

Underwater acoustic signal denoising Based upon Empirical Mode Decomposition and Discrete Wavelet Transform

*Thesis Submitted towards the partial fulfillment of requirement for the award of degree of
Masters in Engineering*

In

Wireless Communication

Submitted by

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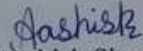
June , 2014

DECLARATION

I, Aashish Sharma, hereby certify that the work which is being presented in this dissertation entitled "Underwater signal denoising based upon EMD and STFT" by me in partial fulfilment of the requirements for the award of degree of Master of Engineering in wireless communication Engineering from Thapar University, Patiala, is an authentic record of my own work carried out under the supervision of **Dr. Surbhi Sharma Assistant Professor, ECED** and refers other researcher's works which are duly listed in the reference section.

The matter presented in this dissertation has not been submitted in any other University/Institute for the award of any other degree.

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It is certified that the above statement made by the student is correct to the best of my knowledge and belief.

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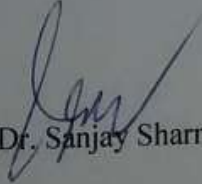


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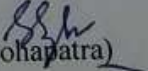
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ABSTRACT

Underwater acoustic communication is a rapidly growing field of research and engineering. The wave propagation in an underwater sound channel mainly gets affected by channel variations, multipath propagation and Doppler shift which keep lot of hurdles for achieving high data rates and transmission robustness. Furthermore, the usable bandwidth of an underwater sound channel is typically a few kHz at large distances. In addition, there is no typical underwater acoustic channel; every body of water exhibits quantifiably different properties. In order to achieve high data rates it is natural to employ bandwidth efficient modulation. The main problem with the underwater communication is addition of random noise in the signal. The noise in underwater is of various types such as ambient noise, ship noise, deep water noise, aquatic noise, shallow water noise etc. There are various techniques based upon signal processing and stochastic replay to denoise the signal.

Keeping in mind the complex and random nature of underwater communication two effective methods have been presented in this thesis. One is EMD (Empirical Mode Decomposition) based upon stochastic replay method and other is DWT (Discrete wavelet Transform) based upon Short Time Fourier Transform (STFT). Based upon these two techniques various thresholding techniques have been applied on different types of synthetic underwater acoustic signals embedded with noise and considerable degradation of noise is seen and also there is considerable improvement in SNR of the signal.

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List of Abbreviation Used

DFT	Discrete Fourier Transform
DCT	Discrete Cosine Transform
DWT	Discrete Wavelet Transform
STFT	Short Time Fourier Transform
EMD	Empirical Mode Decomposition
IMFs	Intrinsic Mode functions
USC	Under Water Sound Channel
AWGN	Additive White Gaussian Noise
PDF	Probability Density Function
HF	High Frequency
LF	Low Frequency
WPD	Wavelet Packet Decomposition
UFB	Uniform Filter Bank
SPG	Spatial Processing Gain
OSNR	Optimum Output Symbol SNR
SNR	Signal to Noise Ration
LFM	Linear Frequency Modulation
AUV	Autonomous Underwater Vehicle
MIMO	Multiple Input Multiple Output
GTL	Guide source Target Localization
MSE	Mean Square error
WSSUS	Wide Sense Stationary Uncorrelated Scattering
UWA	Under Water Acoustics
DFE	Decision Feedback Equalizer
EEMD	Ensemble Empirical Mode Decomposition
NADA	Noise Assisted Data Analysis
BLMS	Block Least Mean Square Algorithm
CWT	Continuous Wavelet Transform
QMF	Quadrature Mirror Filter
LP	Low Pass
HP	High Pass
SURE	Stein's Unbiased Risk Estimator
AM	Amplitude Modulation
FM	Frequency Modulation
PEF	Prediction Error Filter
AR	Auto Regressive
AIC	Akaike's Information Theoretic Criteria
WPT	Wavelet Packet Transform
CPT	Cosine Packet Transform
GBT	Gabor Transform

1.1 Under Water Acoustic Communication

The need for underwater wireless communications exists in applications such as remote control in off-shore oil industry, pollution monitoring in environmental systems, collection of scientific data recorded at ocean-bottom stations, speech transmission between divers, and mapping of the ocean floor for detection of objects, as well as for the discovery of new resources. Wireless underwater communications can be established by transmission of acoustic waves.

Underwater communications, which once were exclusively military, are extending into commercial fields. The possibility to maintain signal transmission, but eliminate physical connection of tethers, enables gathering of data from submerged instruments without human intervention, and unobstructed operation of unmanned or autonomous underwater vehicles.

1.2 Problems in Under Water Acoustic Communication

Underwater communications in general mainly gets affected due to following main factors:-

Channel Variations

The channel variations [1] in underwater acoustic communication occur due to following reasons:-

- Temperature
- Salinity of water
- pH of water
- Depth of water column or pressure and Surface/bottom roughness.

Doppler's Shift

- Due to the movement of the water surface, the ray getting reflected from surface can be seen as a ray actually getting transmitted from a moving transmitter, and thereby, having Doppler shift in the received.
- When the receiver and transmitter are moving with respect to each other, the emitted

signal will either be compressed or expanded at the receiver. Thereby, Doppler effect is observed.

Geometric Spreading

Geometrical spreading is the spreading of energy in space. What we mean by this is that when a certain amount of energy is radiated from a source it spreads over a certain volume. This spreading is very much dependent on which kind of radiation we have. For the 1D case there will be no geometrical spreading because the volume we radiate into is just a thin line. When we have 2D radiation the energy spreads over a cylindrical surface. The amplitude of the wave will then decrease proportionally to the distance, $1/\sqrt{r}$. For the 3D case, which is the most relevant for real situations, the energy spreads in all directions. This means that the energy will spread across a spherical surface, and the amplitude of the wave decreases proportionally to the distance, $1/r$.

When waves propagate there will be energy losses because some of the waves energy will be converted to heat. This heat is created by friction or viscosity caused by the wave action. This absorption is proportional to the frequency squared.

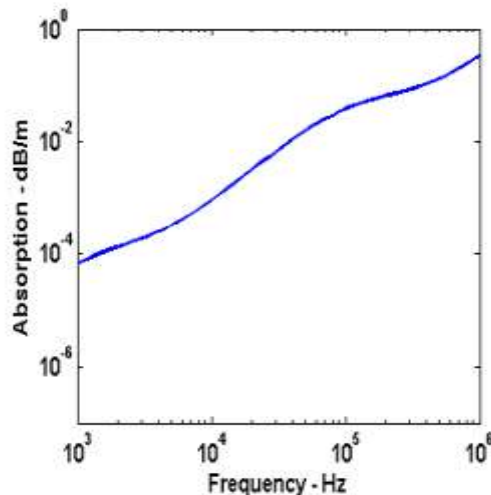


Figure 1.1: Absorption vs Frequency

In figure 1.1 the absorption is plotted as a function of frequency for a wave propagating in seawater. As one can see this causes a frequency selective fading channel

Doppler spread

When either the transmitter or/and the receiver in a communication system is in motion the signal will experience a frequency shift called a Doppler shift.

The signal will also experience a Doppler shift when interfering with waves at the surface. The Doppler spread is a measure of the spectral broadening caused by these Doppler shifts in the communication channel. This Doppler spread is highly dependent on weather conditions such as wind.

Solution to underwater noise problem

Channel tapping[2] 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, DWT, EMD [3] and other STFTs like DCT etc. and the results thus produced are very promising. Based upon the results of the techniques applied on the noisy image 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 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, an estimation of the channel impulse response 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 classical 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. 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 decomposition (EMD) & Discrete Wavelet transform (DWT).

1.3 Fundamentals of Ocean acoustics

The ocean is an extremely complicated acoustic medium. The most characteristic feature of the

oceanic medium is its inhomogeneous nature. There are two kinds of inhomogeneities:-

- Regular
- Random

Both strongly influence the sound field in the ocean. The regular variation of the sound velocity with depth leads to the formation of the “underwater sound channel” [4] and, as a consequence, to long-range sound propagation. The random inhomogeneities give rise to “scattering of sound” waves and, therefore, to fluctuations in the sound field.

1.3.1 Sound Velocity in the Ocean

Variations of the sound velocity c in the ocean are relatively small. As a rule, c lies between 1450 and 1540 m/s. But even, small changes of c significantly affect the propagation of sound in the ocean.

Numerous laboratory and field measurements have now shown that the sound speed increases in a complicated way with increasing temperature, hydrostatic pressure (or depth), and the amount of dissolved salts in water. A simplified formula for the speed in m/s was given by:

$$C = 1449.2 + 4.6T - 0.055T^2 + 0.00029T^2 + (1.34 - 0.01T)(S - 35) + 0.016z \quad (1.1)$$

Here the temperature T is expressed in $^{\circ}\text{C}$, salinity S in parts per thousand, depth z in meters, and sound velocity c in meters per second. The above equation. is valid for:

$$0^{\circ} \leq T \leq 35^{\circ}\text{C}, \quad 0^{\circ} \leq S \leq 45 \text{ ppt}, \quad \text{and} \quad 0^{\circ} \leq z \leq 1000 \text{ m}$$

The Eq. (1.1) is sufficiently accurate for most cases. However, when the propagation distances have to be derived from time-of-flight measurements, more accurate sound speed formulae may be required (i.e. ≤ 0.1 m/s). These are provided by accurate velocity meters.

1.3.2 Dependence of c on T , S and z

Fig. 1.2 shows the typical Temperature profile with surface of the sea at higher temperature than the temperature at the sea bed. Here we can see, temperature decreases with depth till some depth value $300 \text{ } z = \text{m}$ and after that getting constant. This corresponds to a summer profile of a

typical sea.

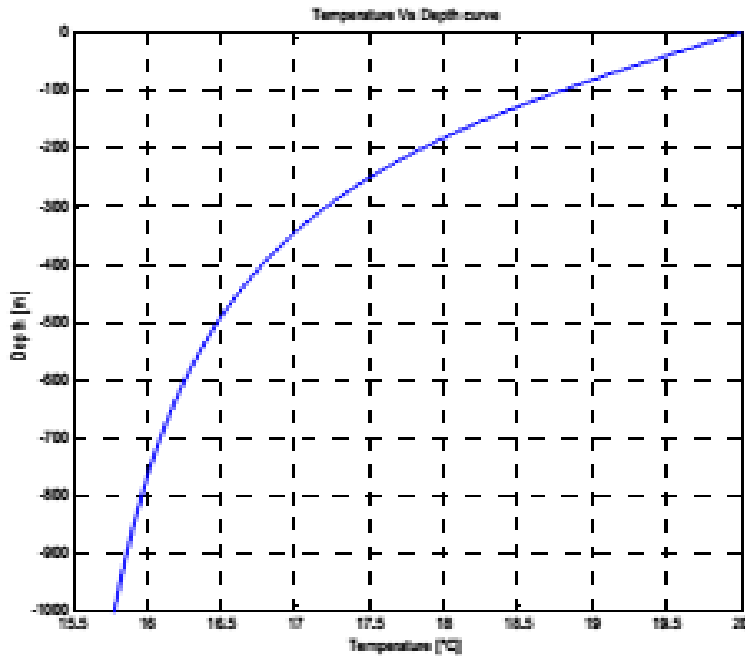


Figure1.2: Temperature vs Depth[5]

Sound velocity varies with temperature, salinity and depth. The impact of temperature and pressure upon the sound velocity, is shown in Figure.1.2. This can be viewed in three domains. In the first domain, temperature is the dominating factor upon the velocity of sound. In the second domain or transition domain, both the temperature and depths are dominating upon the velocity of sound. In the third domain, sound velocity purely depends on depths. These three domains can be seen in Fig. 1.2, first domain is till depths of 200 m, transition domain is from 200-400 m and the third domain is above 400 m.

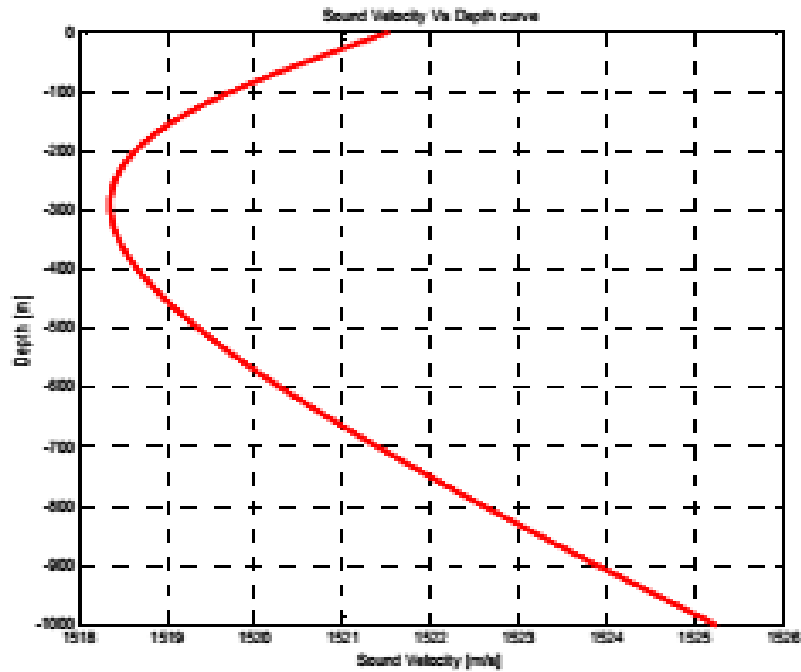


Figure 1.3: Sound velocity vs. Depth [6]

Dependence of sound on salinity, S is shown in Fig.1.3. Here, with the increase of S , velocity of sound, c , also increases keeping the shape of the profile unaffected.

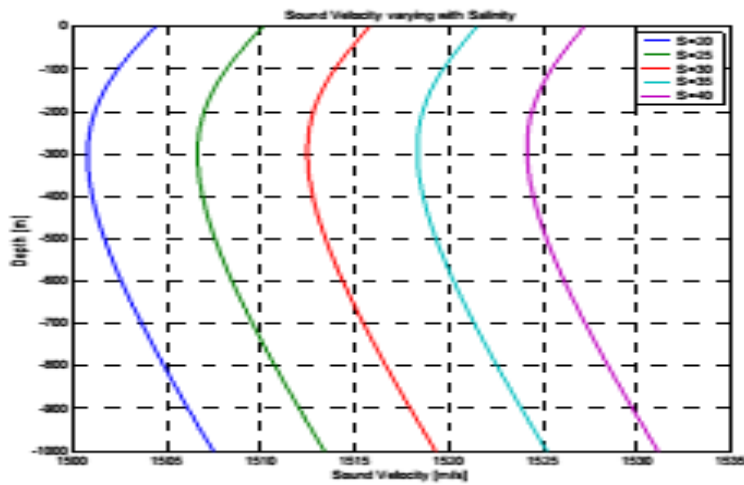


Figure1.4: sound velocity vs salinity [7]

1.3.3 Typical Vertical Profiles of Sound Velocity

The shape of the sound velocity profile $c(z) = c(T(z), S(z), z)$ is the most important for the propagation of sound in the ocean.

The $c(z)$ profiles are :-

- Under water Sound Channel of First kind
- Under Water Sound Channel of Second kind

At depths below 1 km variations of T and S are usually weak and the increase of sound velocity is almost exclusively due to the increasing hydrostatic pressure. As a consequence sound velocity increases almost linearly with depth or surface, and, therefore, not undergoing scattering or absorption at these boundaries.

- *Underwater Sound Channel of the first kind, $c_o < c_h$*

c_o – velocity at the surface,

c_h – velocity at a depth ‘h’

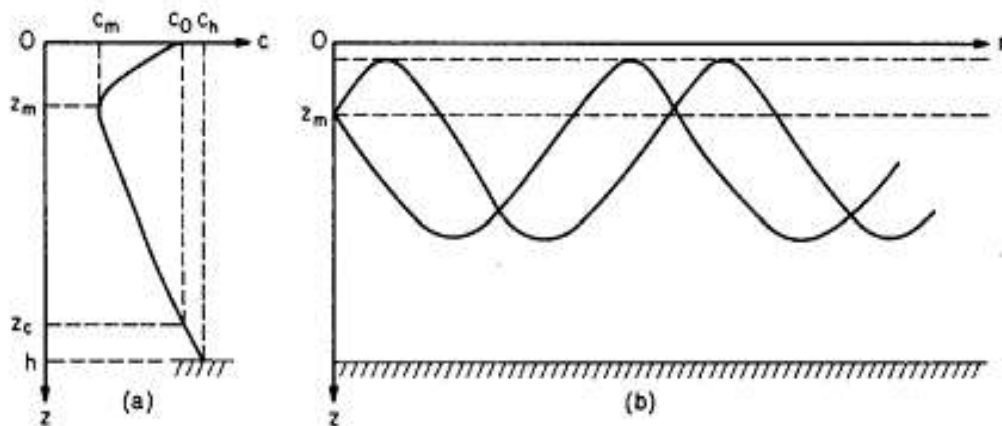


Figure1.5: Underwater sound channel of the first kind ($c_o < c_h$). (a) profile $c(z)$, (b) Ray diagram Underwater sound channel of the first kind ($c_o < c_h$). (a) profile $c(z)$, (b) Ray diagram[8]

Waveguide propagation can be observed in the interval depths of $0 < z < c$. The depth $z = 0$ and $z = z_c$ are the boundaries of the USC. The channel traps all sound rays that leave a source located on the USC axis at grazing angles.

$$\chi < \chi_{max} \text{ with } \chi_{max} = [2(c_o - c_m) / c_m]^{0.5} \quad (1.2)$$

where c_m and c_o are the sound velocities at the axis and boundaries of the channel, respectively. Hence, the greater the difference $c_o - c_m$, the larger is the interval of angles in which the rays are trapped, i.e. the waveguide is more effective.

- **Underwater Sound Channel of the second kind $c_o > c_h$**

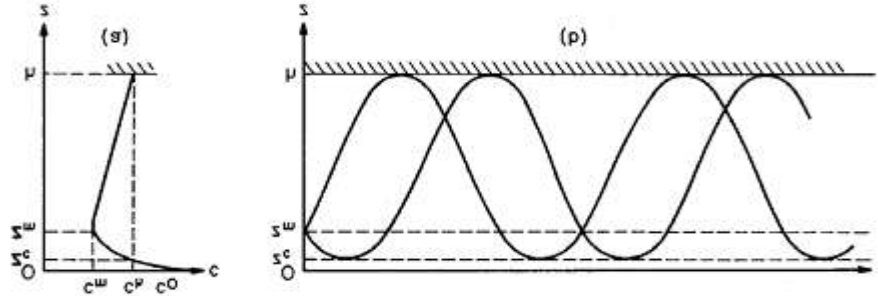


Figure1.6: Underwater sound channel -second kind ($c_o > c_h$). (a) profile $c(z)$, (b) Ray diagram[9]

1.4 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 [10] 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 Figure.1.7

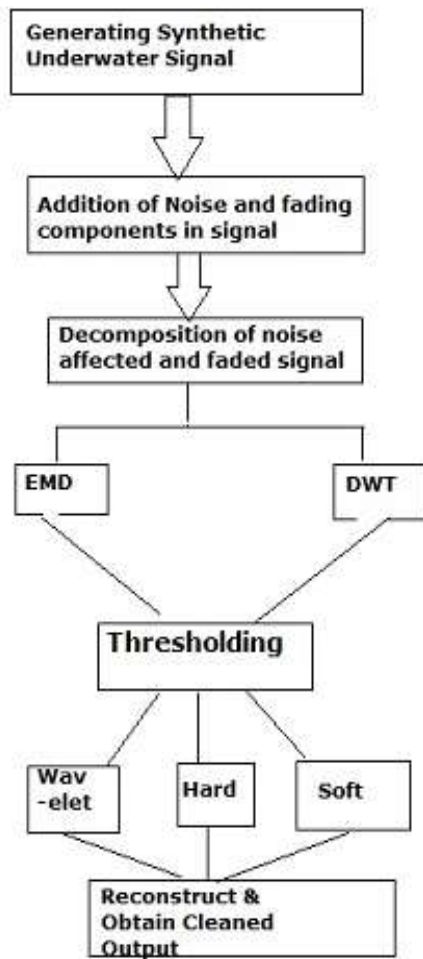


Figure1.7: General System Overview

- **Synthetic underwater signal**

Generation of a real underwater acoustic signal in laboratory condition is very difficult. So in order to get equivalent results, equivalent signals have been used. In this project in order to obtain significant and equivalent results bird sound, beats, and glockenspiel signals have been used in MATLAB.

- **Addition of noise and fading components**

Since the use of real signals cannot be taken into consideration because of absence of real environment the noise components and fading components have been added in MATLAB. The noise added is AWGN and Rayleigh fading channel has been used. The classical AWGN channel is always considered as the starting point to develop basic systems performance as it allows for simpler analysis of the communication system

The Rayleigh fading model is one of the most widely used fading channel model which assumes that there exist no direct line of sight path between the transmitter and the receiver and all the arriving signals at the receiver are due to reflected waves. The normalized Rayleigh distribution is given below:

$$p(a) = \begin{cases} 2a \exp(-a^2) & a \geq 0 \\ 0 & a < 0 \end{cases} \quad (1.3)$$

- **Decomposition of signal**

Generally for research purposes of rigorous motions Fourier transform 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, an estimation of the channel impulse response is beneficial for sinking or revoking detrimental multi-path effects. In this perspective, there are numerous denoising techniques. In the standpoint of techniques which are to be used here, the techniques used here have been implemented on noisy image viz. DFT, DWT, EMD and other STFTs like DCT etc. and the results thus produced are very promising. Based upon the results of the techniques applied on the noisy image DWT & EMD techniques have been applied on synthetic underwater acoustic signals and the results have been shown

EMD (Empirical Mode Decomposition)

Recently, the empirical mode decomposition (EMD) technique was introduced for analyzing signals from nonlinear, non-stationary processes. One advantage of this technique is that the basic functions are derived from the sensor signal itself as opposed to being fixed a priori, like in the DFT and DWT. This makes it suitable for signals from dynamic processes. Consequently, the EMD technique has been applied for sensor signal processing in several domains including water waves, biomedical engineering, time series analysis and damage detection. The EMD technique implicitly performs “sensor signal denoising” since it decomposes the original signal into several high-frequency (HF) and low-frequency (LF) intrinsic mode functions (IMFs). Several authors have developed EMD-based methodology for explicitly denoising signals. A thresholding-based approach that estimates the noise level in each IMF was presented in this approach assumes that the noise in the signal is spread over all of the IMFs. Huang et al. [11] developed a window-based approach to determine the noise level in each IMF; like, this method

is applied to all the IMFs. The approach proposed is an energy-based technique. The results of these approaches demonstrate that EMD is effective for explicitly denoising signals.

DWT (Discrete Wavelet Transform)

Wavelet analysis was first introduced in seismology to provide a time dimension to seismic analysis that Fourier analysis lacked. Fourier analysis is ideal for studying stationary data, but it is not well suited for studying data with transient events. Wavelets were designed with such non stationary data in mind and with their generality and strong results have quickly become useful to a number of disciplines. Different basis functions can be used to decompose the various frequency bands. These basis functions are called as mother wavelets. These mother wavelets for each wavelet family differ from each other by scaling and shifting parameters. In signal processing analysis wavelet transform provides a time-frequency representation of a signal with variable sized windows which also gives precise frequency information at low frequencies and precise time information at high frequencies.

- **Signal Restriction**

After the decomposition of signal thresholding technique (HARD, SOFT, WAVELET) is applied in order to suppress the noisy coefficients.

EMD-Thresholding

A Near to impeccable similar to or in comparison to the input signal is acquired by restricting the IMFs afore signal refurbishment. If $\Gamma[., \tau_j]$ is a restricting function, then τ_j is the threshold parameter. In context to EMD there are two kinds of thresholding:-

Hard Thresholding

Hard limiting is mathematically given by:-

$$K_j^\wedge(t) = U_j(t) \quad \text{if } |U_j(t)| > \tau_j \quad (1.4)$$

$$= 0 \quad \text{if } |U_j(t)| \leq \tau_j \quad (1.5)$$

Soft Thresholding

The soft limiting indentures the separated sections by τ_j in limit approaching zero as given by:-

$$K_j^\wedge(t) = U_j(t) - \tau_j \quad \text{if } |U_j(t)| \geq \tau_j \quad (1.6)$$

$$= 0 \quad \text{if } |U_j(t)| < \tau_j \quad (1.7)$$

$$= U_j(t) + \tau_j \quad \text{if } |U_j(t)| \leq \tau_j \quad (1.8)$$

Wavelet – Thresholding

Thresholding is used in wavelet domain to smooth out or to remove some coefficients of wavelet transform sub-signals of the measured signal. The noise content of the signal is reduced effectively under the non-stationary environment. The denoising method that applies thresholding in wavelet domain has been proposed by Donoho [12] as a powerful method. The method is based on applying the wavelet transform of a signal and passing it through a threshold.

Hard, soft and SURE SINK [13] are three types of thresholds. Hard and Soft are similar to EMD but SURE SINK is different from other techniques as follows:-

For wavelet thresholding, each coefficient of noisy signal is compared with a threshold in order to decide whether it constitute a desirable part of the original signal. To decide about the desirable part SURE SINK algorithm has been used in which

$$\hat{\mu} = E_{\mu} \{ ||\mu - \hat{\mu}||^2 s + E_{\mu} \{ ||y(t)||^2 + 2\nabla \cdot y(t) \} \} \quad (1.9)$$

$$\hat{\mu} = E_{\mu} \{ ||\mu - \hat{\mu}||^2 s \} \quad (1.10)$$

μ = estimated threshold for signal

$\hat{\mu}$ = set threshold of the the SURE algorithm

$$||y(t)||^2 = \sum_{i=1}^s [\min (|Y_i|, \tau)]^2 \quad (1.11)$$

- **Reconstruction of Signal**

The signal denoised using EMD (Empirical Mode Decomposition) does not require any kind of reconstruction because EMD not only denoises the signal but also reverts back the signal into original domain. Thus for EMD there is no need of any kind of inverse transform for reconstruction of signal. But in case of DWT i.e. Discrete Wavelet Transform we need Inverse Transform because DWT can decompose a signal but cannot revert back the original signal without the help of inverse transform.

1.5 Organization of Dissertation

This dissertation consists of 5 chapters which are organized as below:

Chapter 1: Introduction, in this chapter concept of underwater acoustic communication has been introduced which takes into consideration about how the communication takes place and major problems faced during the communication, along with these a section describing fundamental of

ocean acoustics has also been included which elaborates various phenomena mathematically as well as diagrammatically that occur under the water. After that methods which are used have been proposed in the other sections.

Chapter 2: Literature review. In this chapter study of the work which has been done regarding designing various methods for underwater acoustic signal denoising has been done.

Chapter 3: Analysis of Denoising Techniques. This chapter discusses in detail the various methods involved in denoising of signal.

Chapter 4: Denoising with wavelets. This chapter discusses about the various results computed in MATLAB for both the techniques applied on three different types of signals.

Chapter 5: Conclusion and Future Scope. In this chapter whole project work has been concluded and future scope for further study has been discussed.

“On Denoising and Best Signal Representation” by Hamid Krim, et al. (1999) [14]. In this paper a denoising technique based upon best choice of signal has been developed. In context to the signal a risk estimator based upon mean square error has been derived. This estimator minimizes the noisy coefficients of noise embedded signal reconstructed using wavelets. The noise removal by estimator also considers the cost function. Thus by minimizing the cost best basis algorithm is chosen. This method is limited to one-dimension signal and future work is proposed for two dimensional signals.

“Denoising via Empirical Mode Decomposition” by A.O. Boudraa, et al. (2001) [15]. This paper presents signal denoising scheme based upon Empirical Mode Decomposition (EMD). The EMD approach does not have any prerequisites, as it is based upon data given at present. Based upon EMD various threshold techniques like soft, hard, average, median, SG filter based have been used. But the SNR performance of EMD –SG is better than all other thresholding techniques. This denoising technique can be extended to EEMD for further improvement in SNR of signal.

“Development of Noise Reduction Algorithm for Underwater Signals.” by CHU-KUEI TU, et al. (2004) [16]. In this research paper a denoising technique has been developed based upon the Discrete Wavelet Transform. In this method ocean interference and ambient noise disturbance have been taken into account during the propagation of signal. One real signal and one synthetic signal has been used for the analysis of signal. This method utilizes genetic algorithm to get better threshold value. The results show that technique used is better than classical wavelet technique.

“Adaptive Array Processing for High-Speed Acoustic Communication in Shallow Water”, by Pierre-Philippe J. Beaujean, et al. (2004) [17]. This paper presents a novel multichannel signal-processing technique, which is capable of achieving stable high-speed underwater acoustic communication with a fairly low complexity of implementation, is presented. This technique splits

the space and time processing into two separate suboptimal processes. The main advantage of this technique was the reduction of computational complexity and instabilities associated with large tap vectors at large spread factors. Experimental results also showed that the channel spread factor influenced significantly the performance of the communication system.

“NARCISSUS-2005: A Global Model of Fading Channel for Application to Acoustic Communication in Marine Environment.” By X. Cristol (2005) [18]. In this paper the latest version of an operational numerical model of acoustic impulse response in random sea-channel, with application primarily to communication in marine environment is presented. As far as underwater activities due to problems like Sonar detection of target-echo in deep waters, it was possible to robustly deal with only rough models of sea-surface scattering. Typically, for modelling forward propagation, only some global empirical reflection coefficients, that simultaneously contained the mean specular part and more-or less accurately the mean energy of the random part of the reflected field; the final deliveries of such models were some loosely defined mean levels.

“Denoising Underwater Signals Propagating Through Multi-path Channels”, by Arnaud Jarrot *et al.* (2005) [19]. Based upon the channel impulse response, multipath propagation effects in this paper three denoising methods have been studied namely, Wavelet Packet Decomposition (WPD), Uniform Filter Bank (UFB) and warping based denoising approach. The results of comparison show that these three methods help in reducing noise but WPD & UFB have serious drawbacks as they are not able to remove interference from closely arrived signals. In comparison to these classical methods the proposed warping method gives better results as it leads to high reduction of noise and shows significant improvement of the matched filter estimation.

“Detrending and Denoising with Empirical Mode Decompositions”, by Patrick Flandrin *et al.* (2005) [20]. EMD decomposes a signal into AM-FM modes and provides an easier way to detrend and denoise the signal as it takes into account only the data given at the moment rather than any other prerequisites. The results obtained after EMD based analysis of signal as they demonstrate potential usefulness of EMD on other signals too.

“Automatic Underwater Image Pre-Processing”, by Stephane Bazeille et al. (2006) [21]. A unique technique for underwater image restoration has been proposed taking into consideration reflection and refraction phenomena. The advantage of this method is that it does not require any a priori knowledge of the conditions and parameter setting is not required. The main advantage of this method is its flexibility, the code generated using this method in MATLAB can be easily converted into C language. Thus due to these advantages and also taking into consideration underwater perturbations this method is well advanced over other classical methods for underwater image processing.

“Simulation Study of Multi-path Characteristics of Acoustic Propagation in Shallow Water Wireless Channel”, by TAO Yi et al. (2007) [22]. This paper is a practical study of shallow water channel acoustic propagation at Taiwan straits. The process has been performed taking into consideration propagation distance, water depth and sound profile and last but not least the movement of transmitter and receiver.

“Using Empirical Mode Decomposition for Underwater Acoustic Signals Recognition”, by Chung-Ling Hung et al. (2007) [23]. In this paper, an effective technique for evaluating acoustic signals recognition is presented, which utilizes the Empirical Mode Decomposition (EMD). The performance of signal recognition achieved by the EMD approach associated with three different similarity measures has been evaluated. Experimental results show the eminent performance. The cosine similarity measure and the correlation metric have achieved similar performance. Therefore, the proposed method have demonstrated to be promising for acoustic signals recognition and EMD is suitable for feature extraction.

“A Study of Spatial Processing Gain in Underwater Acoustic Communications”, by T. C. Yang (2007) [24]. This paper discusses about spatial gain processing in underwater acoustic communication. This paper analyses the effect of Bit errors resulting in ISI and fading of signal. The improvement in the OSNR through the use of multiple channels over that of a single channel is termed the SPG. SPG for a multichannel DFE is a function of the number of receivers, the receiver separation, and the array aperture. To achieve a maximum OSNR and minimize the computational complexity, the optimal strategy is to space the receivers according to the coherence length of the signal. When the receiver separation is much larger than the signal

coherence length, one can improve the OSNR by adding more receivers. The increase tapers off when the receiver separation decreases to below the signal coherence length.

“Weak Signal Extraction Based on Wavelet Packet Transform in Sea Noise Background”, by Chang-Yuan Ye et.al. (2009)[25]. This paper tells us about noise filtering based upon wavelet packet which has a remarkable property of analyzing non-linear and non-Gaussian signals. The results show that using the threshold parameters based upon wavelet packet decomposition LFM signal can be extracted significantly which is similar to novel signal irrespective of the fact that it occurs under low SNR condition.

“Underwater Wireless Communication System: Acoustic Channel Modeling and Carry Frequency Identification”, by Hou Pin Yoong et.al. (2009) [26]. This paper demonstrates the modeling of seawater acoustic channel to obtain the optimum carrier frequency for autonomous underwater vehicle (AUV) wireless communication system. This paper presented a study on modeling of underwater wireless communication with a detail model on the channel characteristic, environmental noise, signal to noise ratio and the Doppler Effect. The modeling of the underwater channel had been derived to mathematically quantify the underwater channel characteristic. Optimum frequencies are obtained with the highest SNR along the transmission range.

“Development of EMD-based denoising methods inspired by Wavelet thresholding”, by Yannis Kopsinis et.al. (2009)[27].In this paper, the wavelet thresholding principle is used in the decomposition modes resulting from applying EMD to a signal. The novel techniques presented exhibit an enhanced performance compared to wavelet denoising in the cases where the signal SNR is low and/or the sampling frequency is high. These preliminary results suggest further efforts for improvement of EMD-based denoising when denoising of signals with moderate to high SNR would be appropriate.

“Underwater Acoustic Communication Channels: Propagation Models and Statistical Characterization”, by Milica Stojanovic et.al. (2009)[28].In this paper an overview of the

channel properties, aiming to reveal those aspects of acoustic propagation that are relevant for the design of communication systems has been given.

“Signal Processing for Underwater Acoustic Communications”, by Andrew C. Singer et.al. (2009)[29]. This paper provides a brief overview of signal processing methods and advances in underwater acoustic communications, discussing both single carrier and emerging multicarrier methods, along with iterative decoding and spatial multiplexing methods. The systems employed to date leverage state-of-the-art signal processing methods, including multichannel equalizers, with explicit embedded phase tracking and symbol timing, Doppler tracking and signal resampling, and spatial multiplexing methods in MIMO-turbo equalization transmitter/receiver systems.

“Analyze the coherence of ambient noise in the Bay of Bengal Ocean region”, by V. G. Sivakumar et.al. (2010)[30]. This paper investigates the effect noise spectrum over a different wind speed and the signal coherence with sensor separation are examined for a number of line array processor in the pacific ocean region .To clarify the effect of sensor separation on the noise field, the relatively simple case of a semi-infinite ocean with Isovelocity profile is considered.

“Improving Resolution and SNR of Correlation Function with the Increase in Bandwidth of Recorded Noise Fields during Estimation of Bottom Profile of Ocean”, by Md. Jahangir Alam et.al. (2010)[31].This paper is a study of SNR variations in underwater signal due to ambient noise. SNR and resolution of cross-correlation of acoustic ambient noise fields recorded at two sensors are directly proportional to the bandwidth of noise fields. That means SNR and resolution increases with the increase in bandwidth. This results have been verified using both mathematics and simulation. Increase of SNR and resolution of cross-correlation function indicate that exact positions of the correlation peaks can be determined more accurately.

“Research on Underwater Acoustic Target Source Localization Algorithm Using a Guide Source” by XU GUO JUN et.al. (2010)[32]. This paper studies about the a denoising processing method for the GTL algorithm using the Gabor filter method. The concept is illustrated via both simulation and analysis of data collected from an acoustic propagation

experiment in South China Sea. The analytic results show that the ranging efficiency of the GTL algorithm is improved by the denoise processing using the field average method.

“An approach for underwater image denoising via wavelet decomposition and high-pass filter” by *Sun Feifei et.al. (2011)[33]*. In this paper, a new approach for underwater image denoising by combining wavelet decomposition with high-pass filter has been proposed. Thereby both the low-frequency components of the back-scattering noise and the uncorrelated high-frequency noise can be effectively depressed simultaneously. After analyzing the theory, a denoising algorithm based on wavelet and high-pass filtering has been put forward. This algorithm overcomes the shortcoming of wavelet in the field of processing backscattering noise. The experimental results show that the method in this paper can improve the denoising effect at certain extent.

“Denoising Algorithm using Wavelet for Underwater Signal Affected by Wind Driven Ambient Noise”, by *K.Mathan Raj et.al. (2011)[34]*. The objective of this paper is to denoise the underwater acoustic signals affected by wind driven ambient noise. A new mathematical model has been developed for wavelet denoising. This new denoising method is based on the modified universal threshold value estimation method and new thresholding method. This method reduces the ambient noise content in the denoised signal and improves the SNR of the signal

“Vector Hilbert-Huang Transform Signal Processing Method based on Wavelet Transform”, by *Zhu Zheng et.al. (2011)[35]*. This paper proposes a kind of vector HHT signal processing method based on wavelet transform. The new method can effectively eliminate mode mixing resulting from intermittent signal and noise, and exact decomposition results can be achieved. The improved vector HHT method is used in processing acoustic vector signal, and the data obtained from a certain sea experiment in Dalian is analyzed by the new method.

“Frame-Based Time-Scale Filters for Underwater Acoustic Noise Reduction”, by *Hui Ou et.al. (2011)[36]*. In this paper a TSF specifically designed to recover narrowband acoustic signals from a noisy underwater environment has been proposed. The studies were conducted for two underwater ambient noise sources: snapping shrimp and rainfall. TSF provided high quality reconstructions with significantly improved SNR and limited joint TF distortions (i.e., MSE

calculated for WVD). The analysis of noise-corrupted signals was conducted on a two-dimensional TS space, which was obtained using a frame-based wavelet transform. To preserve the signals' TF characteristics, they were filtered through a TS support region that contained most of the TS energies. The TS support region was calculated by thresholding the wavelet decomposition coefficients. A two-dimensional smoothing procedure was applied on the TS support region to suppress discontinuities at the edge of the passing region

“Empirical Mode Decomposition Technique with Conditional Mutual Information for Denoising Operational Sensor Data”, by Olufemi A. Omitaomu et.al. (2011)[37]. This paper presents a new approach for denoising sensor signals using the Empirical Mode Decomposition (EMD) technique and the Information-theoretic method. The EMD technique is applied to decompose a noisy sensor signal into the so-called intrinsic mode functions (IMFs).

“Stochastic Replay of Non-WSSUS Underwater Acoustic Communication Channels Recorded at Sea” by Francois-Xavier Socheleau, et al. (2011) [38].In this paper a channel model driven by real data is derived. This model relies on the assumption that a channel recorded at sea is a single observation of an underlying random process. From this single observation, the channel statistical properties are estimated to then feed a stochastic simulator that generates multiple realizations of the underlying process. It has been shown that the analysed underwater acoustic communication channels can be well modelled by trend stationary random processes

“Wavelet Based Denoising Algorithm of the ECG Signal Corrupted by WGN and Poisson Noise”, by Sheikh Md. Rabiul Islam et al. (2012) [39]. In this paper, a denoising algorithm that can be used for real-life ECG signal to increase signal to noise ratio for accurate diagnoses has been presented.

“Estimation of noise model and denoising of wind driven ambient noise in shallow water using the LMS Algorithm”, by S. Sakthivel Murugan et al. (2012) [40]. In this paper, the estimation of power spectral density for ambient noise due to wind at various speeds ranging from 2.11 m/s to 6.59 m/s is analyzed and inferred that the effect of wind is dominating at frequencies from 100 Hz to 5 kHz. A noise model for estimating the effect of wind at different wind speeds for various frequencies is developed and found that it suits well with the practical data. The analysis shows that noise level increases as wind speed increases.

“The Study on Time-variant Characteristics of under Water Acoustic Channels”, by Fangkun Jia et al. (2012) [41]. In this paper, based on conventional ray theory we have established N-path deterministic model, while taking advantage of BELLHOP, and introducing WSSUS channel model for shallow UWA channel transmission characteristics, and also have improved a shallow UWA time-variant channel model testing system performance. Comparing with the deterministic model, Simulation results show that the model is more intuitive and realistic.

“Channel Estimation or Prediction for UWA” by Mauro Biagi et al. (2013) [42]. This paper tackles with the dualism between channel estimation and channel prediction and its impact on adaptive modulation, both from a bandwidth and power point of view also in the presence of acoustic interference. The result shows that adaptivity is worth even if requires some processing both at the transmit and receive sides.

“A new time-frequency representation for underwater acoustic signals: the denoised hearingogram”, by Philippe Courmontagne et al. (2013) [43]. This paper describes an innovative approach in order to reduce the noise level in a time-frequency representation based on human perception which is termed the denoised Hearingogram. Several experiments on real data, corresponding to marine mammal signatures have shown that the denoised Hearingogram allows to show a good information restitution inducing a better signal interpretation.

“Dynamic Threshold Technique for Noise Removal in Narrowband Displays of Underwater Acoustic Systems”, by Mr. Kashif Waqas et al. (2013) [44]. This is a novel technique in its approach and implementation. This technique produced good results as can clearly be inferred from above discussions. The approach is dynamic and capable of adjusting according to the new noise conditions, these dynamic changes are real time as dynamic calculation are being performed at every instance. Thresholding can also be applied on other displays as well. One of the important future works is its application on other displays and their results.

“Study of Multiresolution denoising techniques for Oceanic traffic noise in the region of low Frequency”, by Saththivel K et al. (2013) [45]. In this paper, two different noise removal methods are studied and all are classical methods on wavelet packet (WPD) decomposition and uniform filter bank (UFB) decomposition. As shown through experimental results, the WPD-based and UFB-based denoising techniques are well-suited in ship driven noise signal.

Performances of the noise removal techniques are compared to those implemented filter, and demonstrate that techniques give good results for the denoising of acoustic data.

“Research on Chaotic Character of Ship-Radiated Noise Based on Phase Space Reconstruction” by *Meng Qingxin et al. (2013)* [46]. In this paper, the method is applied to ship radiated noise obtained through both onshore acquisition system and underwater hydrophones. Utilizing the delay coordinate reconstruction method, the two primary parameters, delay time and embedding dimension are determined. By optimizing these two parameters, the reconstructed attractor is gained with prominent structure of nonlinear dynamics.

“Soft Decision Feedback Equalizer for Channels with Low SNR in Underwater Acoustic Communications”, by *Xiaoxia YANG et al. (2013)* [47]. The soft DFE uses the expectation of the decision as the feedback signal. It overcomes the drawback in the hard DFE that there is no correct information to feedback when the decision is wrong. This soft DFE has a better performance, especially when the SNR is low. This performance is useful for the real sea test. On the one hand, it can combat the loss of the SNR brought by the timing synchronization.

3.1 Signal Denoising Techniques

Underwater denoising techniques are classically based on the projection of the ambient noisy signal on a new space, in which the signal and the noise do not overlap. The ambient noise in view of new space projection is eliminated by preserving the signal into subspace only. Applying into inverse projection technique, a denoised form of the original signal is recovered. In view of applying projection techniques, is the class of unitary transforms [48] since they have the more useful properties for underwater signal processing. Among all, unitary transforms assure that the existence of an inverse transform technique and preserve the acoustic signal energy on the transformed space. Fig3.1. Wenz model [49] of the power spectral density of the underwater ambient noise. The underwater denoising techniques considered here are based on this framework: the acoustic signal is projected on a new space with a unitary transform technique, properly filtered in this new space and, with the inverse unitary transform technique, estimated back to the original signal space.

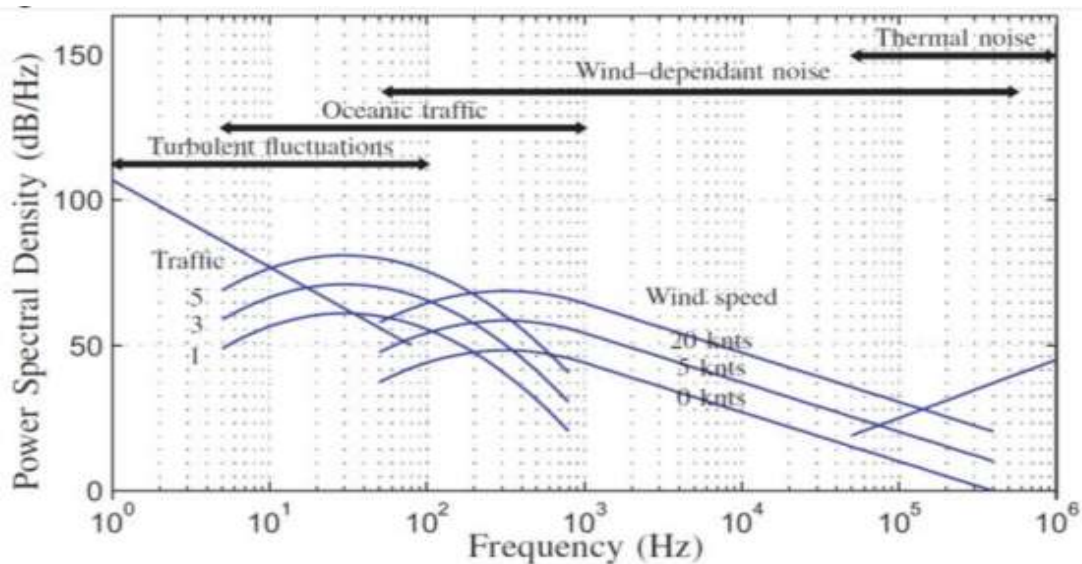


Figure3.1: Wenz model of the power spectral density of the underwater ambient noise [50].

The recovery of a signal from observed noisy data is a classical problem in signal processing. Especially for the case of additive white Gaussian noise a number of filtering methods have been proposed. Linear methods such as the Wiener filtering [51] are largely used because linear filters are easy to implement and design. However, these methods are not so effective when signals contain sharp edges and impulses of short duration. Furthermore, real signals are often non-stationary. To overcome these difficulties nonlinear methods have been proposed and especially those based on Wavelets thresholding [52]. The idea of thresholding relies on the assumption that signal magnitudes dominate the magnitudes of the noise in a Wavelets representation, so that Wavelets coefficients can be set to zero if their magnitudes are less than a pre-determined threshold. A limit of the Wavelets approach is that the basis functions are fixed, and thus do not necessarily match all real signals. To avoid this problem time-frequency atomic signal decomposition can be used. As for Wavelets packets, if the dictionary is very large and rich with a collection of atomic waveforms which are located on a much finer grid in time-frequency space than Wavelets and cosine packet tables, then it should be possible to represent a large class of real signals. But, in spite of this, the basis functions must be specified.

Recently, a new signal decomposition method called Empirical mode decomposition (EMD) has been introduced by Huang et.al. for analyzing data from non-stationary and nonlinear processes. The major advantage of the EMD is that the basis functions are derived from the signal itself. Hence, the analysis is adaptive in contrast to the traditional methods where the basis functions are fixed. In this paper, a denoising scheme using EMD is proposed. The EMD is based on the sequential extraction of energy associated with various intrinsic time scales of the signal starting from finer temporal scales (high frequency modes) to coarser ones (low frequency modes). The total sum of the IMFs matches the signal very well and therefore ensures completeness. The basic idea of the proposed scheme is to preprocess each IMF using thresholding, as in Wavelets analysis, of filtering before complete signal reconstruction.

3.1.1 Empirical Mode Decomposition (EMD)

The EMD involves the adaptive decomposition of given signal, $x(t)$, into a series of

oscillating components, IMFs, by means of a decomposition process called sifting algorithm.

The name IMF is adapted because it represents the oscillation mode embedded in the data. With this definition, the IMF in each cycle, defined by the zero crossings of, involves only one mode of oscillation, no complex riding waves are allowed. The essence of the EMD is to identify the IMF by characteristic time scales, which can be defined locally by the time lapse between two extrema of an oscillatory mode or by the time lapse between two zero crossings of such mode.

The EMD picks out the highest frequency oscillation that remains in the signal. Thus, locally, each IMF contains lower frequency oscillations than the one extracted just before. Furthermore, the EMD does not use any pre-determined filter or Wavelet function. It is fully data driven method. Since the decomposition of the EMD is based on the local characteristics time scale of the data, it is applicable to nonlinear and non-stationary processes. The EMD decomposes into a sum of IMFs that: (1) have the same numbers of zero crossings and extrema; and (2) are symmetric with respect to the local mean. The first condition is similar to the narrow-band requirement for a stationary Gaussian process. The second condition modifies a global requirement to a local one, and is necessary to ensure that the IF will not have unwanted fluctuations as induced by a symmetric waveforms. The sifting process is defined by the following steps:-

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 by the time period amid two maximas of an oscillatory style or by the time delay between two zero crossings.

Mathematically:-

$$s(t) = \sum_{j=1}^M y_j(t) \cos\theta_j(t) \quad (3.1)$$

Where y_j – amplitude

θ_j - Phase

The disintegration Process

The process to obtain the IMFs from the given signal 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_{jup}) and an

inferior casing (Y_{jlow}), respectively is done. After that Calculation of the value-by-value average of the superior casing and inferior casing is performed

$$m_j = (Y_{jup} + Y_{jlow})/2. \quad (3.2)$$

Where, m_j =average of upper casing and lower casing

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

$$d_j = Y_j - m_j. \quad (3.3)$$

Where d_j = extracted signal

After that a Check is performed such that d_j satisfies the two situations for being an IMF or not.

If d_j is not an IMF, previous steps are continual until d_j satisfies the two conditions.

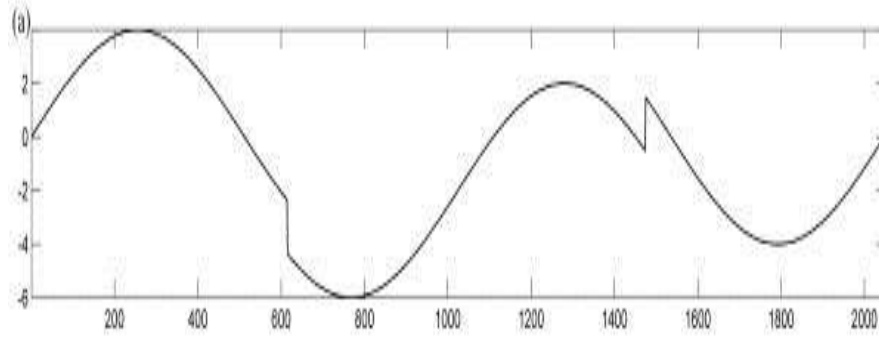
Once an IMF is engendered, the lingering signal

$$r_j = y_j - d_j \quad (3.4)$$

Where r_j = residual signal after performing sifting is held as the novel signal, and stages before this are repeated to spawn the second IMF, and so on. The sifting is thorough when either the residual function turn into monotonic, or the bounty of the residue cascades beneath a preset trifling rate so that auxiliary sifting would not vintage any expedient constituents. The sorts of the EMD modus operandi warranty the reckoning of a finite number of IMFs contained by a finite quantity of recapitulations. At the end of the process, the original signal

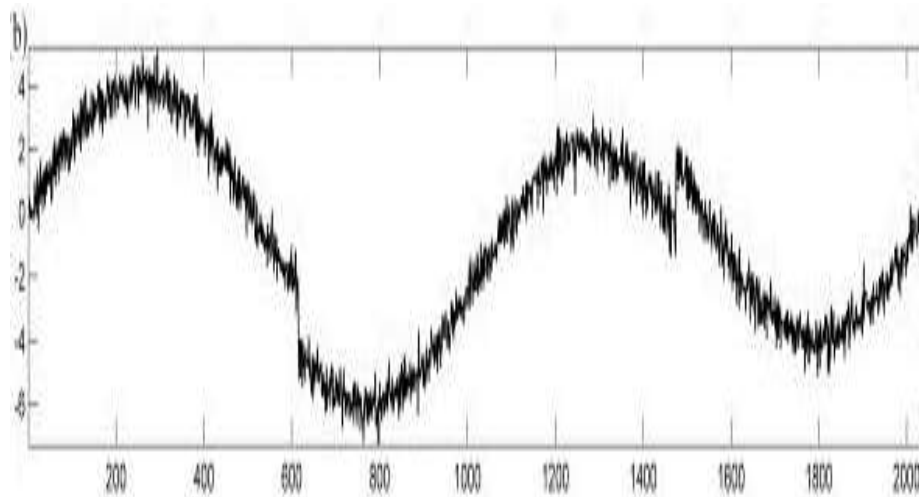
$$y_j = \sum_{i=1}^{M-1} d_{j,i} + r_{j,M} \quad i=1, \dots, M \quad (3.5)$$

Where r_j is the final residue that has near zero amplitude and frequency, M is the number of IMFs, and $d_{j,i}$ are the IMFs. Figure 3.2 and Figure 3.3 depict the clean and noisy signal respectively and Figure 3.4 shows sifting process applied on signal Y_j



Clean Signal

Figure 3.2



Noisy Signal

Figure 3.3

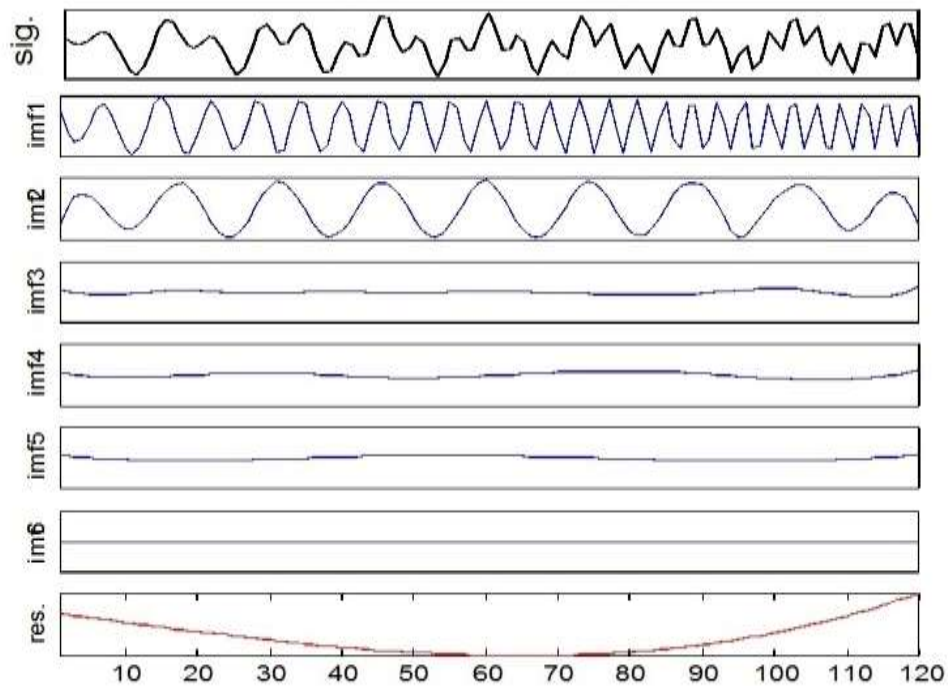


Figure 3.4: Sifting process of EMD

EMD-Thresholding

A Near to impeccable similar to or in comparison to the input signal is acquired by restricting the IMFs afore signal refurbishment. If $\Gamma[., \tau_j]$ is a restricting function, then τ_j is the threshold parameter. In context to EMD there are two kinds of thresholding-

Hard Thresholding

The non-linear hard thresholding function U is defined as:

$$\begin{aligned}
 K_j^\wedge(t) &= U_j(t) \quad \text{if } |U_j(t)| > \tau_j \\
 &= 0 \quad \text{if } |U_j(t)| \leq \tau_j
 \end{aligned}
 \tag{3.6}$$

$$\tag{3.7}$$

where τ_j is the threshold set by the user . In hard thresholding all the transformed coefficients with magnitudes that exceed the set threshold value are retained, and all the others are set to zero. One difficulty with hard thresholding is that removal of all fine detail from the signal may produce fictitious oscillations and create contrast where none previously existed.

Soft Thresholding

The soft limiting indentures the separated sections by τ_j in limit approaching zero as given by

$$\hat{K}_j(t) = U_j(t) - \tau_j \quad \text{if } |U_j(t)| \geq \tau_j \quad (3.8)$$

$$= 0 \quad \text{if } |U_j(t)| < \tau_j \quad (3.9)$$

$$= U_j(t) + \tau_j \quad \text{if } |U_j(t)| \leq \tau_j \quad (3.10)$$

In soft thresholding all the transform coefficients with magnitudes smaller than the threshold value are set to zero, and all the remaining coefficients are reduced in magnitude by the amount of the threshold value. The advantage of this method is that the results are not as sensitive to the precise value of the threshold T selected, as in the “keep or kill” strategy of hard thresholding. The disadvantage of this method is that the general shape of the signal might be slightly affected since even the large coefficients are modified using this scheme. The figure 3.5 depicts the threshold level for hard and soft threshold methods

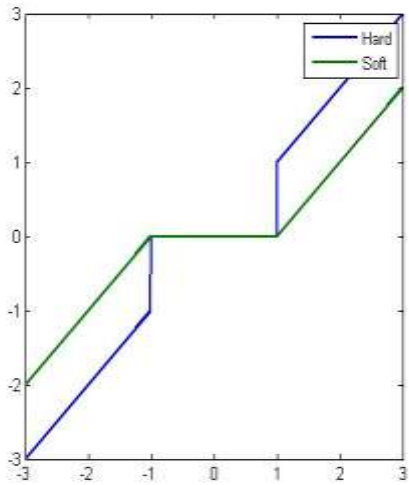


Figure3.5: Hard and Soft Thresholding

The original signal $x(n)$ can be reconstructed from the IMF components as given in Equation 1, where n represents the number of IMF and k refers IMF order and 'r' is residue. Each IMF component refers one scale and that scale is concentrated in that particular IMF component. But inherent mode mixing issue in EMD makes the IMF component either consisting of signals of widely disparate scales, or a signal of a similar scale residing in different IMF components. This makes the individual IMF devoid of physical meaning. This is called as mode mixing or scale separation problem.

Soft or Hard Threshold

- It is known that soft thresholding provides smoother results in comparison with the hard thresholding. More visually pleasant results, because it is continuous.
- Hard threshold, however, provides better coefficient preservation in comparison with the soft one.
- Sometimes it might be good to apply the soft threshold to few detail levels, and the hard to the rest.

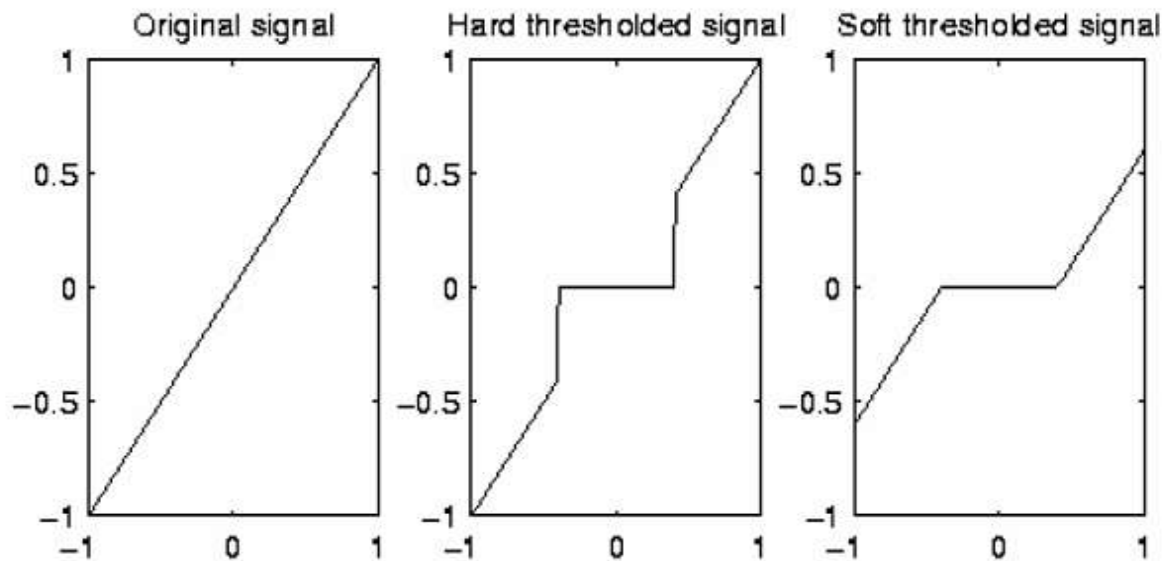


Figure 3.6: Comparison of Thresholding Techniques

3.1.2 Ensemble Empirical Mode Decomposition (EEMD)

Ensemble EMD (EEMD) is a new noise assisted data analysis method (NADA) proposed by Z. Wu and N. E. Huang [53] to overcome the scale separation problem in EMD. EEMD defines the true IMF components as the mean of an ensemble of trials. In each trial white noise of finite amplitude is added to the signal and then EMD is applied to this signal. The principle of the EEMD is simple: the added white noise would populate the whole time-frequency space uniformly with the constituting components of different scales. When signal is added to the uniformly distributed white background, the bits of signal of different scales are automatically projected on to proper scales of reference established by the white noise in the background. Since the noise in each trial is different in separate trials, it is canceled out in the ensemble mean

of enough trials. EEMD methodology explained as:

1. Add white noise series $w(n)$ to the targeted data $x(n)$ and decompose the data $x(n)$ into IMFs.
2. Repeat step 1 for multiple times with different white noise series and ensemble (mean) of corresponding IMFs of the decompositions gives the final IMF.

3.1.3 Block Least Means Square Algorithm (BLMS)

In BLMS [54] algorithms the input signal is partitioned into non overlapping blocks of length L . These blocks of data are applied to an FIR filter of order N , one block at a time and the filtering coefficients updated for every block. The filter output vector is obtained by convolving the input data sequence $x(n)$ with the filter coefficient vector and can be realized by the overlap and save method.

3.1.4 Short-Time Fourier Transform Algorithm

The Fourier analysis techniques provide a frequency domain presentation of the signal. These methods can be applied to signals whose frequency structure does not vary with time (i.e., stationary signals). When the signal is non-stationary, it is desirable to have a description that involves both time and frequency. The short time Fourier transform (STFT) can be viewed as an extension of the Fourier transform devised to map the signal into the two dimensional time-frequency plane. The STFT uses a sliding window function $g(t)$ to segment the signal into small uniform blocks of time. Each block is made short enough so that the signal may be considered essentially stationary within that segment. The Fourier transform is then applied to each time segment to produce the STFT representation given by

$$S(\tau, t) = \int_{-\infty}^{+\infty} x(t)g^*(t - \tau) e^{-j2\pi f t} dt \quad (3.11)$$

where $S(\tau, t)$ displays the evolution of the signals frequency information over time. A plot of the squared magnitude of $S(\tau, t)$ is called a spectrogram, and it provides a measure of the signal energy in the time - frequency plane. Many different window functions $g(t)$ may be selected in practice, and the choice will effect the resulting STFT. Once a window function has been chosen

its shape will determine the resolution of the time information (Δt) in the time - frequency plane. As a result of the uncertainty principle, the time resolution, and the frequency resolution (Δf) of a given signal are inversely related and their product has a lower bound of $1/4\pi T$ [55]. This produces a trade-off of time resolution for frequency resolution. Since the choice of window will fix Δx (and also thus Δf) over the entire signal length, the STFT partitions the time - frequency plane into a uniform grid. The drawback of this property is that both Δt and Δf are fixed throughout the analysis of the signal, and cannot simultaneously provide good time resolution (requiring short windows) and good frequency resolution (requiring long windows).

3.1.5 WAVELET ANALYSIS

Wavelet Packet Decomposition

Wavelet analysis has found a myriad of applications in areas ranging from financial research to engineering analysis. It is particularly well suited for signal processing applications such as image compression, sound enhancement, and statistical analysis. This chapter presents the underlying theory of wavelet analysis including both the mathematical basis, which stems from Fourier analysis, and the multirate implementation in filter banks.

Wavelet analysis is easiest to understand as an extension of the more familiar Fourier analysis. Therefore this chapter first discusses Fourier analysis before introducing wavelet analysis.

The Continuous Wavelet Transform

In Fourier analysis the signal is decomposed into a series of different frequency sinusoids. Mathematically the STFT can be viewed as an inner product of the signal with a two parameter basis function given by $g(t-x) \exp(-j2\pi f t)$. In wavelet analysis the signal is also decomposed into a family of two parameter basis functions $\Psi(t)$, (where $\Psi(t) = Y[(t-x)/a]$), with specific properties. These basis functions are called wavelets.

One advantage of wavelet analysis is that it allows selection of a wide variety of basis functions, as opposed to being restricted to the sinusoids of Fourier analysis. Two important characteristics of wavelets are that; 1) the wavelet function $Y(Y)$ be of finite duration, and 2) the wavelet function $\Psi(f)$ have zero average value (like that of Fourier sinusoids). The second characteristic requires that the basis functions oscillate above and below zero, and gives rise to the name

wavelet or small wave . Although there are numerous functions that meet the necessary properties to be classified a wavelet only a few classes have thus far been shown to be of general interest in signal processing. The Haar, Daubechies, Coiflet, and Symmlet are a few of the more popular classes and are shown in Figure 3.7

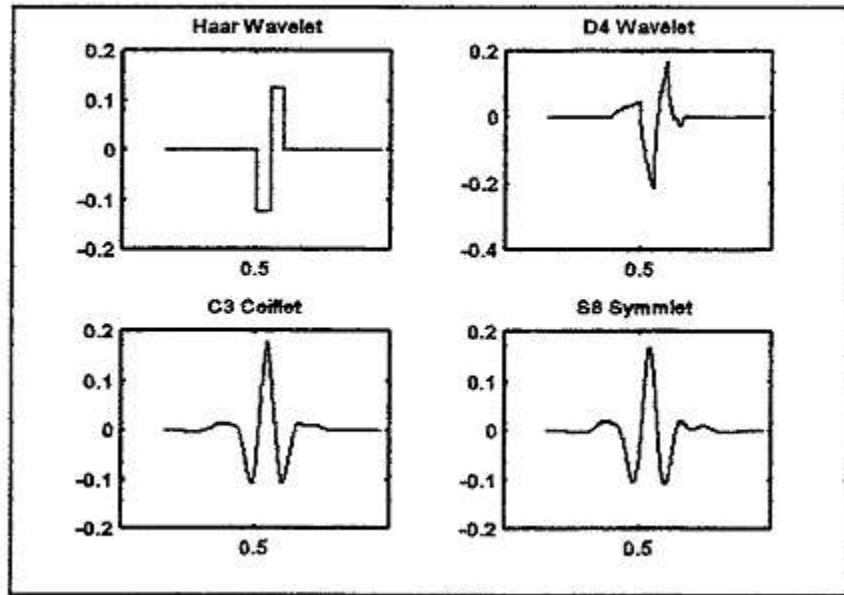


Figure 3.7: Four wavelets in the time domain [56]

The continuous wavelet transform (CWT) of a signal $x(f)$ is defined as:

$$C(t,x)=\frac{1}{\sqrt{a}} \int x(t)\psi^*(t-x)/a dt. \quad (3.12)$$

where $\psi(t)$ is the analysis wavelet. The parameter x denotes translation in time, and the scale factor a denotes dilation in time. The factor $1/\sqrt{a}$ normalizes the energy of the CWT. The scale factor in wavelet analysis plays an analogous role to inverse frequency in Fourier analysis. For example, consider the signal $x(t) = \cos(t/a)$, where a denotes the scale factor. If a is made larger the function will oscillate slower in time, and is thus expanded or stretched. If a is made smaller $x(t)$ will oscillate faster, and is therefore contracted in time. The scale factor a is therefore a method to expand or contract the analysis wavelet in the time domain. (Recall that this will have the opposite effect on the analysis wavelet in the frequency domain). The time

resolution and frequency resolution of the CWT is also controlled by the scale factor. Low scales (small values of a) correspond to high frequency wavelets and provide good time resolution. High scales (large values of a) correspond to low frequency wavelets with poor time resolution but good frequency resolution. Figure displays the Symmlet 8 wavelet for decreasing values of the scale factor a , in both the time and frequency domain. It is clear from the figure that, as a decreases, thinner (more localized) time domain wavelets and fatter (less localized) frequency domain wavelets are produced.

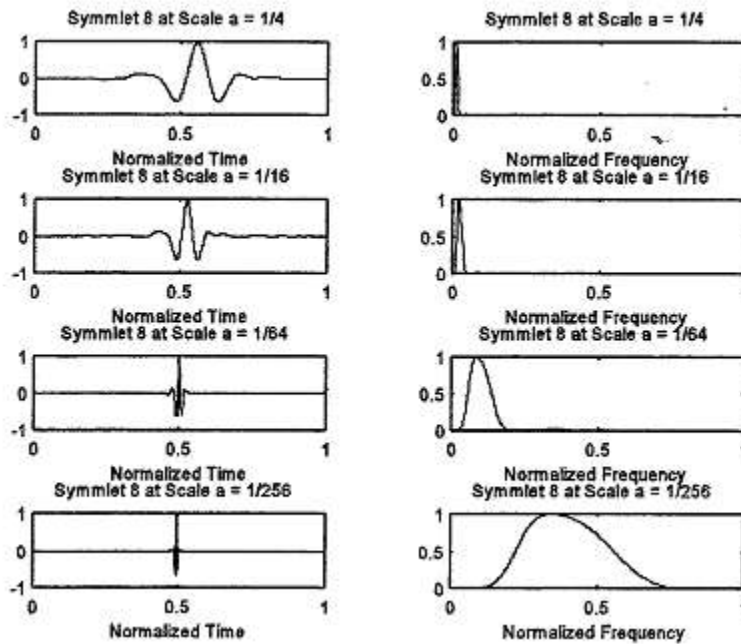


Figure3.8: Symmlet 8 wavelet in the time and frequency domains as a function of the scale parameter a . The scale factor a decreases from the top to bottom plots. [57]

So in summary, large values of a mean high scales, low frequencies, good frequency resolution, and poor time resolution. A second advantage of wavelet analysis is the Multiresolution capability it provides in the time - frequency plane. A comparison of the time - frequency mapping of the STFT and the CWT is shown in Figure 3.9. The STFT produces a uniform grid with a constant time resolution and frequency resolution, while the CWT has time resolution and frequency resolution that depend on the scale. Note that the CWT time resolution improves at higher frequency and the frequency resolution degrades.

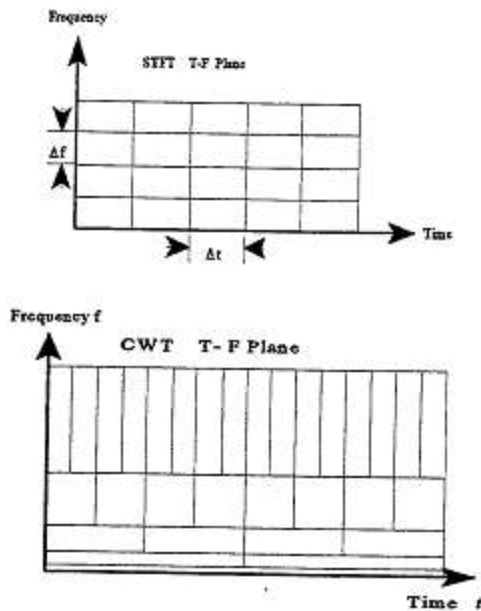


Figure3.9: Time - Frequency plane for STFT and CWT.

Similar to the STFT spectrogram, the CWT scalogram is defined as the squared magnitude of $C(x, a)$, and it is a measure of the energy of the signal in the time – scale plane . Further insight to the multi-resolution capability of the CWT can be gained by comparing the influence of signals in the time - scale plane. Figure 3.4 shows a comparison of the regions of influence of the spectrogram and scalogram for two different signals. The top plots display an impulse function at $t = t^0$. Note that the scalogram permits a narrow time localization of this signal in the low scale portion of the plot. The lower plots display the regions of influence for a signal composed of two sines at frequencies f_1 and f_2 .

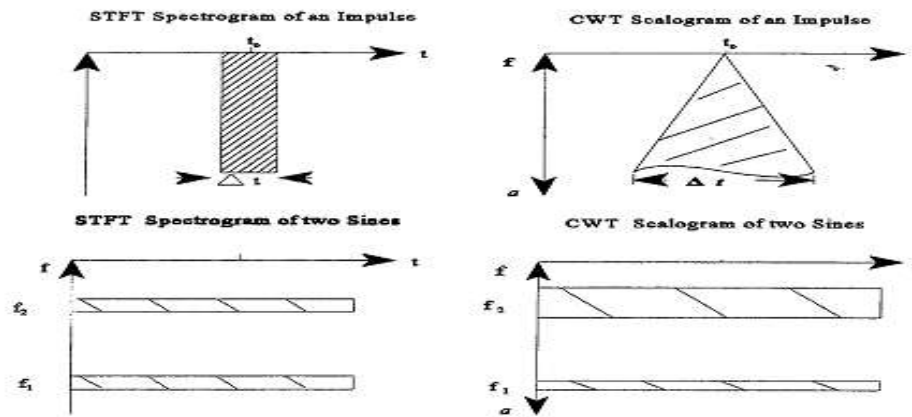


Figure 3.10: Spectrograms and Scalogram for two signals. Top plots display transforms for an impulse function. Bottom plots display transforms for two sines.

The Discrete Wavelet Transform

The discrete wavelet transform (DWT) is defined by restricting the scale and time parameters of the CWT to discrete values. The DWT of a discrete signal $x(n)$ is defined by:

$$C(a,b) = \frac{1}{\sqrt{a}} \int x(t) \psi^*(t-x)/a dt. \quad (3.13)$$

where a, b, n are the discrete versions of $a, x,$ and t of Equation respectively. The scaling factor is further restricted to be given by $a = a^J, J = 0, 1$

The choice of a will govern the accuracy of the signal reconstruction via the inverse transform. It is popular to choose $a = 2$, because it provides small reconstruction errors and permits for the implementation of fast algorithms. Setting $a = 2^J$ produces octave bands called dyadic scales. At each scale as J increases, the analysis wavelet is stretched in the time domain, and compressed in the frequency domain by a factor of two. The result being that the DWT output at each dyadic scale J produces more precise frequency resolution and less precise time resolution.

Also note that as J increases the translation term $b/2^J$ becomes smaller, and thus b must necessarily increase to cover all translations. The result is that the DWT output grows in length by a factor of two at every scale. This produces extremely large DWT vectors at the higher

scales. This computational difficulty can be alleviated by realizing that at each successive octave, the DWT output contains information at half the bandwidth compared to that of the previous scale, and thus can be sampled at half the rate according to Nyquist's rule. This decimation (or subsampling) is accomplished mathematically by restricting values of the shift parameter b . Letting $b = k \cdot 2^J$ where k is an integer, and replacing a by 2^J yields the decimated DWT given by:

$$C(2^J, k \cdot 2^J) = \sum_{n=1}^N \frac{1}{\sqrt{2^J}} x(n) \psi^*(2^{-J}n - k) \quad (3.14)$$

where $J = 0, \log_2(N)$ and $k = 1, N \cdot 2^{-J}$. The term $k \cdot 2^J$ in the argument of the DWT, indicates that $C(a,b)$ is decimated by a factor of two at each successive scale J by retaining only the even points. The resulting DWT coefficients form a $[J \times k]$ matrix where each element represents the similarity between the signal and the analysis wavelet at scale J and shift k . It is common practice therefore to rewrite Equation 3.14 explicitly in terms of the parameters J and k , leading us to the decimated DWT equation defined as:

$$C_{j,k} = \sum_n \sqrt{1/2^J} x(n) \psi^*(2^{-J}n - k) \quad (3.15)$$

The Symmlet 8 wavelet is shown at various scales J and shifts k in Figure 3.11

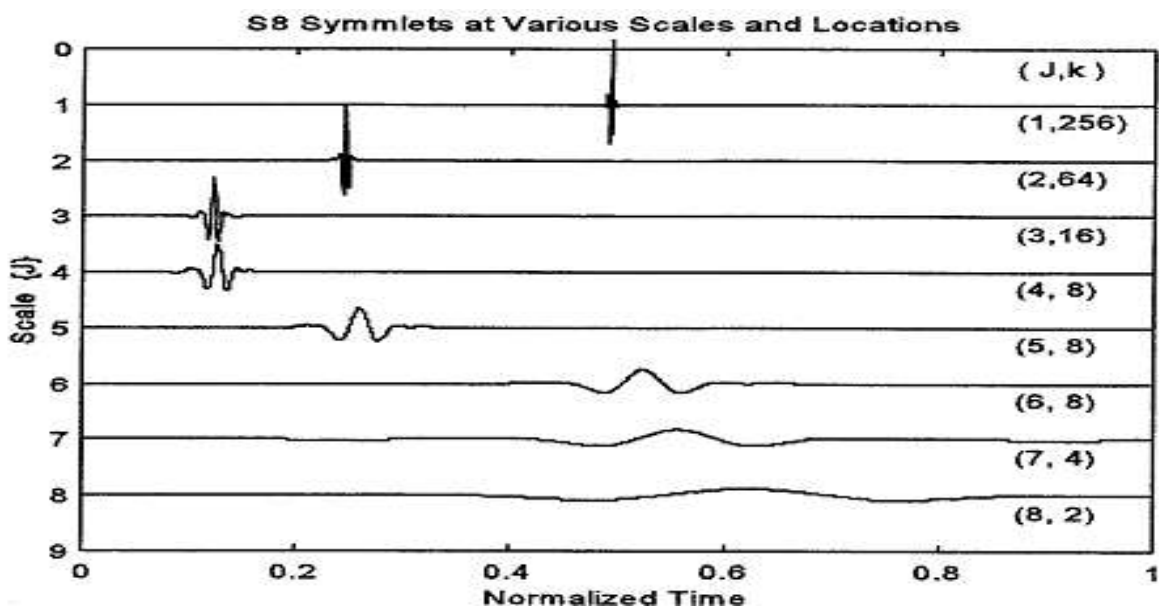


Figure 3.11: Symmlet 8 wavelet at various scales J and positions k . [58]

An efficient way to implement the DWT of Equation 3.11 using filters was developed by Mallat [59]. This scheme uses a complementary pair of lowpass (LP) and highpass (HP) filters. These filters equally partition the frequency axis and are known as quadrature mirror filters (QMF). Figure 3.11 displays the filter arrangement and the frequency response characteristics of the QMF. The output of the HP filter contains the details of the signal while the output of the LP filter contains the rough shape of the signal. Since each filter output covers only half the original frequency range of the input, each can be decimated by a factor of two by retaining only the even points. The combined decimated output of the two filters is a data set which comprise the DWT coefficients at the first scale. This process is repeated on the LP filter output to produce further decomposition of the signal into LPHP and LPLP parts at the next scale. The filtering and decimating operations can be continued until the number of samples is reduced to two. At each successive iteration (scale) the frequency range of the output is reduced in half by the LP filter, and the frequency resolution is improved by the decimation.. Figure 3.12, displays the resulting transformed coefficients in a tree structure.

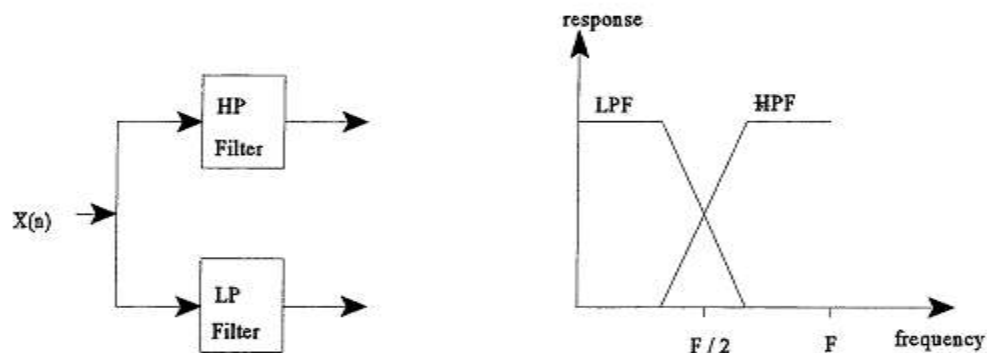


Figure3.12: Schematic representation of quadrature mirror filters.[60]

The decimated DWT described above will produce an orthogonal decomposition of the input signal only if the QMF pairs (i.e., the wavelets) are properly chosen. Such filter pairs have to possess specific mathematical properties and exhibit restrictive symmetry characteristics.

Although the DWT filtering operations are linear and time invariant, the decimation combined with the filtering results in a time-variant system. Recall, that a time variant system implies that

shifts in the system input will not produce an equivalent shift in the system output. In fact, a shift of even a few samples in the signal's starting point can completely change the wavelet decomposition coefficients. This difficulty complicates the performance of signal detection, feature extraction, and classification in the wavelet transform domain.

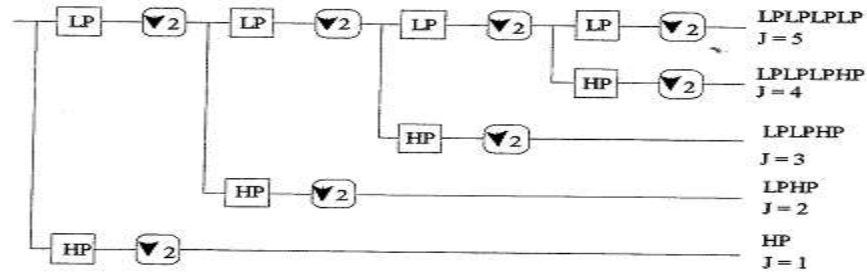


Figure3.13: DWT implementation using filtering and down sampling operations.

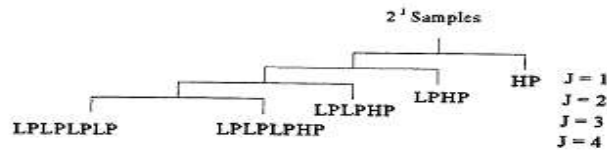


Figure3.14: DWT tree structure.

A number of proposals have been made to deal with the time - variant nature of the wavelet transform. One method processes multiple time shifted versions of the input and averages the results, this is called "cycle spinning"[61]. Another method calculates all possible circulant shifts of the input signal using a fast algorithm developed by Beylkin [62], and averages the results. This has been shown to be equivalent to the undecimated DWT, and is a non-orthogonal transformation. A third approach is to seek an optimal shift of the input signal. In this case the transform becomes shift invariant, and orthogonal, but is signal dependent, since the shift is only optimal for the signal under consideration. Some of these techniques have been applied to enhance signal denoising

3.2 Threshold Methods

Three commonly used threshold determination methods for WAVELETS are: SOFT threshold, Stein's Unbiased Risk Estimator (SURE), HARD threshold. Hard and Soft Threshold work in a similar fashion to that in EMD, so only SURE Threshold is discussed here.

SURE Threshold

The SURE threshold, δ_s , selects a threshold based on unbiased risk estimators [63]. First implemented by Donoho [64], this method minimizes a risk function to determine an optimum threshold. The unbiased risk estimate used for soft thresholding is defined as follows:

$$RISK(X) = 1 + (X^2 - 2) I(|X| \leq \delta_s) + \delta_s^2 I(|X| > \delta_s) \quad (3.16)$$

where $X \sim N(\theta, 1)$, $I(\bullet)$ is the indicator function, and δ_s is the threshold. Using the model defined by (5.1) the threshold becomes

$$\delta_s = \min \left\{ \sum_{j=1}^J \sum_k RISK\left(\frac{w_{j,k}}{\sigma}\right) \right\} \quad (3.17)$$

where the wavelet coefficients $w(j,k)$, divided by the standard deviation have replaced the variable X in the unbiased risk estimate. This technique suffers from the sparse wavelet coefficient problem mentioned for the universal threshold and is often combined with the universal threshold in a hybrid threshold method.

3.3 Signal Reconstruction of DWT

Reconstruction of the original signal from the wavelet coefficients $C(J, k)$ is achieved by reversing the quadrature mirror filtering and down sampling operations. The reconstruction will be exact however only if the QMFs (i.e., the wavelets) are properly chosen and exhibit some restrictive mathematical properties. Such perfect reconstruction filters do exist, and are constructed by designing a second pair of QMF's that perform the interpolation (up-sampling) and filtering operations. These synthesis filters entirely compensate for any amplitude, phase, and aliasing distortion of the analyzing filter QMF's. Together, the analysis and synthesis filters form a two channel QMF bank, shown in Figure 3.15 The result is that the two channel QMF bank behaves like a linear, time invariant system

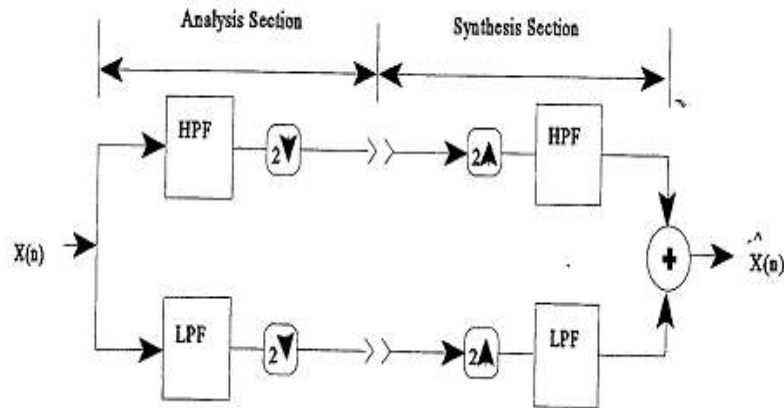


Figure3.15: Two channel quadrature mirror filter [65]

3.4 Colored Noise

The calculation of the threshold value by the methods prescribed above is restricted to the case of signals in white Gaussian noise. Extension to colored noise environments was proposed by Johnstone and Silverman [66]. This method treats each scale of the transformed data as a Gaussian distribution. A threshold value is then calculated and applied to each scale. An alternate approach is to apply a pre-whitening transform to the data prior to its decomposition, which alleviates the need to calculate a separate threshold for every scale. The use of a pre-whitening transform was found to produce better results than that of applying level wise thresholding on the data analyzed in this study.

The general denoising procedure chosen in this work can thus be summarized as follows:-

1. Apply a pre-whitening transform to the input data.
2. Decompose the input into a suitable basis using wavelet-based transforms.
3. Suppress the noisy coefficients by applying a non-linear thresholding method.
4. Reconstruct the signal using the inverse transform.

4.1 Proposed System model of Denoising Algorithm

The algorithm used to denoise the signal has been summarized in the figure 4.1. After that each step has been explained in detail.

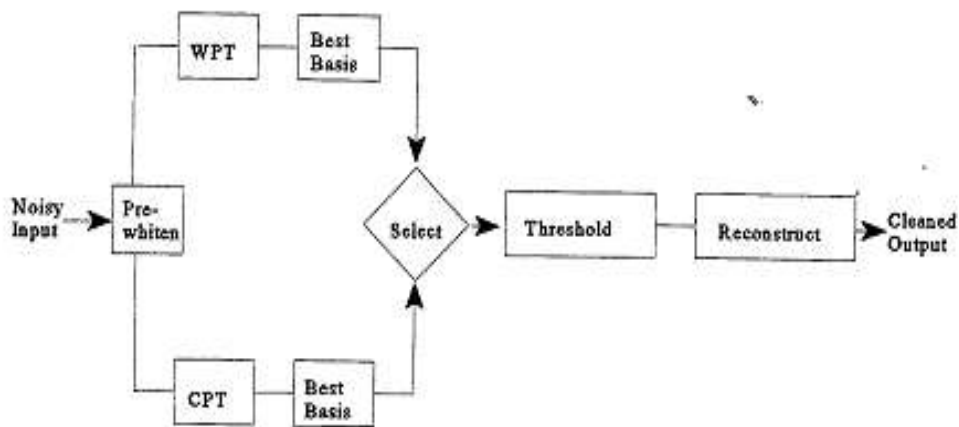


Figure 4.1: Algorithm of Denoising

- **Pre-whitening**- Applying a pre-whitening transform to the input data permits extension of the thresholding rules to colored noise environments. The output of the filter will be a colored version of the signal in additive white noise.

The details of the AR model and whitening filter are given below.

Autoregressive Modeling

Any stationary random processes can be modeled as the output of a linear time-invariant filter that is subject to a white noise input. The filter in an AR model is an infinite impulse response (IIR) filter with a transfer function given by:-

$$H_a(z) = \frac{1}{A(z)} \quad (4.1)$$

Where

$$A(z) = a_0 + a_1 z^{-1} + a_2 z^{-2} + \dots + a_p z^{-p} \quad (4.2)$$

The coefficients a_i of this all pole filter can be found by solving a system of linear equations

relating the q 's to the correlation matrix of the random process to be modeled. The AR model parameters can also be derived directly from the data without the need to compute the correlation matrix or solve the system of linear equations. One clever technique for computing the parameters recursively is known as the Burg Method [67]. This is the method used by Frack[68], and has the advantage of guaranteeing a stable filter by ensuring that all poles of the model are kept within the unit circle. One disadvantage of the Burg Method is that it requires data lengths greater than a few thousand points to produce good estimates.

Prediction Error Filter

A linear predictor is designed to estimate the current or future values of a random sequence based on knowledge of the past sequence values. The output of a prediction error filter (PEF) is taken as the difference between the estimate of the linear predictor and the actual sequence, as shown in Figure 4.2

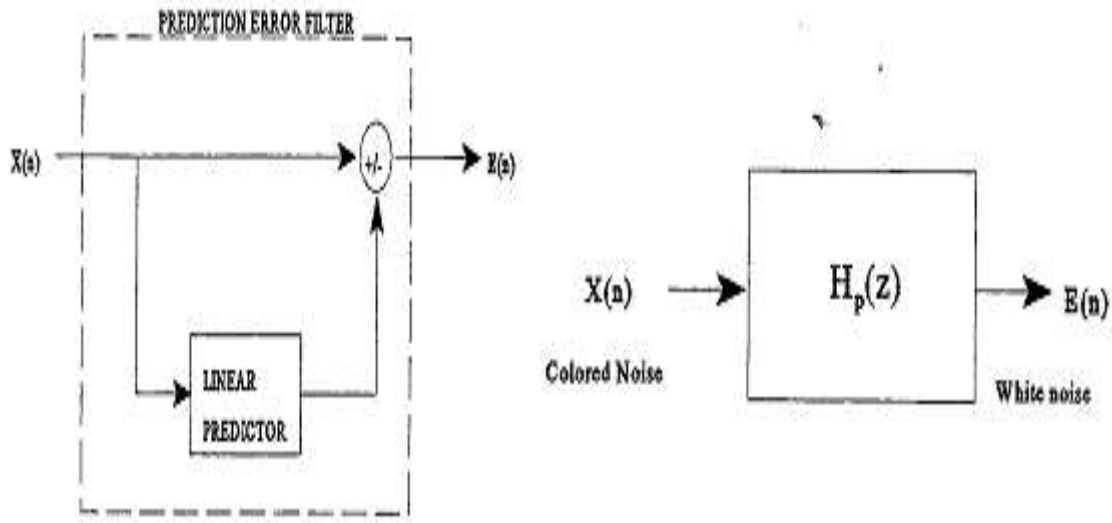


Figure4.2: Prediction Error Filter

The transfer function for a PEF can be represented by a finite impulse response filter (FIR) of the form:

$$H_p(z) = a_0 + a_1z^{-1} + a_2z^{-2} + \dots + a_pz^{-p} \tag{4.3}$$

If the order p of the PEF is chosen sufficiently large, the output error terms $e(n)$ will be orthogonal and of constant variance, and therefore $e(n)$ will be white noise. To construct the pre-

whitening filter, the transfer function of the PEF is selected to be the inverse of the AR process that models the input colored noise. The output of the PEF will be a colored version of the signal in additive white noise. Figure 4.3 displays the process.

Selecting the model order to use for the AR model and thus also the prewhitening filter is a difficult problem, since theoretical criteria are known to provide inaccurate results when applied to data that is not truly generated from an AR process

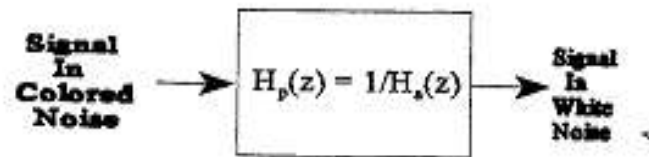


Figure4.3: Pre-whitening Filter

A number of different estimators are available to calculate the model order, and they are based on locating the minimum in a quantity related to the prediction error variance. One such estimator is Akaike's information-theoretic criteria (AIC) [69], and is described by the equation

$$\text{AIC}(P) = N \ln(\sigma_p^2) + 2P \quad (4.4)$$

where N is the length of the data, P is the model order and σ_p^2 is the prediction error variance obtained at that order. The AIC provides a distinct minimum at the optimum model order P . This is the criteria chosen for deciding the AR model order in this study.

- **Normalizing the Noise-** Recall that the threshold values are computed as a multiple of the estimated noise standard deviation σ . Once σ has been estimated, the input data can be scaled such that the noise appears at unit variance. This permits the threshold value to be computed independent of the data. Scaling of the input to produce $N(0,1)$ noise is accomplished by using the `norm rescale.m` function in Matlab and is required preprocessing for use of all denoising tools.
- **Signal Decomposition-** The choice of a wavelet basis plays an important role in the results obtained by the analysis. Choosing the proper wavelet can have drastic effects on the overall performance of the denoising technique.
- **Thresholding-** The algorithm permits selection of either of the three threshold methods

(soft, hard, or semi-soft). It also permits use of any of the threshold value calculations (Tu, Ts, Tm, Th). However, in the cases studied here, the combinations of soft thresholding at value Tm, or hard thresholding with the threshold value Tu proved to be the most effective.

- **Reconstruction**- Each cleaned segment is individually transformed back to the signal domain and the segments are weighted and overlapped to allow for smooth reconstruction

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.

Generating synthetic underwater acoustic signal and addition of noise:-.

After the generation of signal noise and fading components are added in the signal. Let us suppose $x(t)$ is the input signal , then after adding noise

$$Y_i = X_i + Z_i \sim N(X_i, n) \quad (4.5)$$

After addition of AWGN channel, Rayleigh Channel is added which is given by

$$p_X(x) = \frac{2x}{\Omega} e^{-\frac{x^2}{\Omega}}, x \geq 0 \quad (4.6)$$

$$\Omega = E(X^2)$$

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 compared with a threshold in order to decide whether it constitute a desirable part of the original signal. To decide about

the desirable part SURE SINK algorithm has been used in which

$$\hat{\mu} = E_{\mu} \|\mu - \hat{\mu}\|^2 s + E_{\mu} \{ \|y(t)\|^2 + 2\nabla \cdot y(t) \} \quad (4.7)$$

$$\hat{\mu} = E_{\mu} \|\mu - \hat{\mu}\|^2 s \quad (4.8)$$

μ = estimated threshold for signal

$\hat{\mu}$ = set threshold of the the SURE algorithm

$$\|y(t)\|^2 = \sum_{i=1}^s [\min(|Y_i|, \tau)]^2 \quad (4.9)$$

4.2 Channel Probing

To validate and define more precisely the channel distribution model $d_l(k)$ and $w_l(k)$ are isolated. $d_l(k)$ is driven by slow varying phenomena that lead to fading fluctuations over a period of a few seconds to several minutes, whereas the scatterers induce fading with a coherence time usually in the order of tens to hundreds of milliseconds. $w_l(k)$ is driven by fast fading phenomenon.

The decomposition of non-stationary multicomponent signals in “intrinsic” AM-FM contributions is possible thanks to the empirical mode decomposition (EMD) introduced by Huang et.al. EMD is appealing to solve this problem primarily because the AM-FM mode decomposition is appropriate to the analysis of non-stationary signals, but also because it is data-driven and does not require any predetermined basis functions. In addition, it makes no assumption about the harmonic nature of oscillations, and can thus guarantee a compact representation as shown in Figures 4.4 and 4.5. Each channel tap is therefore represented in the empirical mode space as

$$g_l(k) = \sum_{q=0}^{Q_l-1} m_{l,q}(k) + r_l(k) \quad (4.10)$$

Where, $m_{l,q}$ is the qth of the Q_l modes resulting from EMD of the tap g_l and r_l is the decomposition residue.

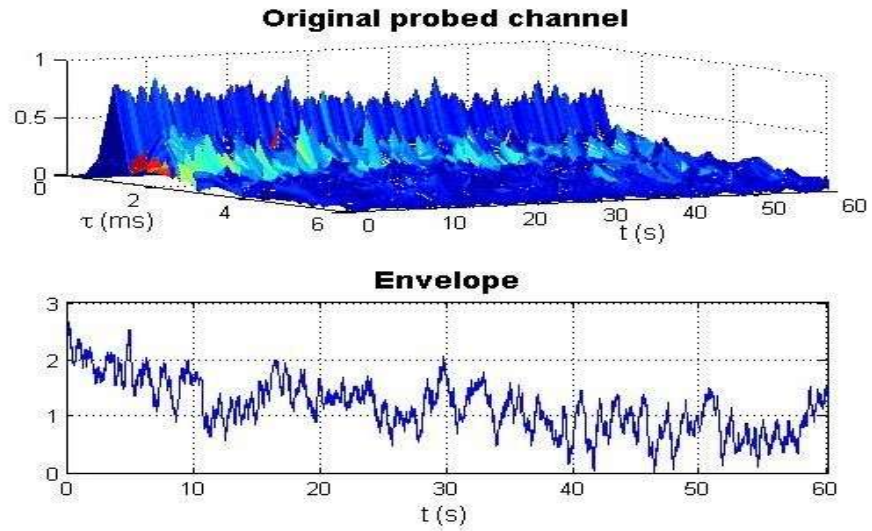


Figure 4.4: Channel Envelope

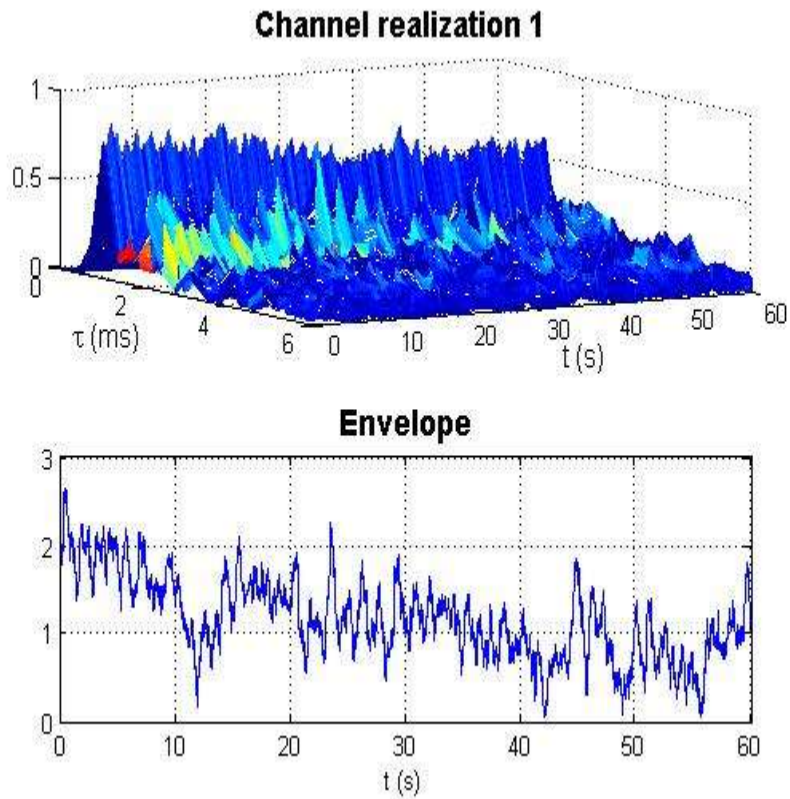


Figure 4.5: Realization of channel taps

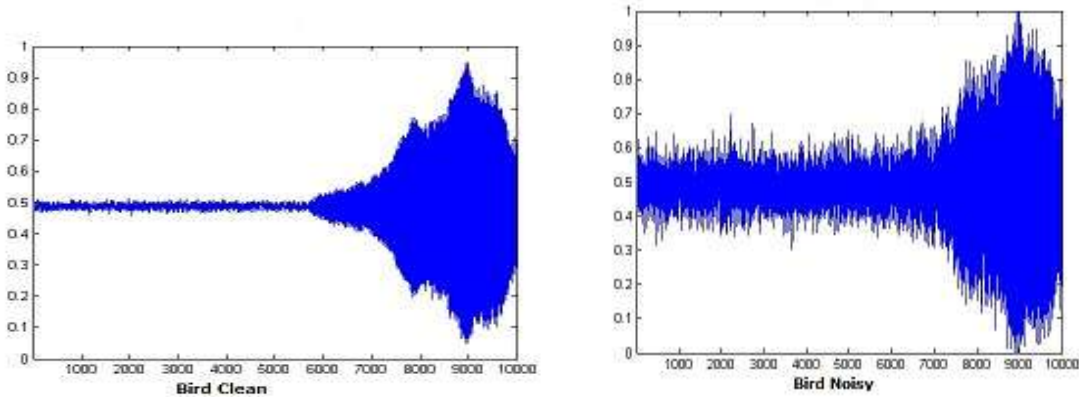
4.3 Simulation Results

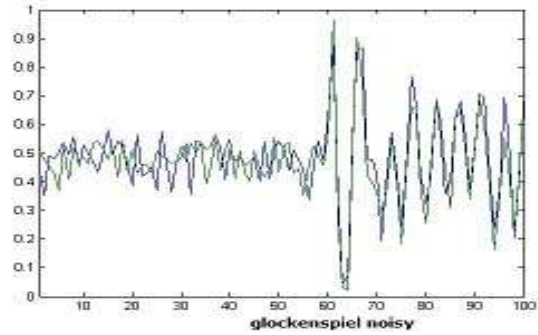
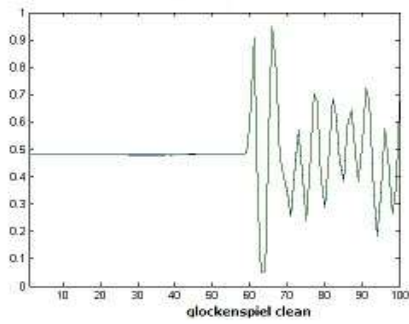
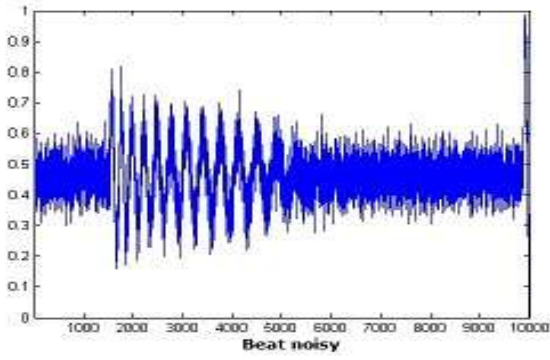
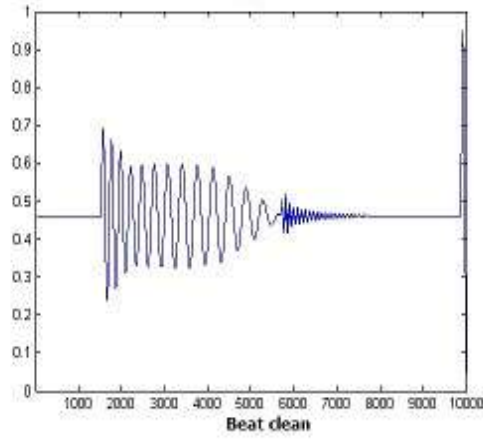
To investigate the denoising pattern, we have accomplished mathematical replications for three very short frequency signals attained using MATLAB which work unvaryingly as underwater acoustic signal. The novel signals as well as noise effected signals are shown in figures 4.6 (a) and (b), respectively. Each noisy signal is decomposed using the EMD and the Wavelets. The significant results are obtained for bird sound, beats, and glockenspiel signals. Figures 4.7(a) & (b) - 4.9(a) & (b) show the noisy and denoised versions of 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

$$\text{SNR} = -10\log_{10}\left(\frac{|\text{SNR}_{\text{clean}} - \text{SNR}_{\text{noisy}}|}{|\text{SNR}_{\text{clean}}|}\right)^2 \quad (4.11)$$

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






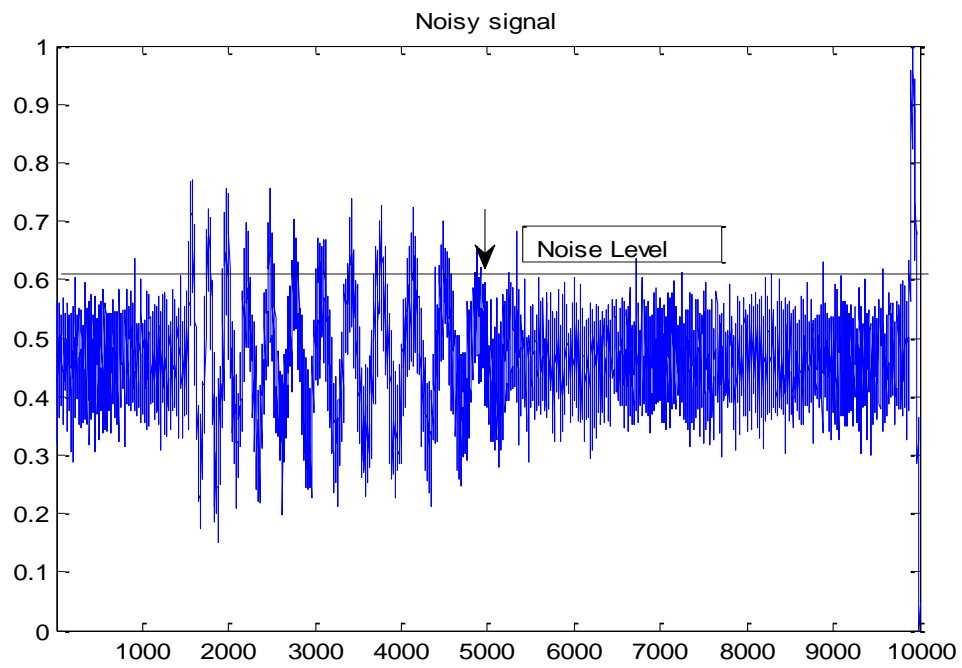
(a)

(b)

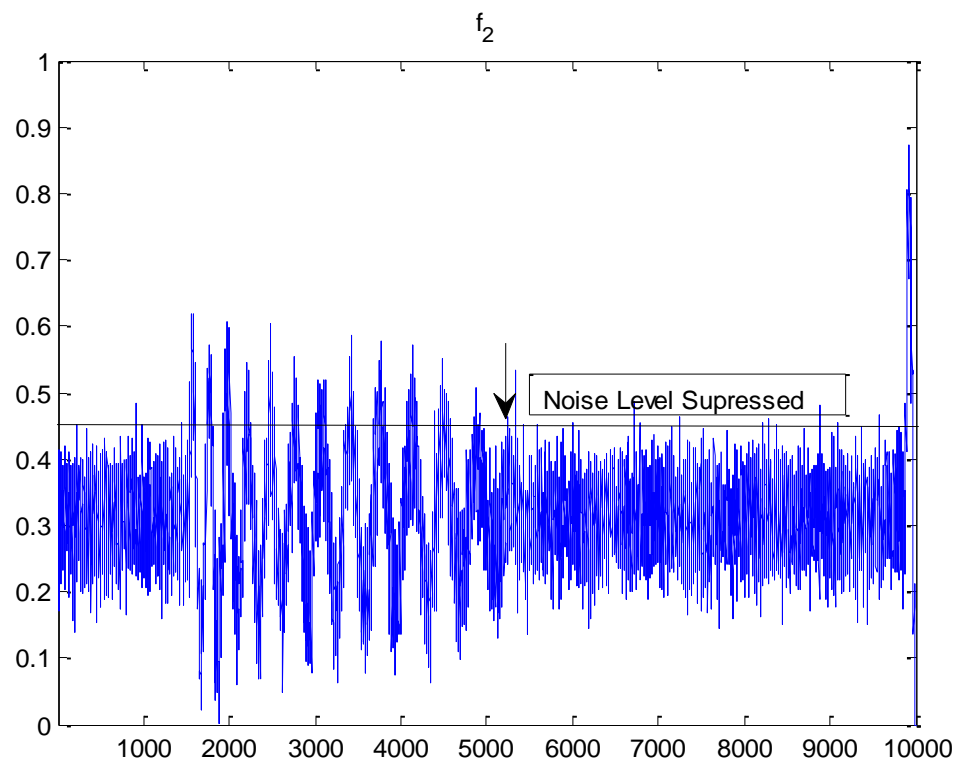
Figure 4.6: (a) Clean signals. (b) Noise effected versions

Table 4.1: SNR comparison of the three synthetic signals at different thresholds.

Signals 	Bird	Beats	Glockenspiel
SNR Input	I	II	III
	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(SURE)	11.34	11.78	10.20

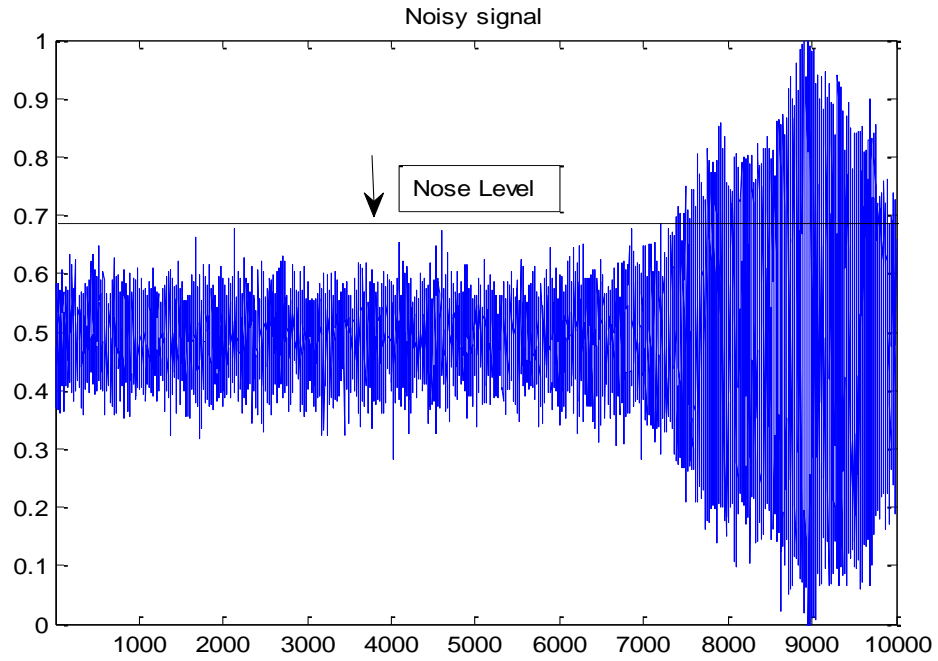


(a).After adding noise

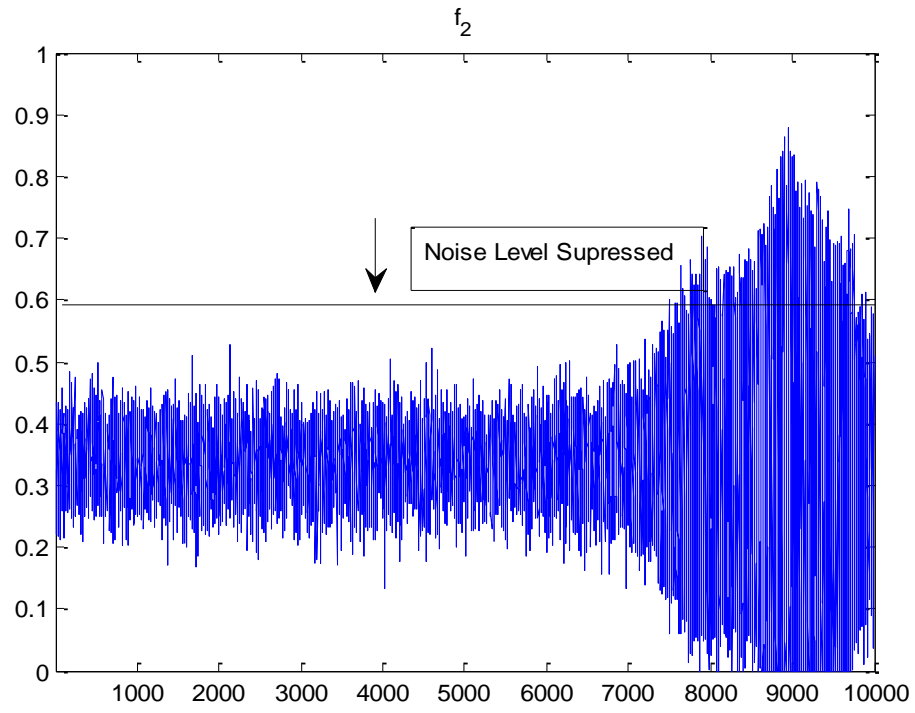


(b). After Suppressing Noise

Figure4.7 (a)&(b): Comparison of noise level in beats signal

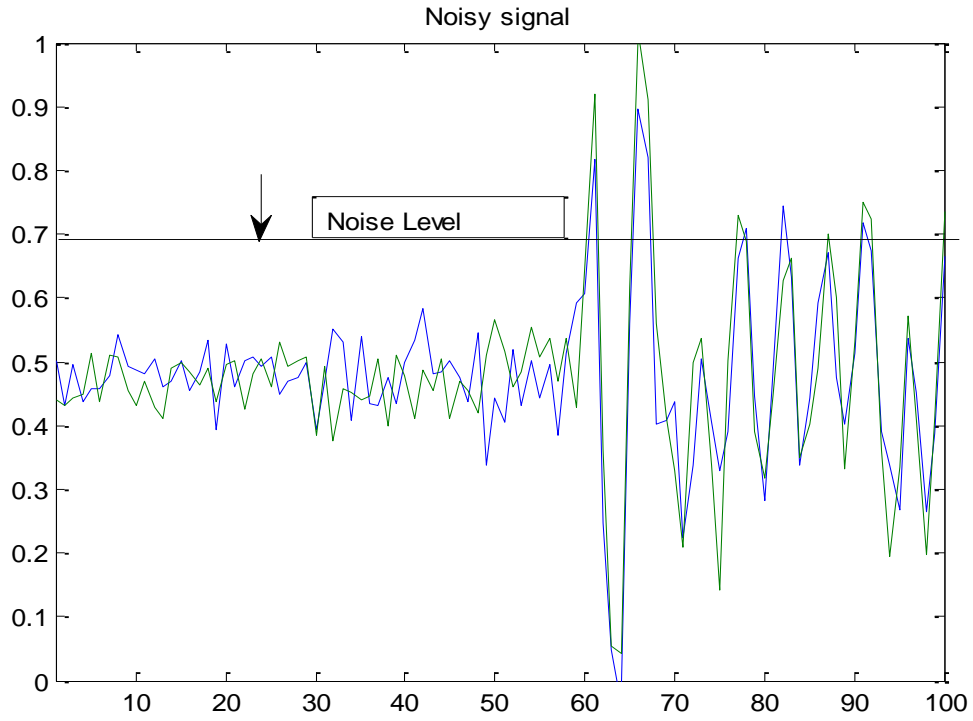


(a).After adding noise

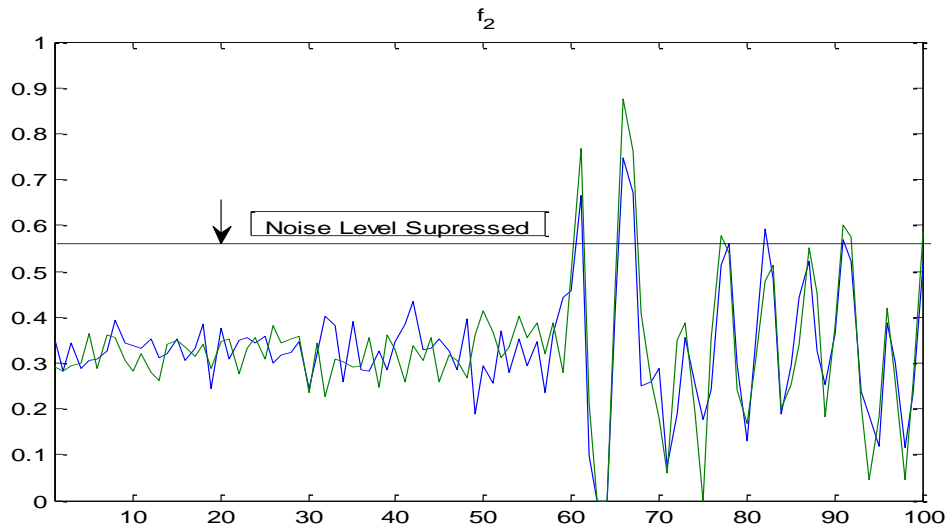


(b). After Suppressing Noise

Figure 4.8(a)&(b): Comparison of noise level in bird sound signal



(a).After adding noise



(b). After Suppressing Noise

Figure 4.9 (a) & (b); Comparison of noise level in glockenspiel sound signal

5.1 Conclusion

The stochastic replay of channels recorded at sea proves to be a very useful way of designing and validating underwater acoustic communication systems. From a single measured impulse response, it is possible to independently evaluate the impact of various physical phenomena on the communication link with a good statistical significance level. It has been shown that the analysed underwater acoustic communication channels can be well modelled by trend stationary random processes. Before Denoising the signal the signal is decomposed using stochastic replay. Using stochastic replay various components such as noise, fading (small scale and large scale fading) components are separated and analyzed. After stochastic replay denoising technique is applied on equivalent underwater acoustic signal using two denoising schemes namely EMD and DWT. 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 SNR comparison of the three signals with various thresholds show that Wavelet Soft technique gives the best SNR of 22.27db for bird sound , 22.38db for beats sound and 22.98 for glockenspiel sound.

5.2 Future Scope

Channel probing has been implemented in Matlab using stochastic replay, Moreover Signal denoising has been done using EMD (Empirical Mode Decomposition) and DWT (Discrete Wavelet Transform). In order to extend this work and improve the SNR for underwater acoustic signal EEMD (Enhanced Empirical Mode Decomposition) can be used to improve the channel response. Apart from DWT there are various other signal transforms such as Cosine Packet Transform (CPT) and Gabor Transform(GBT) which can be used to test the response of signal

and reduce the level of noise. Moreover the study of underwater acoustic communication can be studied under dynamic environment and determination of the carrier frequency for the same can be done and after that transmission bandwidth can be defined.

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