Time Frequency Analysis of Underwater Ambient Noise in Tropical Littoral Waters

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***Abstract*— This paper investigates better time frequency representations of littoral water ambient noise recorded at 30 meter of depth in Indian tropical water. Linear time frequency representations (TFR) like spectrogram and Continuous Wavelet Transform are compared by combining natural and anthropogenic ambient noise sources from the tropical waters. Underwater ambient noise is represented by appropriate wavelet. Statistical and image quality parameters are used to quantify the quality of these TFRs for passive sonar systems.**

Keywords—Ambient Noise, Littoral Water, Short time Fourier Transform, Continuous Wavelet Transform.

I. INTRODUCTION

The ambient noise behavior depends on numerous factors including type of source, propagation characteristics and environmental fluctuations [1, 2]. The underwater noise sources include ambient noise which is independent of the acoustic system and caused by natural and anthropogenic noise sources. The littorals present the unique characteristics of ambient noise behavior due to the repeated surface and bottom interactions. Tropical conditions further complicate acoustic signal due to rapid variations in the surface temperature [3].

The ambient noise data have been recorded in the Arabian Sea using fixed underwater sensors placed at 30 m depth from the sea surface. The sensors have been placed horizontally along the east west direction with 100 m spacing between the sensors. The recorded data is digitized at the sensor itself at 256 KHz rate with post filtering by an anti-aliasing filter. The digitized data is received by an underwater junction box where it is put in serial format and modulated to optical format. It is transmitted to the shore based data handling system via a fiber optic cable for further processing.

To extract the time-frequency information from non-stationary signals, the Time-Frequency Analysis (TFA) methods belonging analytically appealing model can be used effectively. Short Time Fourier Transform has been extensively used for finding signatures of ambient noise sources like Whales [4, 5] and other transients [6-9]. In many applications, such as passive sonar signal processing [10], the spectrogram does not provide enough freedom to the user. When the interest is to obtain the information of the ambient noise sources using spectrogram, it is very complex to choose the good parameter set i.e. window type and length, overlapping parameter, etc. The scalogram [11-13] also found to offer significant results by using wavelets. The statistical features from time frequency representations have been used for ambient noise source descriptions [14], and image quality parameters have been evolved to ensure a quality of image expected [15]. This paper uses both statistical features and image quality parameters in the quest to find better the time frequency representation for ambient noise in littoral tropical waters.

The remainder of the paper is organized as follows. Section II describes Short time Fourier transform and its visual impression at different wind speeds. Section III presents Continuous Wavelet selection criterion and representation of ambient noise signals using suitable wavelet. Results and conclusions from quantification of time frequency representations are described in section IV.

II. SPECTROGRAM : A TRADITIONAL TOOL

Dennis Gabor adopted the Fourier transform to analyze only a small section of the signal at a time, this technique called windowed Fourier transform. Gabor's adaptation, also called the Short-Time Fourier Transform (STFT), maps a signal into a two-dimensional time and frequency domain [16, 17]. It conveys approximately about both when and at what frequencies a signal event occurs i.e. time and frequency of an event. STFT of a signal $x(t)$ is expressed as,

$$X(t,f) = \int_{-\infty}^{\infty} x(\tau) w(t-\tau) e^{-j\omega t} d\tau$$

where, $X(t,f)$ is STFT of signal $x(t)$, and $w(t)$ is window function. However, due to the time window introduced by the STFT, the spectrogram does not satisfy the marginals as well as the time frequency support and the time frequency

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localization. The spectrogram suffers from a time frequency localization trade-off and assumes stationarity of the signal in short intervals of time given by the size of the window *w(t)*.

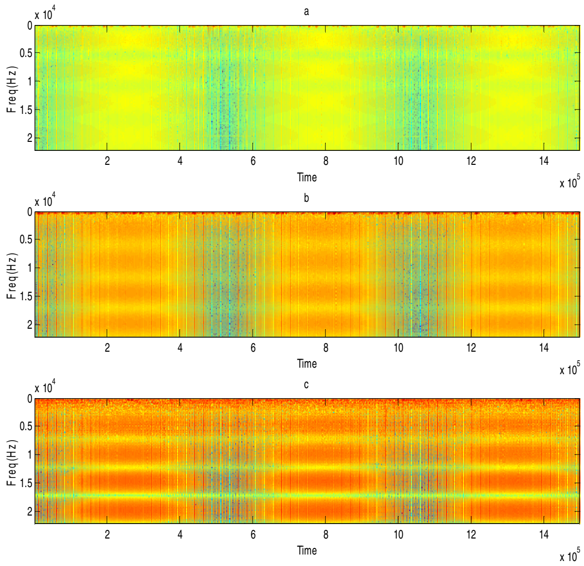

Fig.1. Spectrogram at different wind Speeds (a) 0.53m/s (b) 2.22m/s (c) 4.6m/s

The spectrogram is not a single distribution, but rather a class of distributions, determined by the window size and shape. It is possible by choosing different window sizes to obtain better frequency or time resolution, but not both simultaneously. The better frequency resolution requires a long window (narrow band spectrogram), whereas, the better time resolution requires a short window (wide band spectrogram). Often, a compromise window between the two extremes is quite suitable, and that is why the spectrogram has been such a powerful method. However, the limitation is that one window cannot give both good time and frequency resolution. Spectrogram of ambient noise is obtained at various wind speeds 0.53m/s, 2.22m/s,4.6m/s. The hanning window is used of window length as 4096 and 50% overlap. At higher wind noise magnitude is increased as shown in Fig. 1. Different noise sources like a ship and mammal signals are added to this ambient noise, and their spectrogram is quantified using statistical and image quality parameters.

III. CONTINUOUS WAVELET TRANSFORM

The Wavelet compares the signal with a set of functions obtained from the scaling and the shifting of a base wavelet and thus enables variable window sizes in analyzing different frequency components within a signal. The wavelet analysis calculates the correlation between the signal under consideration and a wavelet function ψ *(t)*. The similarity between the signal and the analyzing wavelet function is computed separately for different time intervals and different scales, resulting in a two dimensional representation. The analyzing wavelet function ψ *(t)* is also referred to as the mother wavelet. The wavelets are generated from a single basic wavelet ψ *(t),* so-called mother wavelet, by scaling and translation. This wavelet function is given by,

$$\psi_{a,b}(t) = \frac{1}{\sqrt{|a|}}\psi(\frac{t-b}{a})$$

a is the scale factor it gives the frequency related information (scale is inversely proportional to frequency), *b* is the translation factor which gives the time related information and the factor $\sqrt{a}$ is for energy normalization across the different scales. The Continuous Wavelet Transform (CWT) is given as follows,

$$CWT_x^{\psi}(b,a) = \frac{1}{\sqrt{|a|}}\int_{-\infty}^{\infty} x(t)\psi^*(\frac{t-b}{a})dt$$

CWT gives the time-scale representation of the signal *x(t)* which is the function of scale *a* and time lag b. MRA is possible in CWT since this gives the better time resolution at lower scale(higher frequencies) and better frequency resolution at higher scales (lower frequencies). The Wavelet analysis often speaks in terms of the approximations and details. The approximation coefficients are the high-scale, low-frequency components of the signal. The detail coefficients are the low-scale, high-frequency components [16, 17]. The differences between different mother wavelet functions such as Haar, Daubechies, Coiflets, Symlet, Biorthogonal etc. consist in how these scaling functions and the wavelet functions are defined. Before using wavelets for its time scale representation at different wind speeds, a suitable wavelet is identified to represent tropical littoral water by observing standard deviation versus scale, and the maximum energy reflected.

The mother wavelet, which gives more energy among all wavelet families, can be called as best suit wavelet for a signal. Likewise, Morlet wavelet family gives maximum energy for the simulated sine wave because the shape of basis function of Morlet family is mostly matches with sine wave. Similarly, for the square wave Haar Wavelet gives maximum energy as the shape of basis function is same as the square wave. In the same way, ambient noise is analysed to find best suit Wavelet and it is observed that the 'Coif4' and 'dmey' gives the maximum energy.

The minimum standard deviation of the wavelet coefficients gives best suit wavelet family. In this case, the CWT coefficients of ambient noise signal refer to the amount of the wavelet overlaps with the original signal. The greater the coefficient the greater is the overlapping. Thus lower the standard deviation, more consistently will a given wavelet describe a particular waveform as most of the values of the coefficients will lie closer to the expected value. From the Fig. 2, the graph of standard deviation versus scale, it is observed that 'Coif4' and 'dmey' wavelet family gives minimum standard deviation for higher scale. The CWT coefficients are calculated for the scale values ranging from 1 to 500. Same results as energy based approach are obtained using this approach. Thus, it can be concluded that for the ambient noise data available, 'Coif4' and ‘dmey’ can be adjusted as the most appropriate mother wavelet.

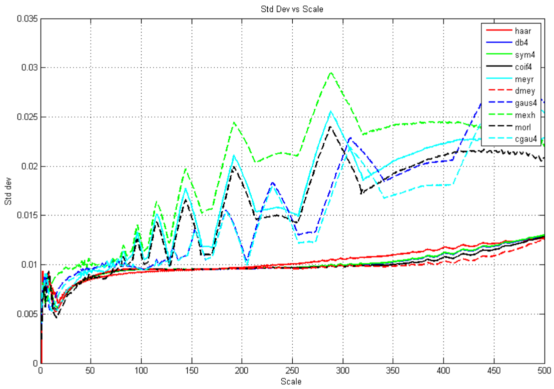

Fig.2. Standard deviation of wavelet coefficients versus scale

CWT is obtained using ‘coif4’at various scales 35, 45 and 60 including the scale at which maximum energy. Figure 3 shows CWT representation of ambient noise at different wind speeds.

VI RESULTS AND DISCUSSIONS

The spectrograms and CWT representations are obtained for various wind speed. Similarly a natural source of ambient noise as Whale signal and a ship signal as anthropogenic noise are added to ambient noise signal separately. Their spectrogram and CWT representations are shown in Fig. 4 and Fig. 5 respectively. These time frequency representations are compared using statistical parameters such as mean, skewness and kurtosis both on time and frequency axis as shown in table I. The STFT and CWT images are also compared on the basis of image quality parameters like dynamics and mean square error and average distance as shown in table II.

For varying wind speed overall noise throughout the frequencies has been increased which has shown clearly in STFT compared to CWT representations. CWT representations are better for other sources of ambient noise specifically contributing to lower frequencies like ship and whale. Skewness has been better represented STFT and Kurtosis parameters are better for CWT. Table II shows image quality parameters. The mean square error and average distance can define STFT representation where as image dynamics shows spectral variations tracked by CWT.

Results obtained show the preliminary investigations for the parameters which can be better facilitate proper time frequency representations. Further, in detail investigations are required using additional image quality and statistical parameters with higher number of ambient noise sources and its variants taking into considerations. By using suitable thresholds, these quantified representations will conclude the best suitable time frequency representation for sonar operators to improve detection of specific ambient noise source signatures. Such quantification of TFRs for underwater ambient noise would be one of the important tools to characterize variations in the tropical littoral waters.

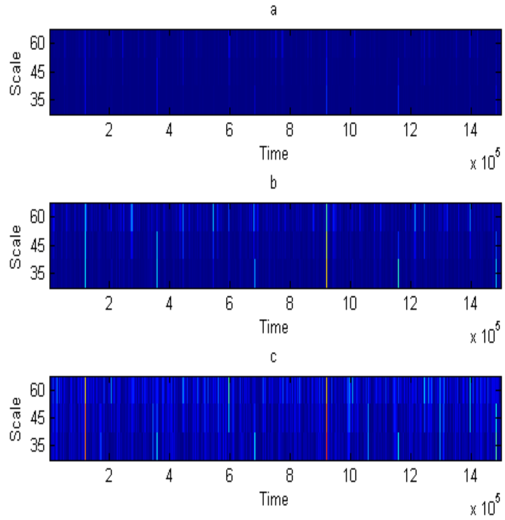

Fig. 3 CWT of at different wind Speeds (a) 0.53m/s (b) 2.22m/s (c) 4.6m/s

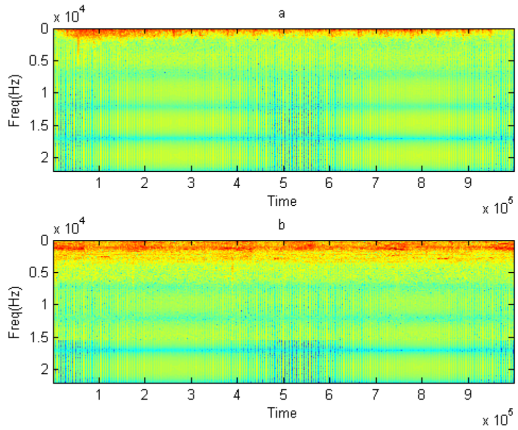

Fig. 4. (a) STFT of Ambient noise with Ship Signal (b) STFT of ambient noise with Whale Signal

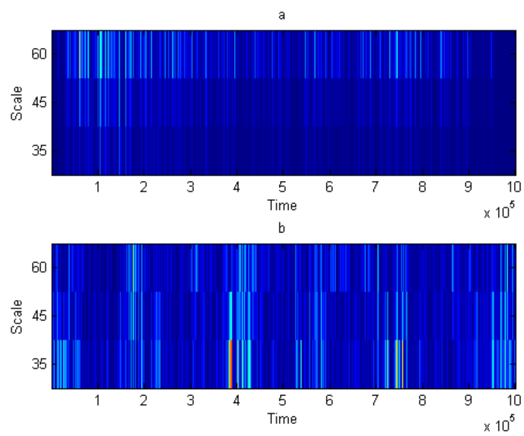

Fig. 5. (a) CWT of Ambient noise with Ship Signal (b) CWT of ambient noise with Whale Signal

TABLE I. STATISTICAL PARAMETERS

Signal / Statistical Parameter	STFT				
	Mean Frequency	*Frequncy Skew*	*Frequency Kurtosis*	*Temporal Skew*	*Temporal Kurtosis*
0.53 wind	9396	0.49	1.34	0.041	1.34
2.22 wind	9260	0.51	1.37	0.195	1.32
4.64 Wind	6863	0	1.29	0	1.34
	CWT				
0.53 wind	100	0	1.62	0.505	1.45
2.22 wind	140	0.01	1.39	0.781	1.5
4.64 Wind	105	0	1.36	0	1.54

TABLE II. IMAGE QUALITY PARAMETERS

Signal/ Image Quality Parameters	STFT			CWT		
	MSE	*Dynamics*	*Average Distance*	*MSE*	*Dynamics*	*Average Distance*
Ambient Noise (2.22m/s)	17.2100	-2.2112	2.4063	0.0001	-2.7009	0.0053
Ambient Noise (4.64m/s)	45.6139	-2.3523	5.0222	0.0002	-1.6429	0.0092
Ship+ Ambient Noise	37.6492	-5.2835	2.3054	0.0140	-0.4217	0.0741
Whale +Ambient Noise	133.1948	-5.2159	6.2919	0.2117	-4.7478	0.3205

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