1}^{M-1} d_{j,i} + r_{j,M} \quad i=1,\ldots\ldots,M \qquad (5)$$

Where, M is the number of IMFs, and $d_{j,i}$ are the IMFs. Figure 2 and Figure 3 depict the clean and noisy signal respectively and Figure 4 shows sifting process applied on signal Y_j

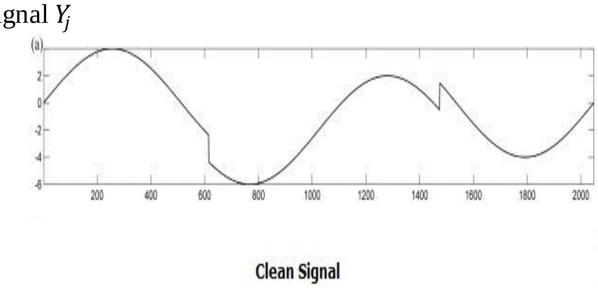


Figure 2

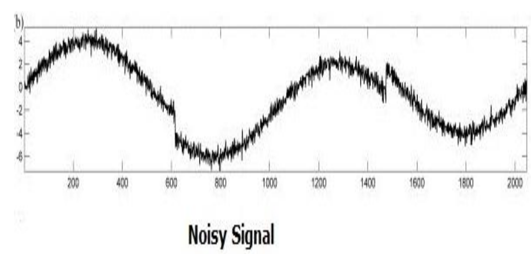


Figure 3

ISSN (Online) : 2278-1021
ISSN (Print) : 2319-5940

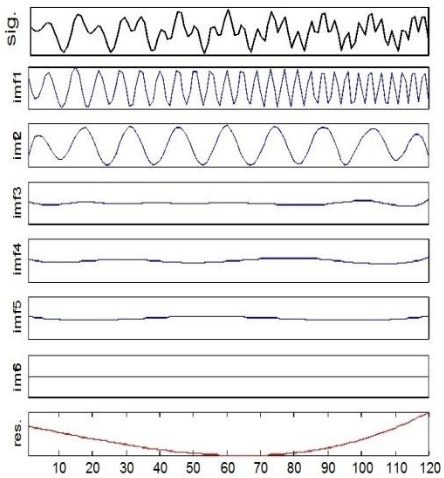


Figure 4- Sifting process of EMD

2) *EMD-Thresholding:-*
A Near to impeccable similar to or in comparison to the input signal is acquired by restricting the IMFs afore input refurbishment. If $\Gamma[., \tau_j]$ is a restricting occupation, then τ_j is the inception bound. In context to EMD there can be two varieties of thresholding:-

1. *Hard Thresholding*- Hard limiting is mathematically given by:-

$$K_j^{\wedge}(t) = U_j(t) \quad if \ |U_j(t)| > \tau_j$$
$$= 0 \quad if \ |U_j(t)| \le \tau_j$$

2. *Soft Thresholding* - The soft limiting indentures the separated sections by τ_j in limit approaching zero as given by:-

$$K_j^{\wedge}(t) = U_j(t) - \tau_j \quad if \ |U_j(t)| \ge \tau_j$$
$$= 0 \quad if \ |U_j(t)| < \tau_j$$
$$= U_j(t) + \tau_j \ if \ |U_j(t)| \le \tau_j$$

The figure 5 depicts the threshold level for hard and soft threshold methods

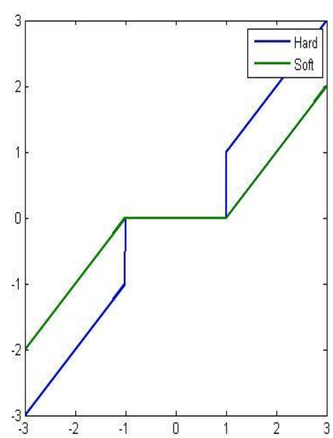


Figure5- Hard and Soft Thresholding

IV. WAVELET DENOISNG

Wavelets have abundant applications in signal dispensation comprising clamor subdual. It has been upheld that denoising in the wavelet dominion is habitually much tranquil than in the other conventional domains [17]. Moreover, it jellies the strident features of the signal to be mended, unlike the customary practices which use convolutional straining .Dissimilar base functions can be used to putrefy the countless frequency ensembles. Mathematically

$$\text{DWT(f. g)}= \frac{1}{\sqrt{f}} \sum y(n)\psi^{*}\left(\frac{k-g}{f}\right) \qquad (6)$$

Where f, g are decomposed functions
y(n) is noisy signal
Ψ is basis function

1) Proposed System Model
For this anticipated methodology, the noise as well as fading is taken into consideration with an equivalent synthetic underwater acoustic signal taken for displaying.
The signal deliberated is of very squat frequency with N outspreading from 10 to 100. The short frequency and low value of N is reflected so that we can scrutinize the signal in a thorough modus. Additionally in this model at a distance from hard and Soft Thresholding Wavelet Thresholding is also deliberated.
For each level of disintegration, in depth noise coefficient are castoff to find the restriction values. The noisy factors are acquired using the methods of the Hard, Soft and wavelet threshold function. For wavelet thresholding, each coefficient of noisy signal is associated by means of an onset in mandate to resolve whether it establish a looked-for measure of the novel input. To decide about the desirable part SURE SINK [19] algorithm has been used in which

$$\mu^{\wedge} = E_{\mu} || \mu - \mu^{\wedge} ||^2 \ \text{s} + \ E_{\mu}\{||\text{y(t)}||^2 + 2\nabla.y(t)\}$$
$$\hat{\mu} = E_{\mu} \|\mu - \hat{\mu}\|^2 s$$

$\mu =$ estimated threshold for signal
$\mu^{\wedge}$= set threshold of the the SURE algorithm

$$||\text{y(t)}||\text{^}2= \sum_{i=1}^{s}[\,min\,(|Y_i|, \tau)]\text{^}2 \quad (7)$$

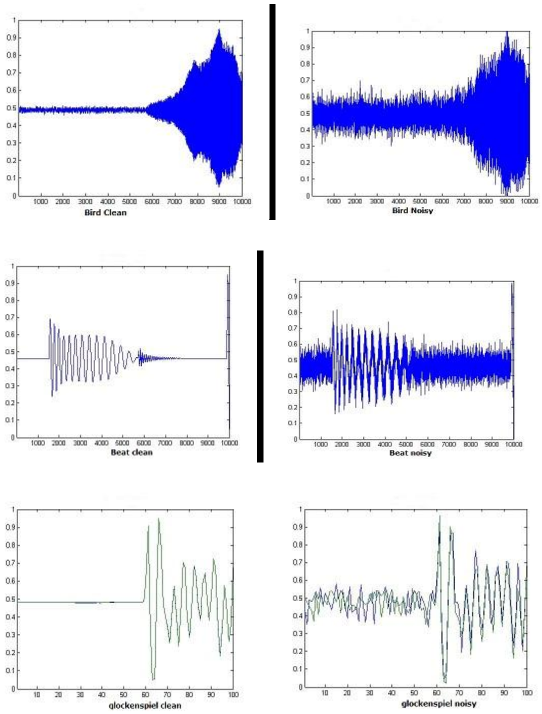
V. SIMULATION RESULTS

To investigate the denoising pattern, we have accomplished mathematical replications for three very short frequency signals attained using MATLAB which work unvaryingly as underwater acoustic signal. The novel signals as well as noise effected signals are shown in figures (a) and (b), respectively. Each noisy signal is putrefied using the EMD and the Wavelets. The significant results are obtained for bird sound, beats, and glockenspiel signals.

Table I shows comparisons of SNR values for Wavelets - hard, wavelet soft and wavelet. EMD-Soft and EMD-hard for different signals. SNR is computed as

$$\mathrm{SNR} = -10\log_{10}\left(\frac{\left\|\mathrm{SNR}_{\,clean} - \mathrm{SNR}_{\,noisy}\right\|^2}{\left\|\mathrm{SNR}_{\,clean}\right\|^2}\right) \qquad (8)$$

From Table I it is concluded that The wavelet -Soft and the wavelet-hard outperform the EMD-soft & EMD-hard and wavelet thresholding.

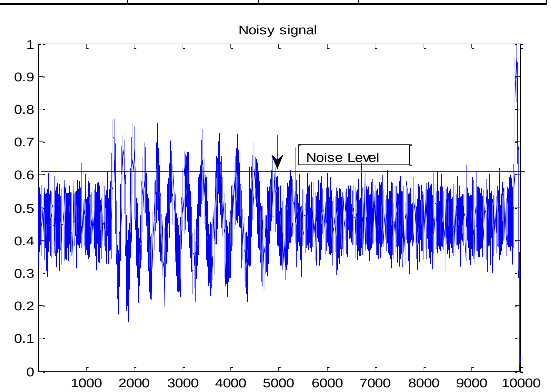


(a) (b)

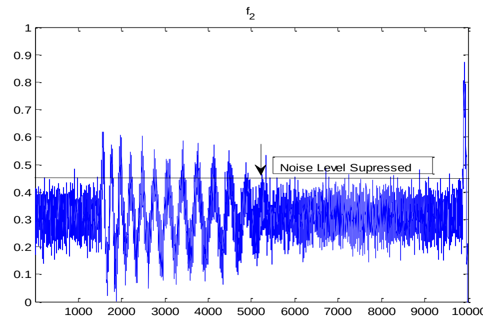
Fig6 .(a) Clean signals.(b) Noise effecte versions

Table I:- SNR comparison of the three synthetic signals at different thresholds

	Signals		
	Bird	Beats	Glockenspiel
	SNR	SNR	SNR
Noise	1.75	1.75	1.75
EMD-Soft	11.56	11.85	10.40
EMD-Hard	10.32	10.44	10.87
Wavelet-Hard	18.73	18.77	18.58
Wavelet-Soft	**22.27**	**22.38**	**22.98**
Wavelet-Threshold	11.34	11.78	10.20

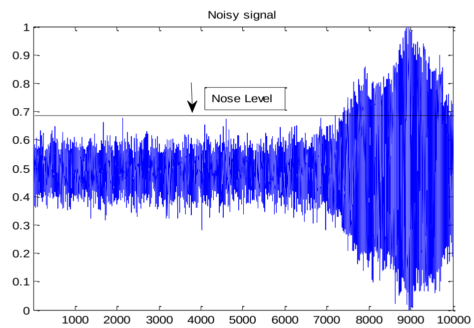


(a).After adding noise

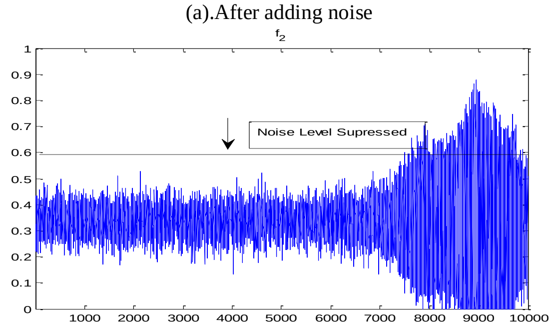


(b). After Suppressing Noise

Fig7(a)&(b); Comparison of noise level in beats signal

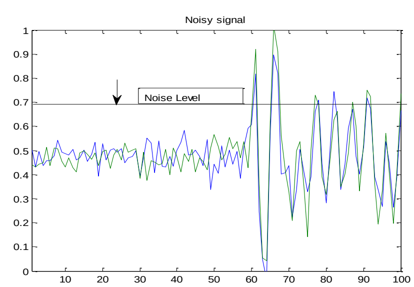


(a).After adding noise

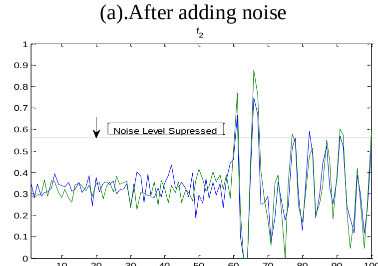


(b). After Suppressing Noise

Fig8(a)&(b): Comparison of noise level in bird sound signal



(a).After adding noise



(b). After Suppressing Noise

ISSN (Online) : 2278-1021
ISSN (Print) : 2319-5940

Fig9(a)&(b); Comparison of noise level in glockenspiel sound signal

VI. CONCLUSION

This paper compares two denoising schemes namely EMD and Wavelet . The technique based on EMD is totally independent of any previous basis functions, it acts according to the given data. The DWT approach though a bit multifarious but better than other classical techniques because it takes into account the sharp features of signal while decomposing as well as reconstructing the signal. The results are obtained using synthetic signals The noise level comparison of the three signals shows the compression of noise level after application of Denoising Techniques. The performance can be further improved if EEMD (Enhanced Empirical Mode Decomposition) and Gabor Transform is applied to the Underwater Acoustic Signal at various thresholds.

ACKNOWLEDGMENT

The authors are extremely grateful Dr. Rajesh Khanna, Professor, Electronics and Communication Engineering department for his timely guidance and his invaluable support

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