Comparative study on the improvement of SNR using wavelet techniques for a linear FM acoustic signal

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Present study is to develop denoising algorithm using wavelet decomposition technique by incorporating the most matchable Gabor wavelet. Performance the denoising technique is assessed by improving the signal to noise ratio and comparing the performance of Gabor wavelet with various other wavelets like Haar, Bior and Symlet wavelets. Ocean background noise is not the same at all time and at all regions. It is very distinct and location specific. Hence the noise prevailed in the region of bay of Bengal, Chennai was collected using the broad band hydrophone, for this study and the simulation was carried out using Mat lab Simulink tool. The results proved that the Gabor wavelet has given a good SNR improvement when associated with other wavelets for this particular work.

[Key words: Underwater acoustic signal processing, underwater ocean background noise, wavelet decomposition, underwater de-noising techniques.]

Introduction

In this research work, a detailed study on the development of adaptive denoising algorithm for the removal of ocean background noises collected from the region of Bay of Bengal, Chennai at a depth of 30 m using a broad band, Omni directional hydrophone. As the ocean background noise will vary with the location, time, depth and various other parameters, the denoising algorithm is fully valid only if the noise data is taken from the ocean. Also, a complete analysis has been made on the power spectral analysis of the wind noise with various parameters like speed of the wind, ocean depth, coherence length and directionality. As wind noise is highly predominant when analyzed with other underwater noises, it is taken for consideration. The results obtained clearly illustrate that the selection of NSL, frequency band, coherence length, directionality are the vital parameters in the design of de-noising algorithm1. Thus, before receiving the original signals, the underwater noises has to be suppressed in the corrupted acoustic signals using matched filter concept2 and wavelet decomposition so as to keep the important signal features as much as possible.

The wavelet helps in simulating the problem solving tool, for most of the engineers, mathematicians and scientists. In the case of transient signals, the wavelet analysis is a powerful tool when associated to that of Fourier analysis, which is more suitable for the signals whose statistical characteristics do not change with respect to time. Wavelet transform is suitable only to analyze the information in low frequency band and not suitable for high frequency band. But this limitation is overcome by wavelet packet transform, as it is suitable to identify and appreciate the information in both the low and high frequency bands. This property makes it an ideal processing tool for the non-stationary transient signals.

This property can also be explained in detail as it has high frequency resolution and low time resolution in low frequency region of the signal and low frequency resolution and high time resolution in high frequency region3. Wavelet packet decomposition is a wavelet transform, in which the signal is passed through large number
WPD is best suited for signals which have oscillatory and periodic behavior, since it provides much freedom in deciding the basis function which is suitable for representing the given function.

In simple we can say that wavelet packet decomposition (WPD) is an extension of wavelet transform which allows best matched analysis to the signal. Hence it decomposes the received signal and thresholds are used to select the coefficient, to remove the noisy part of the signal and a noise free signal can be synthesized.

According to the literature review done, Chu-Kuei Tu has reported in his paper that he has developed a genetic algorithm using wavelet technique for denoising the underwater signals. The results were highly appreciable. In the same way, inspired by the translation invariant wavelet thresholding, Yannis Kopsinis developed a similar technique adapted to EMD, which has lead to enhanced denoising performance.

Gabor wavelets have better time-frequency localization when analyzed with other wavelet packets and also they can be further translated over a finer time-frequency grid. Gabor wavelet is obtained with the Gaussian window. The noisy signal is spread over the spectral channels in which the co-efficient below the determined noise threshold is filtered out. The threshold is calculated by means of higher order statistics.

This part of research work deals with the development of denoising algorithm for the linear frequency modulated input signal which is added up with the original noise data collected from Chennai, the region of bay of Bengal. This paper also aims at discussing the performance of Gabor wavelet in denoising and improving the signal to noise ratio in comparison to Symlet, Bior and Haar wavelets. The results are encouraging.

Materials and Methods

In this research work, the essential of the denoising technique is well established, because of the acoustic ocean background noise environment in the underwater. In this connection, the data collection was made in Chennai, Bay of Bengal, with the passive hydrophone having specifications mentioned earlier. Here, for our research analysis, we have taken the input signal which is standard in any acoustic based instruments and sensor network, in ocean sector, a linear FM signal of 10Hz with weighted function. The simulation was carried out by mixing the signal with the collected noise data which is used for denoising process.

Underwater ocean background noise

It has been understood from the published data sources that, the correlation between wind speed and underwater ocean background noise was first observed by Knudsen et al (1948). Followed by the research work done by Wenz (1962), gave the dependence of ocean background noise on the wind speed and sea state condition. The ocean background noise is characterized based on the frequency levels, which is given in figure 1.

The noise produced by the distant shipping becomes the main source of ocean background noise in the frequency range of 20-500 Hz. After the removal of the noise created by the ships near by the receiver, we can identify some distant ships. Increase in the shipping traffic increases the noise in that region.

Fig 1 Composite of ocean background noise spectra (Wenz1962)

The spray and bubble noise associated with the breaking waves, contribute to the ocean background noise in the frequency range of 500 Hz -100,000Hz. When there is increase in the wind speed the there will be an increase in the ocean background noise.

The thermal noise, which is caused by the random movement of the water molecules, dominates the other n noises in the frequency range greater than 100,000 Hz.

By reviewing the literature, it has been understood that the collection of underwater noise is highly difficult unless proper selection of hydrophone, data acquisition modules and signal conditioning modules is done. The research is carried out with the help of original underwater
acoustic noise data collected from Bay of Bengal, Chennai. The experimental set up includes a reasonably equipped boat to make the measurement at a depth of 30 m depth.

**Experimental setup for the measurement in the sea**

The experimental setup given in figure 2 that includes the boat which is equipped with two Omni directional hydrophone sensor made of piezoelectric material with sensitivity of -170 decibels with re 1V/ μPa, which covers the frequency range of 0.1 Hz to 25 Kilohertz. Data acquisition system and power supply. Operating and survival depth are 600m and 700m respectively. The hydrophone operates at a voltage range of 12V to 24V DC. Ocean background noise where taken at a depth of 30 m which comes in the shallow water region.

The two hydrophones where placed in the “L” shaped PVC pipe with concrete filled in it. This arrangement is to ensure that the hydrophone has to sink because of its self weight in the water at 30 m depth and should not float or drift which may introduce some other irrelevant details.

**Results and Discussion**

The underwater acoustic signal is denoised in this research work by following three important procedures by means of which the noisy signal gets denoised automatically.

- Wavelet transformation of underwater acoustic noisy signal
- Determination of threshold co-efficient
- The de-noised or reconstructed signal is obtained by inverse wavelet transformation

In this research work, initially, the simulated input linear frequency modulated signal is mixed up with noise data which was collected. This noisy signal is projected on a new space, in which there is no overlap of signal and noise. In this new space, the underwater ocean background noise is eliminated by Upholding only the signal in the subspace. In the final stage, the original signal is retrieved by following the inverse projection technique, by means of which the noise is removed.

In view of applying projection techniques, is the class of unitary transforms 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.

Figure 3 illustrate the Wenz model of the power spectral density of the underwater ocean background noise.

![Fig. 2 Experimental setup for the measurement in the sea](image)

**Fig. 2 Experimental setup for the measurement in the sea**

The frequency resolution of the wavelet analysis can be improved by the wavelet packet decomposition which is the generalized form of orthogonal wavelets.

The WPD can be called as the extension of wavelet decomposition, since it decomposes both the detail and approximation co-efficient in each level whereas only the approximation co-efficient are decomposed in wavelet analysis. In WPD the transient signals are decomposed and synthesized in a better way when analyzed with STFT and CWT. In WPD a level by level decomposition of the transient signal is done. It also helps in the transformation from time domain to frequency domain is done. The wavelet transform is a joint function of a time series of interest d(t) and an
analyzing function or wavelet. This transform isolates signal variability both in time t, and also in “scale” s, by rescaling and shifting the analyzing wavelet.

The approximation and detail co-efficient in the WPD is obtained by the following algorithm

\[ u^{i}_{m}(n) = \sum_{k} h(k-2n)u^{2i}_{m-1}(k) \]  
\[ u^{j}_{m+1}(n) = \sum_{k} g(k-2n)u^{2j}_{m-1}(k) \]

Here,  
\[ h(k) \] represents the detail co-efficient and  
\[ g(k) \] represents the approximation co-efficient.

In WPD both these co-efficient are decomposed. The process of reconstructing the original signal from its co-efficient is called synthesis process. It is done by performing the decomposition process in reverse order. The signals are interpolated by 2 at every level and then passed through the reconstruction filter and then added up.

\[ u^{j}_{m+1}(n) = \sum_{k} h(k-2n)u^{2j}_{m-1}(k) + \sum_{k} g(k-2n)u^{2j}_{m-1}(k) \]

It is a non linear technique, in which the wavelet coefficients are threshold on comparing with determined threshold at each level. Thresholding is a signal estimation technique, in which the noise is removed by properly determining the threshold, which determines the efficacy of denoising to a great extent.

Let us consider a decomposition of u into \( u_i \) elements and the resulting vector after thresholding as \( D_T(u) \) with the threshold T. The wavelet threshold coefficients are obtained using either hard or soft thresholding functions.

Hard thresholding: \( D_T(u_i) = 0; |u_i| \leq T \)
\( = u_i; |u_i| > T \)

Soft thresholding: \( D_T(u_i) = 0; |u_i| \leq T \)
\( = \text{sign}(u_i) * (|u_i| - T) \) > T

The estimation of the noise threshold is based on the higher order statistics. The RMS value of the spectral channel is calculated by

\[ S_n(t) = \sqrt{\frac{1}{N} \sum_{i=1}^{N} s^2_n(t)} \]

Using this, the quantity of energy is calculated at a particular time over the spectral channel. The energy is low when the noise alone is present and there will be a considerable high energy when both the signal and noise are present. Based on this RMS value, the coefficients below the maximum RMS probability function are removed.

Window functions
In this research work, Gabor window function is analyzed with Symlet, Bior, Haar functions.

Gabor transform
In the Gabor transform, the signal is multiplied with the window \( w(t) \) function which is Gaussian and the Fourier transform is applied to the windowed signal.

It can be expressed in simple as

\[ \Psi(t) = \frac{1}{(\sigma^2 \pi)^{1/4}} e^{-\frac{t^2}{2\sigma^2}} * e^{2\pi i \tau} \]

The sample Gabor wavelet is illustrated in Figure 4.

![Gabor wavelet](image)

Fig. 4 Gabor wavelet

The spectral channel of a noisy signal exhibits different spectral characteristics. In the time – frequency plane, these components are characterized by the high and concentrated co-efficient whereas the unwanted noise is represented by the low and spread co-efficients. By removing these spread co-efficient, the noise gets removed.

Samples of Symlet, Haar and Bior Wavelets are illustrated in Figure 5.

![Symlet wavelet, Haar wavelet, Bior wavelet](image)

Fig5. Symlet wavelet          Haar wavelet         Bior wavelet

A gated linear FM wave as signal (acoustic) \( e(t) \) is assumed to be transmitted through a mid frequency water channel and the simulated signal is given in figure 6.

![Gated Linear FM signal](image)

Fig.6 Gated Linear FM signal

For analyzing the signal is added with the underwater ocean background noise which collected in Chennai, at Bay of Bengal given in figure 7.

![Time series of the noisy signal](image)

Fig.7 Time series of the noisy signal
The noise data is the real time data collected and is assumed to be stationary, Gaussian, with a Wenz–shaped power spectral density. The results have been obtained with 50 different noise realizations and have to be taken in an average. The proposed de-noising methods reduce the noise while retaining and not distorting the useful information of the processed signal. Each method has different type of performance with regards to the recovery of the signal boundary. Figure 8 illustrate the Schematic representation of the simulation procedure.

The Signal to Noise ratio is used to analyze the performance of the denoising algorithm. Also the SNR is used to quantify how much the signal has been corrupted by the noise. It is defined as the ratio between the signal power to the noise power corrupting the signal. Here $SNR_{IN}$ represents pre SNR and $SNR_{OUT}$ represents post SNR.

$$SNR_{IN} = 10 \times \log_{10} \frac{P_i}{P_n} \text{ (decibels)} \quad (10)$$

$$SNR_{OUT} = 10 \times \log_{10} \frac{P_o}{P_n} \text{ (decibels)} \quad (11)$$

Here, $P_i$ represents the signal power before denoising,

$P_o$ represents the signal power after denoising

$P_n$ represents the noise power

All the proposed methods show a considerable improvement in SNR by reducing noise. But the Gabor transform tool, illustrate a higher performance when analyzed with other techniques.

The signal has got an improvement in the SNR output of 8 decibels for the input range of 88 kilohertz with Gabor wavelet. Here the reference signal is simulated at higher frequencies like 20 kilohertz, 66 kilohertz and 86 kilohertz.

For the same input range, the comparative analysis is done in the following tables which give both the MAT lab output and improved SNR values of Gabor with other wavelets.

Table 1 gives the SNR IN and SNR OUT values of Gabor, Symlet, Bior and Haar at 20, 66 and 88 KHz.

<table>
<thead>
<tr>
<th>Frequency</th>
<th>Gabor Vs Symlet</th>
<th>Gabor Vs Bior</th>
<th>Gabor Vs Haar</th>
</tr>
</thead>
<tbody>
<tr>
<td>20KiloHz</td>
<td>9decibels</td>
<td>9decibels</td>
<td>9decibels</td>
</tr>
<tr>
<td>66KiloHz</td>
<td>15decibels</td>
<td>18decibels</td>
<td>18decibels</td>
</tr>
<tr>
<td>88KiloHz</td>
<td>14decibels</td>
<td>16decibels</td>
<td>16decibels</td>
</tr>
</tbody>
</table>
Table 3 gives the comparative analysis of the MAT lab output of Gabor with other wavelets.

<table>
<thead>
<tr>
<th>Frequency</th>
<th>Gabor with Symlet</th>
<th>Gabor with Bior</th>
<th>Gabor with Haar</th>
</tr>
</thead>
<tbody>
<tr>
<td>20 KHz</td>
<td><img src="image" alt="Graph" /></td>
<td><img src="image" alt="Graph" /></td>
<td><img src="image" alt="Graph" /></td>
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<tr>
<td>66 KHz</td>
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<td><img src="image" alt="Graph" /></td>
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<tr>
<td>88 KHz</td>
<td><img src="image" alt="Graph" /></td>
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</tbody>
</table>
Conclusion

The denoising procedure includes several wavelets to remove the noise and the performance was discussed with the help of SNR improvement. The results obtained was very encouraging as that in the range of input SNR -15 decibels to 0 decibels, the improved output SNR which is discussed in the table 1 and 2 illustrate that the Gabor filter performs better in denoising this ocean noise when analyzed with other wavelets like Symlet, Bior and Haar. This has proved beyond doubt by the reconstruction method that the time series is nicely improved with the Gabor filter.

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References