Journal of Marine Science and Technology

Volume 23 | Issue 4 Article 3

STUDY OF DIFFERENT DENOISING METHODS FOR UNDERWATER ACOUSTIC SIGNAL

V. Vijaya Baskar
Sathyabama University, Chennai, India.

V. Rajendran
SSN College of Enggineering, Chennai, India., v_vijaybaskar@yahoo.co.in

E. Logashanmugam
Sathyabama University, Chennai, India.

Journal of Marine Science and Technology, Vol. 23, No. 4, pp. 414-419 (2015)
DOI: 10.6119/JMST-014-0506-1

STUDY OF DIFFERENT DENOISING METHODS FOR UNDERWATER ACOUSTIC SIGNAL

V. Vijaya Baskar[1], V. Rajendran[2], and E. Logashanmugam[1]

Key words: ambient noise, EMD, EEMD, wavelet, denoising.

ABSTRACT

Marine Engineering faces certain challenges in recent times due to the prevalence of ambient conditions caused by imbalance in the ecosystem. Underwater ambient noise is primarily a background noise, which is a function of time, location and depth. It is of prime importance to detect the signals such as the sound of a submarine or an echo from a target, surpassing and surmounting this ambient noise. In the absence of the sound from ships and marine life, underwater ambient noise levels are dependent mainly on wind speeds at frequencies between 500 Hz and 50 KHz (Urick, 1984). Since there is a possibility of signal and noise present in the same frequency, it becomes indispensable to find out a suitable algorithm to perform denoising. In this paper the functioning of different denoising methods: wavelet, Empirical Mode Decomposition (EMD) in time domain, Ensemble Empirical Mode Decomposition (EEMD) and frequency domain based EMD are studied and the results are compared. The proposed frequency domain algorithm produced better results in the frequency ranging from 50 Hz to 25 KHz, with less signal error - an encouraging result. This work is calibrated through a comparison made with the existing methods and the outcomes obtained are found to be better than the existing algorithms like wavelet, EMD in time domain, etc.

I. INTRODUCTION

Underwater acoustics has become the natural interest to many researchers throughout the world because that it is so complex to study and analyze. Underwater ambient noise is a constituent of background noise that depends on depth, time and location. Self noise does not belong to the category of ambient noise (Urick, 1984). Ambient noise is the residual noise that would exist even after recognizable sources of sound are removed. The various sources of sound are the breaking waves, marine life, other natural sources and rain. Shipping also becomes an important factor for the noise generation along with several other manmade sources like military sonar. Noise due to wind is a major contributor to the total ambient noise.

1. Ambient Noise in Shallow Water

Shallow water ambient noise is highly random due to the wave guide nature of the environment and bottom reflection (Yang and Kwang, 1997). Ambient noise is more prevalent in shallow water as the noise is pinned between the sea floor and the surface of the ocean . In shallow water (depth from 5 - 200 m), acoustic systems like sonar, echo sounder and sub bottom profiler suffer a huge loss due to the massive presence of ambient noise. Shallow water regions are distinguished from deep water regions by the relatively greater role played by the reflecting and the scattering boundaries. Also the differences from one shallow water region to another are primarily caused by differences in the structure and composition of the sea floor.

2. Denoising

The recovery of the signal buried in ambient noise is important for the target's signal detection, recognition and classification at a low signal-to-noise-ratio. A major task in the de-noising process is to locate the better domain in which separation of noise from the meaningful signal takes place more effectively.

Tu and Jiang explained the effects of ocean intervention and ambient noise on undersea sound signal while propagation takes place in an ocean. Received signals should be processed accurately so that the weak signals can be distinguished more effectively. They also proposed a method for denoising of this kind of signal, wherein the transformation of undersea sound signals was done using wavelet. A revolutionary transition in the denoising methods took place with the use of 'Empirical Mode Decomposition', which was suggested by Flandrin et al. (2004).

Later Zhao et al. (2011) introduced a novel adaptive shrunken denoising method. It was based on EEMD and is being used now to improve Electrocardiogram (ECG) signals. EEMD had a better influence in improving Signal to Noise Ratio (SNR) in terms of maintaining the original characteristic

Paper submitted 07/05/13; revised 03/15/14; accepted 05/06/14. Author for correspondence: V. Vijaya Baskar (e-mail: v_vijaybaskar@yahoo.co.in).
[1] Sathyabama University, Chennai, India.
[2] SSN College of Enggineering, Chennai, India.

waveform. Better estimates of noise were guaranteed by adaptive threshold value and this method was demonstrated to be was very useful for effectively denoising ECG signal. Application of this EEMD, along with adaptive threshold value, has enough potential for biomedical signals especially and in other fields too.

In this paper, a simulated signal was considered as the sonar signal and it was added with a real time wind noise signal to get a noisy signal. Wind noise was measured with sensitive hydrophones. The output of hydrophone is the voltage signal and it was converted into Pascal based on the sensitivity of hydrophone (Vijayabaskar and Rajendran 2010). This signal was applied as the stimulus to the denoising algorithm and the denoised signal was obtained. The performance of different denoising methods (wavelet, EMD, EEMD) has been compared. This paper is organized as follows: In section II wavelet based denoising algorithm is discussed. Denoising using EMD based on time domain approach is described in section III. Denoising using EEMD based on time domain thresholding is explained in section IV. The proposed denoising approach using EMD based on frequency domain thresholding and the results of different denoising algorithm are discussed in the end.

II. DENOISING OF WIND GENERATED AMBIENTNOISE USING WAVELET

Here decomposition of noisy signal was done using different wavelets. After decomposition by wavelet, the threshold was applied using different threshold functions with soft, hard and non-negative garrote threshold (Gao, 1998). The RMSE value was calculated for different wavelets and threshold functions. The computed values are presented in Table 1. From the table it is clear that RMSE value is less for ‘sym8’ wavelet when compared to other wavelets and moreover, most of the wavelets perform well along with non-negative garrote threshold, i.e., with less RMSE value.

Here, the Universal method for fixing threshold value was modified by introducing two constants ‘k’ and ‘m1’ to obtain higher quality output signal and it was combined with non-negative garrote threshold function in the denoising process.

The modified threshold equation is given by (Rajeev et al., 2011).

$$\lambda = \mathrm{k.\, m1.}\, \sigma\sqrt{2\log 2(\mathrm{N})} \tag{1}$$

Where, N denotes number of samples of noise and σ denotes standard deviation of noise, it is noticed that if two factors i.e. k and m1 are introduced in universal threshold equation, then new threshold value gives better results; especially to recover the original signal.

Here the values of k and m1 are fixed after repeated trials. Initially m1 value was fixed and k value varied to obtain better result. After many trials k value was fixed as ‘0.5’, which gave better results when compared to other k values. Then the value of m1 was varied and the output was better for the value m1 = 3.

Table 1. RMSE value for different threshold function.

Wavelet Type	RMSE Value for Different Threshold Method		
	Hard	Soft	Non negative garrote
Haar	0.001339103	0.001303089	0.001326211
db2	0.000836217	0.000837207	0.000836016
db4	0.000618673	0.000620417	0.000618689
db5	0.000602552	0.000603077	0.000602235
db8	0.000595174	0.000595174	0.000595174
sym4	0.000617997	0.000619197	0.000617785
sym8	0.000594376	0.000595753	0.000594325
coif4	0.000594698	0.000596959	0.000594531
coif2	0.000615408	0.000617598	0.000615114
Dmey	0.000593861	0.000593861	0.000593861

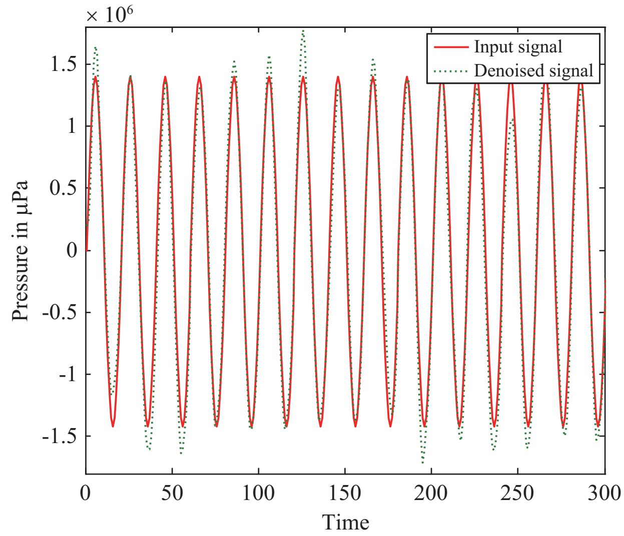

Fig. 1. Input and denoised output signal using sym8 wavelet.

The wavelet ‘sym8’ was selected, which gave better results than other wavelets. Decomposition was done using sym8 wavelet, the value, when above the threshold, was considered as signal, otherwise as noise. Then the modified universal threshold along with non-negative garrote threshold was applied to the decomposed signal.

After applying the threshold value, inverse wavelet was applied in the end to obtain the original signal. The comparison of original and denoised signals is presented in Fig. 1. It shows that the denoised signal does not exactly resemble the original input signal.

III. DENOISING USING EMD BASED ON TIME DOMAIN APPROACH

The Empirical Mode Decomposition is different from other methods of analyzing data through non-stationary and nonlinear processes. This has been introduced by Huang et al. This

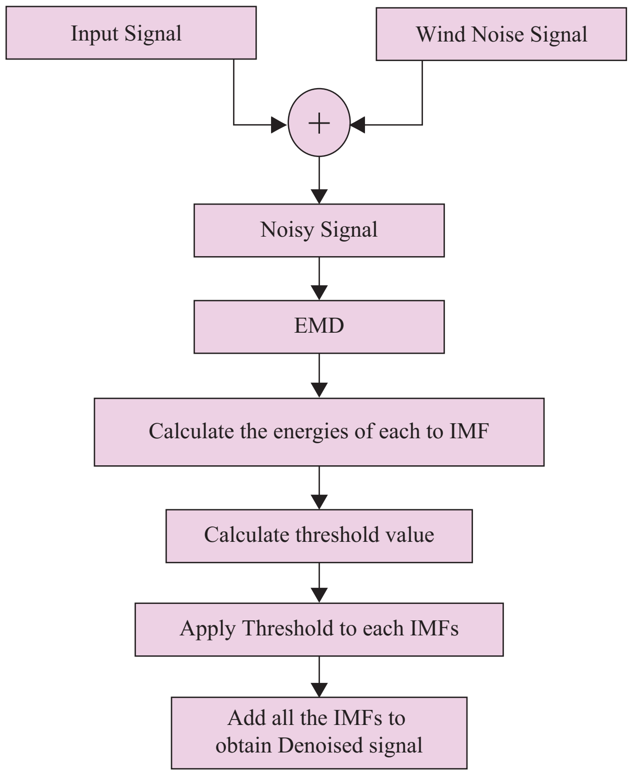

Fig. 2. EMD based denoising algorithm using time domain thresholding.

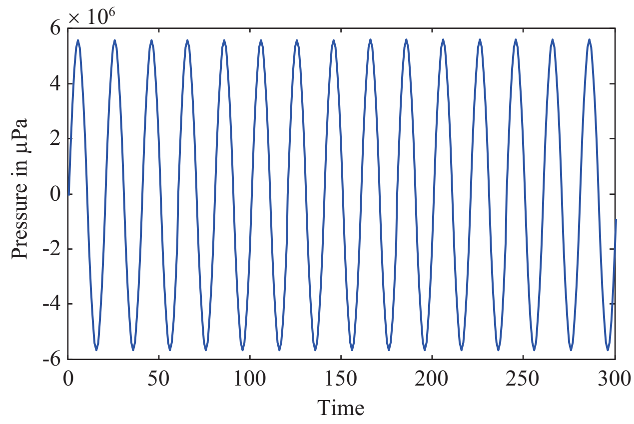

Fig. 3. Sample input signal of 10 mv amplitude.

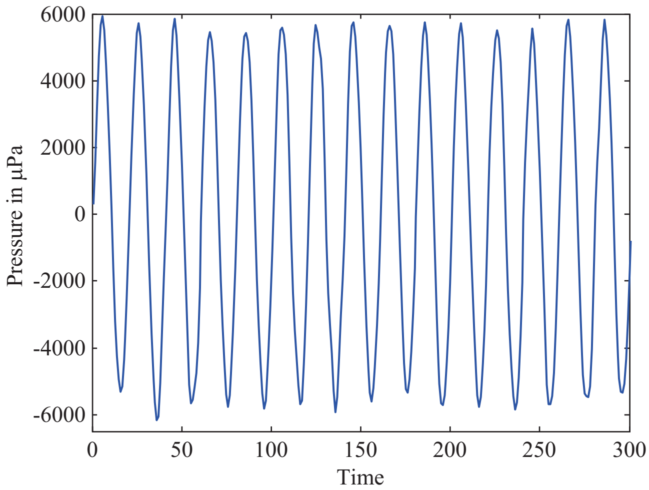

Fig. 4. Denoised signal obtained using EMD based on tme domain approach.

is used to decompose signals in an adaptive manner into a sum of AM and FM components containing raw intrinsic building blocks (Huang et al., 1998). Since in EMD, decomposition is based on and derived from the data, it is an adaptive method. Here, the data $x(t)$ is decomposed in terms of Intrinsic Mode Decomposition (IMF) (c_j) and residue. i.e.

$$x(t) = \sum_{j=1}^{n} c_j(t) + r_n(t) \tag{2}$$

Here r_n is the residue of data $x(t)$, after n number of IMFs being extracted. IMFs are simple oscillatory functions with varying amplitudes and frequencies. The denoising algorithm using EMD based on time domain approach is shown in Fig. 2. In this time domain algorithm, EMD was applied to the noisy signal. Then the noisy signal was decomposed into a set of IMF's. Energy of each IMF had been calculated and then the threshold value. The IMFs were shrunken using the non negative threshold function and then added, to get the denoised output.

This algorithm works well as long as the noise amplitude is lesser than the signal amplitude. When the noise amplitude is greater than half of the signal amplitude, the output signal is not satisfactory. It starts degrading as the noise amplitude increases. It is evident from Fig. 3 and Fig. 4 that the denoised signal amplitude is much lesser than the original input signal and the denoised signal is not holding exact resemblance to the input.

IV. DENOISING USING EEMD BASED ON TIME DOMAIN APPROACH

In the EMD based time domain thresholding approach, the output signal was not satisfactory and also the amplitude of the output signal was not up to the mark. So the same time domain thresholding approach is used along with Ensemble Empirical Mode Decomposition (EEMD) to improve the output signal (Chang, 2010).

The step by step Function of EEMD method is as follows:

i) Initially adding a series of white noise to the signal that is considered as a target.
ii) Next is extracting IMF through decomposition of noise added data.
iii) Repeating step 1 and step 2 several times, with dissimilar series of white noise each time.
iv) Final results are the extraction of ensemble of corresponding IMFs of the decomposition.

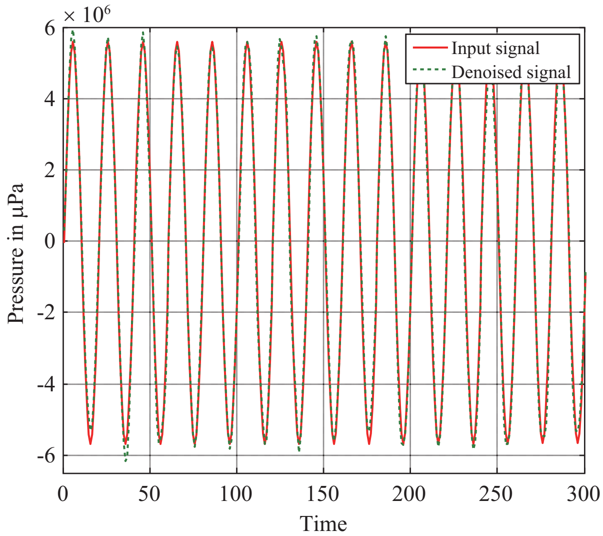

Fig. 5. Input (10 mv) and denoised output signal comparison graph (EEMD Method).

The input and denoised signals are presented in Fig. 5. In EEMD based denoising algorithm, the output amplitude is same as that of the input signal amplitude, unlike as in the case of EMD based denoising algorithm. Though the denoised signal amplitude is quite satisfactory, the output signal does not resemble the input signal exactly.

Shortcomings: This algorithm takes more time to produce output due to more number of iterations and also the output signal produced needs improvement. So it is necessary to propose a new algorithm to eliminate this issue.

V. PROPOSED DENOISING METHOD USING EMD BASED ON FREQUENCY DOMAIN APPROACH

In this proposed algorithm, EMD is used as a denoising tool. Earlier EMD based denoising methods were adopted using time domain thresholding.

The proposed algorithm is based on frequency domain thresholding and this algorithm is shown in Fig. 6. This algorithm is simple and produces better results than the other available algorithms. As the value of threshold depends on the noise signal, this algorithm works well for different wind noise signals. This Proposed frequency domain thresholding approach works well for different wind noises i.e. noise samples collected for various wind speeds.

We have eliminated IMF1 during the course of denoising process, since IMF1 is more noisy. Then, we have applied Fast Fourier Transform (FFT) to other IMFs. Different threshold values have been tested and better outputs obtained, when the threshold value is set between 70% and 90% of maximum FFT amplitude i.e. in each IMF, the coefficients of IMF signal, which have FFT amplitude below the threshold value were assigned zero. After applying threshold Inverse Fast Fourier

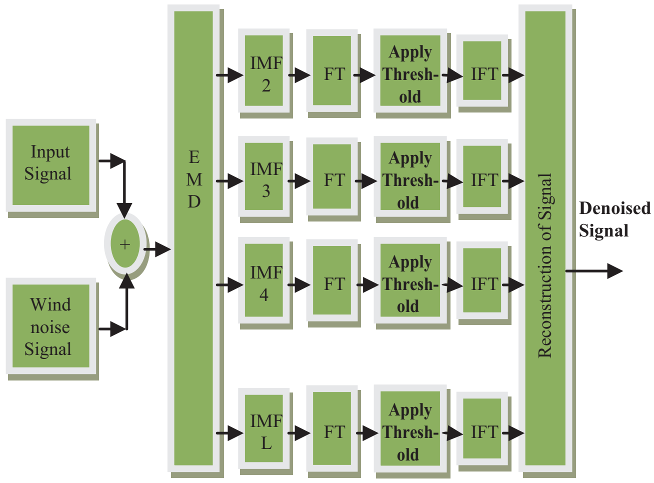

Fig. 6. Proposed denoising algorithm based on EMD.

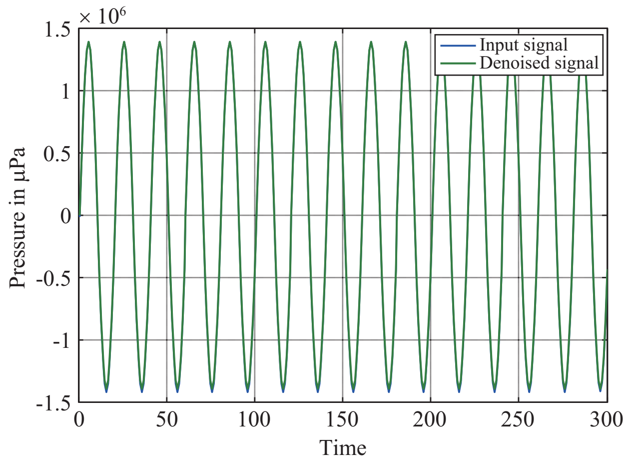

Fig. 7. Input (5 mv) and denoised output signal comparison graph (EMD Method).

Transform (IFFT) was taken to each IMF, and then all the thresholded IMFs were added to get the denoised signal. The input and denoised signals are presented in Fig. 7. The output was good for the threshold values of 70% and above. At 90% threshold the output resembles the input signal very well (Vijayabaskar et al., 2012). From the result it is concluded that the algorithm works well even if the signal amplitude and the noise amplitude are same. Compared to the existing time domain thresholding algorithm, the proposed frequency domain thresholding algorithm fetches better results.

In the proposed algorithm, the input signal amplitude is considered as 5 mv whereas the input signal amplitude was considered as 10 mv for the algorithms, which were discussed in the previous sections. In the existing algorithm (wavelet, EMD based on time domain and EEMD) the denoised signal amplitude is much lesser than the actual input signal and moreover the output does not exactly resemble the input signal. But in the proposed algorithm, the amplitude of denoised

Table 2. RMSE in wavelet (signal amplitude = 10 mv).

RMSE Value at 2.61 m/s	RMSE Value at 3.52 m/s	RMSE Value at 5.06 m/s	RMSE Value at 6.93 m/s
0.0029	0.00061	0.00088	0.0010

Table 3. RMSE in time domain EMD (signal amplitude = 10 mv).

RMSE Value at 2.61 m/s	RMSE Value at 3.52 m/s	RMSE Value at 5.06 m/s	RMSE Value at 6.93 m/s
0.0118	0.00141	0.0071	0.00821

Table 4. RMSE in time domain using EEMD (signal amplitude = 10 mv).

RMSE Value at 2.61 m/s	RMSE Value at 3.52 m/s	RMSE Value at 5.06 m/s	RMSE Value at 6.93 m/s
0.00060	0.00044	0.00063	0.00079

Table 5. RMSE in frequency domain EMD (signal amplitude = 5 mv).

Threshold value in %	RMSE Value at 2.61 m/s	RMSE Value at 3.52 m/s	RMSE Value at 5.06 m/s	RMSE Value at 6.93 m/s
20	0.002991	0.004051	0.002968	0.005838
40	0.000051	0.002512	0.002343	0.002191
50	0.000051	0.001906	0.001448	0.000780
60	0.000051	0.000919	0.001062	0.000780
70	0.000051	0.000045	0.001062	0.000064
80	0.000051	0.000045	0.000055	0.000064
90	0.0001675	0.000045	0.000055	0.000064

signal (at 90% threshold) is same as that of the input signal. Also, here, the denoised signal resemblance with the original signal is good. This result again reveals the reliability of the algorithm for different wind noise signals.

In order to validate the algorithm the Mean Square Error (MSE) is calculated using the following equation.

$$\text{Mean Square Error (MSE)} = \frac{1}{N}\sum_{n=1}^{N}(Z(n)-\hat{Z}(n))^2 \tag{3}$$

Where $Z(n)$ is the input signal without noise and $\hat{Z}(n)$ is the denoised signal.

To compare the performance of different algorithm the (Root Mean Square Error) RMSE value is calculated for different algorithms and various wind speeds. It is presented in Tables 2-5. The RMSE value of the proposed algorithm is given in Table 5 , for different threshold values. From the table it is evident that the RMSE value decreases as the threshold value increases and there is no change in the RMSE value for the threshold above 80%.

Table 6 shows the RMSE value, which is calculated for the wind noise signal of 5.06 m/s, for different denoising methods.

Table 6. RMSE value comparison for different denoising algorithm.

RMSE value for different denoising methods for wind noise signal of 5.06 m/s			
Wavelet	EMD time domain algorithm	EEMD time domain algorithm	Proposed frequency domain based on EMD
0.00088	0.0071	0.00063	0.000055

The RMSE value in the proposed frequency domain algorithm is less compared to the other existing algorithms. The RMSE value is calculated for various wind speeds and it works well consistently in the proposed frequency domain approach. It is concluded that the proposed algorithm produces better results compared to all other available algorithms.

VI. CONCLUSION

The denoising was done using the proposed frequency domain thresholding algorithm with the application of EMD. The output of the proposed algorithm was compared with the existing algorithms, and it shows that the proposed algorithm produces good results in the frequency range of 500 Hz to 25 KHz for different wind noise levels at different wind speeds compared to the existing algorithms. Even RMSE values obtained using the proposed denoising method is far better than the other available methods. This algorithm has been developed and tested for wind noise and therefore can be extended to include other constituents of the ambient noise. The execution time of this algorithm can be reduced with the use of sophisticated hardware processing units or by any time reduction techniques. Extensive tool sets may be developed to classify different categories of noises so that analysis becomes simpler.

REFERENCES

Chang, K.-M. (2010). Ensemble empirical mode decomposition based ECG noise filtering method. Proceeding International Conference on Machine Learning and Cybernetics (ICMLC) 1, 210-213.

Flandrin, P., P. Gonçalvès and G. Rilling (2004). Detrending and denoising with empirical mode decompositions. Proceedings of the 12th European Signal Processing Conference (EUSIPCO'04) 2, 1581-1584.

Gao, H. Y. (1998). Wavelet shrinkage denoising using the non-negative garrote. Journal of Computational and Graphical Statist 7, 469-488.

Huang, N. E. and S. S. P. Shen (1998). Hilbert-Huang Transform and Its Applications, (Interdisciplinary mathematical sciences; v. 5), World Scientific Publishing Co. Pte. Ltd.

Huang, N. E., Z. Shen, S. R. Long, M. C. Wu, H. H. Shih, Q. Zheng, N. C. Yen, C. C. Tung and H. H. Liu (1998). The empirical mode decomposition method and the Hilbert spectrum for non-stationary time series analysis. Proceeding of Roy. Soc. London, 903-995.

Rajeev, A., K. S. Jai, K. G. Vijay, S. Rathore, M. Tiwari and A. Khare (2011). Noise reduction of speech signal using wavelet transform with modified universal threshold. International Journal of Computer Applications 14-19.

Tu, C. K. and Y. Y. Jiang (2004). Development of noise reduction algorithm for underwater signals. Underwater Technology, UT '04.International

Symposium, 175-179.
Urick, R. J. (1984). Ambient noise in the sea. Peninsula Publishing.
Vijayabaskar, V. and V. Rajendran (2010). Wind Dependence of Ambient Noise in Shallow Water of Arabian Sea During Pre-Monsoon. Proceeding of IEEE International Conference on Recent Advances In Space Technology Services & Climate Change - (RSTSCC-2010), 413-416.
Vijayabaskar, V., R. Velayutham and M. M. Philip (2012). Frequency domain based approach for denoising of underwater acoustic signal using EMD. Journal of Intelligent Systems 22, 67-80.
Yang, T. C. and K. Yoo (1997). Modeling the environmental influence on the vertical directionality of ambient noise in shallow water. Journal of Acoustic Society of America 101, 2541-2554.
Zhao, Z., Y. Luo and L. Qing (2011). Adaptive noise removal of ecg signal based on ensemble empirical mode decomposition. Adaptive Filtering Applications, 123-140.