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Removal of Different Noises in Underwater Communication

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Abstract **- Acoustic waves are the most important characteristic to convey data in underwater domain as a practical method. But the oceans are increasingly exposed to sounds from human activities, such as shipping and the building of foundations for offshore construction projects and other different noises. This work presents the capacity of wiener filter and adaptive filter for removal of noise by estimating the signal by means of removing the noise signal from the corrupted signal. This paper compares the performance of adaptive algorithms for noise cancellation in underwater communication signals with different background noises. The proposed work is simulated using MATLAB and analyzed for different inputs with different algorithms.**

Keywords - Underwater communication; Adaptive filters; Wiener filters; Least Mean Square; Normalized Least Mean Square; Recursive Least Square;

1. INTRODUCTION

Underwater signal transmission is a challenging task since the usable frequency range is limited to low frequency and the transmission of electromagnetic waves is impossible due to its high attenuation nature. Hence low frequency acoustic signal is more suited for transmission in underwater. The sea, together with its boundaries, forms a remarkably complex medium for the propagation of sound. It possesses an internal structure and a peculiar upper and lower surface that creates many diverse effects upon the sound emitted from an underwater source. In travelling through the sea, an underwater sound signal becomes delayed, distorted, and weakened. The types of attenuation that affects the sound signal are transmission loss, Spreading Loss, Attenuation Loss, Background noise like Self-Noise, Machinery Noise, Flow Noise, etc.

1.1 Types and sources of underwater noise

Sound travels rapidly through water – four times faster than the air. As in open air, sounds are transmitted in water as a pressure wave. They can be loud or soft, high- or low-pitched, constant or intermittent, and volume decreases with increasing distance from source. Sound pressure is most commonly measured in decibels (dB). Underwater noise has been divided into two main types:

• Impulsive: Loud, intermittent or infrequent noises, such as those generated by piling and seismic surveys

• Continuous: Lower-level constant noises , such as those generated by shipping and wind turbines These two types of MSFD-related noise have different impacts on marine life. In addition, mid-frequency naval sonar may be harmful to marine mammals. The frequency or pitch of the noise is also important, as animals are sensitive to different frequencies.

1.2 Impacts of underwater noise on marine life

Most of the research on the impacts of underwater noise has focused on marine mammals, such as harbor porpoises. There has been less work to understand its effects on fish and other species. In theory, the behavior of any species with the ability to sense or use sound may be affected by manmade noise.

1.2.1 Physical damage

Studies on underwater noise have established that noise can cause permanent injury in some marine animals. In the worst cases, physiological damage caused by noise can lead to death. For example, fish with swim bladders are particularly vulnerable to loud noises, such as those from pile driving, because the gas in their swim bladders is easily expanded by sound pressure. This can cause the swim bladder to rupture. Noise produced by military sonar can cause stranding in beaked whales. It has been suggested that if deep-diving whales surface rapidly in response to noise from sonar they might suffer bubble-related tissue damage similar to that which occurs in decompression sickness in humans, and that this may lead to stranding. Air gun blasts similar to those used in seismic surveys have been shown to cause temporary hearing loss in northern pike fish, whereas the same blasts had no effect on broad whitefish. In turn, effects on hearing may affect animal behavior.

1.2.2 Hunting and communication disturbances

Even at significant distances, it is thought that manmade noises may alter animal behavior by masking the sounds made by the animals themselves. For example, noise from whale-watching boats may interfere with killer whale calls up to a distance of 14 kilometers. Marine mammals, such as whales and dolphins, use sound to hunt, communicate and navigate, for example, using high-pitched clicks that bounce off their prey. Interference with these signals by manmade noise is termed 'masking'. Masking occurs at different frequencies, with each species having its own critical range of frequencies and levels, depending on the type of sounds used by the animal.

1.3 The ultimate effects of underwater noise on people and society

The human impacts of environmental change are often understood in terms of ecosystem goods, such as fish stocks used by humans for food, and ecosystem services, such as tourism. Both of these examples are relevant to underwater noise, which affects fish populations and may have implications for tourism associated with whales and dolphins.

1.4 Objective

The objective of this work is to remove / minimize the background noise and many authors proposed different algorithms to achieve it. Out of many techniques Wiener filters plays an important role in removal of noise from the original signal. Wiener proposed an optimal solution to the problem of noise cancellation but it has some practical limitations. Adaptive filters are the digital filters with an impulse response, or transfer function that can be modified time to time to match with the characteristics of the desired system. Several algorithms have been proposed in earlier days to detect the desired signal. Least mean square (LMS) algorithm was the most efficient method in terms of computation and storage requirements but it has low convergence speed.

The rest of this paper is organized as follows.

Section 2 describes the related work on underwater communication. Section 3 describes the problem statement and proposed work. Section 4 briefly illustrates wiener filters and adaptive filters in section 5. Implementation of proposed work is described in Section 6. Finally, conclusion and future scope are presented in Section 7.

2. RELATED WORK

The authors Caglar Yardim, et al,[1], a geoacoustic parameter estimation algorithm that incorporates both coherent passive fathometry and incoherent passive bottom loss estimation. The water depth and layer thicknesses were inverted with small uncertainties and this facilitated the inversion of other bottom parameters such as sound speed, attenuation, and density.

The authors S.S.Murugan, et al [2] studied the real time data collected from the Bay of Bengal at Chennai by implementing Welch, Barlett and Blackman estimation methods and improved the maximum Signal to Noise Ratio to 42-51 dB.

The authors D.Ramesh, et al [3] developed a mathematical model for wavelet based denoising of a signal which is based on the universal threshold value estimation method. This method reduces the wind driven ambient noise content in the noisy signal and improves the SNR of the signal.

The authors Yen-Hsiang Chen et al [4] implemented a real-time adaptive wiener filter with two micro phones is implemented to reduce noisy speech when noise signals and desired speech are incoming simultaneously.

The authors H.kaur et al [5] implemented the LMS algorithm based on steepest descent algorithm for different input samples and different number of iterations. The simplicity of the LMS algorithm and ease of implementation make it first choice in many applications. The convergence rate is low for this algorithm.

The authors Talwar.R et al [6] compared the performance of different adaptive algorithms like LMS, NLMS, and RLS algorithms for sinusoidal input with different step size and different number of iterations. Three adaptive filter algorithms have been compared by simulation to achieve high convergence rate and minimum mean square error with noise and different values of μ. Every algorithm works on different methods for noise cancellation and improves system performance.

The authors G.V.P.Chandra Sekhar Yadav et al [7] proposed the performance of wiener filter and different adaptive filter algorithms like LMS, NLMS and RLS algorithms for noise cancellation in real time environment like recorded speech as the input and different noise signals are added to it and then desired signal is estimated by using the adaptive algorithms.

The authors Peter H. Dahl, et al [8] proposed "Underwater Ambient Noise", particularly focussed on approximate magnitude and frequency dependence of underwater ambient noise and a partial inventory of its primary sources.

3. PROBLEM STATEMENT AND PROPOSED WORK

The aim of this paper is to minimize or remove the background noise signals from the corrupted acoustic signal in underwater communication. The background noise signal is given to the adder/ subtractor unit and using Weiner filter a similar noise signal is generated by adjusting the filter coefficients. Once the background noise signal and filter generated signal matches, the difference between them yields zero which proves that the back ground noise is removed from corrupted acoustic signal. As the estimate of the reference noise signal is not exact replica of background noise signal, the error signal is not much accurate. In order to get the accurate background noise signal, the obtained error signal is given back to the adaptive filter through adaptive algorithm along with the correction factor. The adaptive algorithm updates the coefficients of the output signal with the help of variable filter coefficients and this updated signal is then again estimated, and this process continues until the required noise free signal is obtained. So, the main task of this work is to remove the background noise using different variable filters. The proposed work is shown in the figure 1.

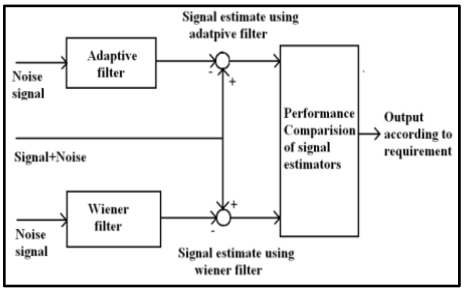

Fig 1: Block diagram of proposed work

In the existing work, the authors H.Kaur and R.Talwar [5] and G.V.P.Chandra Sekhar Yadav et al [7] compared the performance of adaptive filter algorithms like LMS, NLMS and RLS algorithms for sinusoidal input signals and real time speech signals. Now, the same work extended with the recorded real-time underwater communication signal mixed with background noise and compares the performance of adaptive algorithms like LMS, NLMS and RLS algorithms for different step size and different number of iterations. The performance of the algorithms is going to analyze with different input signals with different lengths and parameters.

4. WIENER FILTER

Wiener filter is a statistical method where the estimation of signal is known before processing the signal [3]. Wiener theory defines the optimum value of the filter. The mean square error (MSE), ξ, is defined by the "expectation" of the squared error (e_k). Many adaptive algorithms can be viewed as approximations of the discrete wiener filter. Two signals x_k and y_k are applied to the filter in which y_k is correlated with x_k. The wiener filter produces an optimal estimate of the part of y_k that is then subtracted from y_k to yield error (e_k) as shown in figure 2.

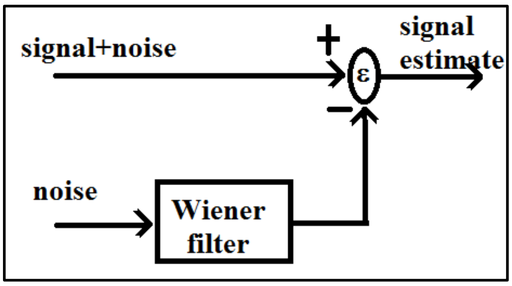

Fig 2: Wiener filter

$$\text{Let } e_k = y_k - \widehat{n_k} = y_k - \sum_{i=0}^{N-1} w(i).x_{k-i}$$

Where x_k and w are the input signal vector and weight vector respectively are given by

$$x_k = [x_k\, x_{k-1}\, x_{k-2}\, x_{k-3}\, \ldots\ldots.x_{k-(N-1)}]^T$$
$$w = [w(0)w(1)w(2)w(3)\ldots\ldots.w(N-1)]^T$$

The mean square error (MSE) is obtained by taking expectation to square of the error e_k^2.

$$\xi = \in \{e_k^2\} = \in \{y_k^2\} - 2W^T R_{YX} + W^T R_{XX} W$$

4.1.1 Performance surface

A plot of MSE against the filter coefficient W is bowl shaped with a unique bottom is shown in figure 3. It is known as the performance surface and is Non-negative. The gradient of the performance surface is given by

$$\nabla = \frac{d\xi}{dw} = 0 - 2P + 2RW$$

Where $P = R_{YX}$ is the N-length cross correlation vector $R = R_{XX}$ is the $N\ x\ N$ auto correlation matrix.

At minimum point of surface, the gradient is zero and filter weight vector has its optimum value W_{opt}.

$$\nabla = 0$$
$$-2P + 2RW = 0$$
$$2P = 2RW$$
$$W_{opt} = R^{-1}P$$

This is known as the wiener-Hopf equation or solution [3]. The task in adaptive filtering is to adjust the filter weights $w(0)w(1)w(2)w(3)\ldots\ldots$ using a suitable algorithm, to find the optimum point on the performance surface.

For real time applications, a way of obtaining W_{opt} on a sample by sample basis is required. Adaptive algorithms are used to achieve this without having to compute R and P explicitly or performing a matrix inversion. The solution to Wiener-Hopf equation is the steepest descent algorithm [11].

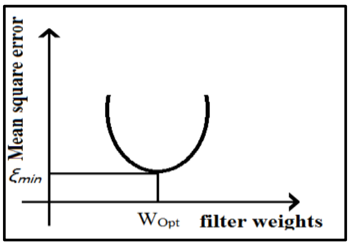

Fig 3: Error performance surface

5. ADAPTIVE FILTER

An adaptive filter consists of two distinct parts: a digital filter with adjustable coefficients, and an adaptive algorithm which is used to adjust or modify the coefficients of the filter [8]. Two input signals y_k and x_k are applied simultaneously to the adaptive filter. The signal y_k is the contaminated signal containing both the desired signal s_k and the noise n_k assumed uncorrelated with each other. The signal x_k is a measure of the contaminating signal which is correlated in same way with n_k. x_k is processed by the digital filter to produce an estimate, $\widehat{n_k}$ of n_k. An estimate of the desired signal is then obtained by subtracting the digital filter output, $\widehat{n_k}$ from the contaminated signal y_k.

$$\widehat{s_k} = y_k - \widehat{n_k} = s_k + n_k - \widehat{n_k}$$

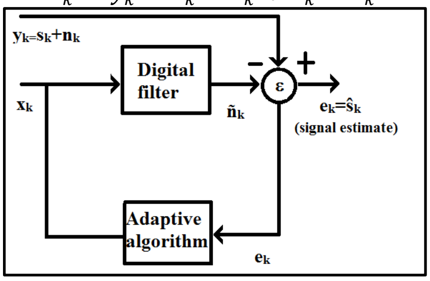

Fig 4: Block diagram of adaptive filter as noise canceller

The main objective of noise cancellation is to produce an optimum estimate of the noise in the contaminated signal and can achieve by using $\widehat{s_k}$ in a feedback to adjust the digital filer coefficients using a suitable adaptive algorithm, to minimize the noise n_k as shown in fig 4, [13].

The output signal $\widehat{s_k}$ serves two purposes:
1) As an estimate of the desired signal and
2) As an error signal which is used to adjust the filter coefficients.

5.1 Adaptive Algorithms

Adaptive algorithms are used to adjust the coefficients of the digital filter. Such that the error signals e_k is minimized according to some criterion. The most commonly used adaptive algorithms are Least Mean Square (LMS), Normalized Least Mean Square (NLMS) and Recursive Least Square (RLS) algorithm for noise cancellation.

5.1.1 Least Mean Square (LMS) Algorithm

One of the most successful adaptive algorithms is the LMS algorithm which is shown in figure 5. Instead of computing W_{opt} in Wiener–Hopf equation, the LMS coefficients are adjusted from sample to sample in such a way to minimize the MSE [4], in descending array as shown in the figure 6.

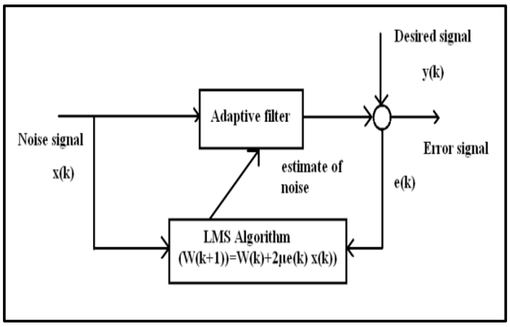

Fig 5: Adaptive filter using LMS algorithm

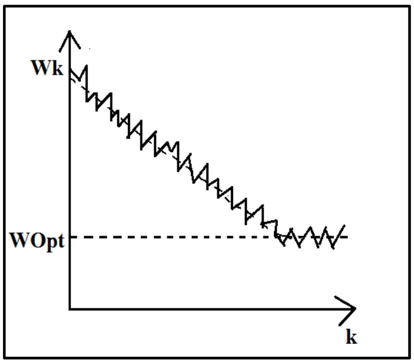

Fig 6: An illustration of the variations in the filter weights

The LMS algorithm is based on the steepest descent algorithm where the weight vector is updated from sample to sample as shown below equation.

$$W_{k+1} = W_k - \mu \nabla_k$$

Where W_k and ∇_k are the weight and the true gradient vectors respectively at the k^{th} sampling instant. μ controls the stability and rate of convergence. The steepest descent algorithm in the above equation still requires knowledge of R and P, since ∇_k is obtained by evaluating the equation.

$$\nabla = \frac{d\xi}{dw} = 0 - 2P + 2RW$$

The LMS algorithm is a practical method of obtaining estimates of the filter weights W_k in real time without matrix inversion in the equation $W_{opt} = R^{-1}P$ or the direct computation of the auto correlation and cross correlation.

$$\nabla = -2P + 2RW$$

In the LMS algorithm, instantaneous estimates are used for ∇. Thus

$$\nabla_k = -2P + 2RW$$
$$\nabla_k = -2x_k y_k + 2x_k x_k^T W_k$$
$$\nabla_k = -2x_k (y_k - x_k^T W_k)$$
$$\nabla_k = -2x_k e_k$$

Where $e_k = y_k - x_k^T W_k$ replace the value of ∇_k in steepest descent algorithm yields

$$W_{k+1} = W_k - \mu \nabla_k$$
$$W_{k+1} = W_k - \mu(-2x_k e_k)$$
$$W_{k+1} = W_k + 2\mu e_k x_k$$

Clearly, the above equation which is LMS algorithm doesn't require prior knowledge of the signal statistics (that is the correlations R and P). The weights obtained by the LMS algorithm are only estimates, but these estimates improve gradually with time as weights are adjusted and the filter learns the characteristics of the signals. The condition of convergence is

$$0 < \mu > 1/\lambda_{Max}$$

Where λ_{Max} is the maximum Eigen value of the input data covariance matrix.

The simplicity of the LMS algorithm and ease of implementation makes the algorithm of first choice in many real-time systems [12]. The LMS algorithm requires approximately 2N+1 multiplications and 2N+1 additions for each new set of input and output samples [4].

5.1.2 Normalized Least Mean Square (NLMS) Algorithm

The main drawback of the pure LMS algorithm is that it is sensitive to the scaling of its input x_k. This makes it very hard to choose a learning rate µ that guarantees stability of the algorithm [6].Adaptive filter using NLMS algorithm is shown in figure 7.

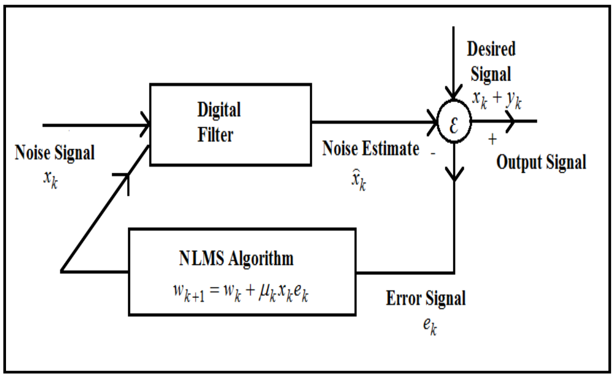

Fig 7: Adaptive filter using NLMS algorithm

The Normalized Least Mean Square filter is a variant of LMS algorithm that solves this problem by normalizing with the power of input.

$$W_{k+1} = W_k + \mu_k x_k e_k$$

Where $\mu_k = \frac{\mu}{x_k^T x_k}$; $\quad 0 < \mu < 2$

In the previous equation, the NLMS algorithm becomes the same as the standard LMS algorithm except that the NLMS algorithm has a time varying step size μ_k. The step size improves the convergence speed of adaptive filter [8].

In practice, sometimes x_k can be very small. To make NLMS algorithm more robust, it can be modified as

$$W_{k+1} = W_k + \frac{\mu}{\delta + x_k^T x_k} x_k e_k$$

So, that the gain constant is always finite.

5.1.3 Recursive Least Square (RLS) Algorithm

The Recursive Least Square algorithm which recursively obtains the filter coefficients that minimizes a weighted linear least squares cost function related to the input signals aims to decrease the mean square error. In the RLS algorithm, the input signals are deterministic, while for the LMS and similar algorithms, they are stochastic. Compared to most of its competitors, the RLS exhibits extremely fast convergence. However, this benefit comes at the cost of high computational complexity. The idea behind RLS filters is to minimize a cost function C by appropriately selecting the filter coefficients W_k, updating the filter as new data arrives. The error signals e_k and desired signal y_k is defined in the negative feedback. Adaptive filter using RLS algorithm is shown in figure 8.

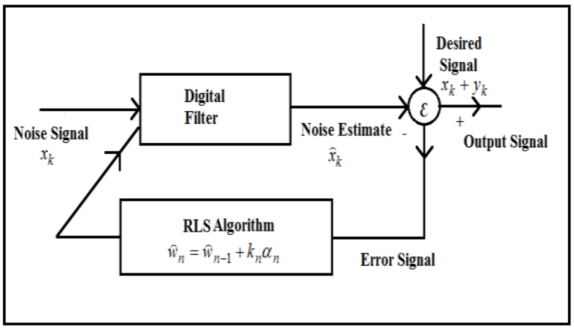

Fig 8: Adaptive filter using RLS algorithm

The error implicitly depends on the filter coefficients through the estimate $\widehat{n_k}$

$$e_k = y_k - \widehat{n_k}$$

The weighted least squares error function C- function has to minimize being a function of e_k is also depends on the filter coefficients.

$$C(W_k) = \sum_{i=0}^{k} \lambda^{n-i} e_k^2$$

Where $0 < \lambda \le 1$ is the "forgetting factor" which gives exponentially less weight for older error samples. The cost function is minimized by taking the partial derivatives for all entries of the coefficient vector W_k and setting the results to zero. Finally the RLS algorithm for an p^{th} order filter can be

$$\alpha_k = y_k - x_k^T W_{k-1}$$
$$g_k = p_{k-1} x_k^* \{\lambda + x_k^T p_{k-1} x_k^*\}^{-1}$$
$$p_k = \lambda^{-1} p_{k-1} - g_k x_k^T \lambda^{-1} p_{k-1}$$
$$W_k = W_{k-1} + \alpha_k g_k$$

Where p=filter order
λ =forgetting factor
δ=value to initialize p_0
W_k=0
$p_0 = \delta^{-1} I$ Where I is the identity matrix of rank p+1

6. IMPLEMENTATION AND RESULTS ANALYSIS

The proposed work is implemented and simulated using MATLAB. As an initial experimental analysis, we have worked on rain roof noise removal by different adaptive algorithms.

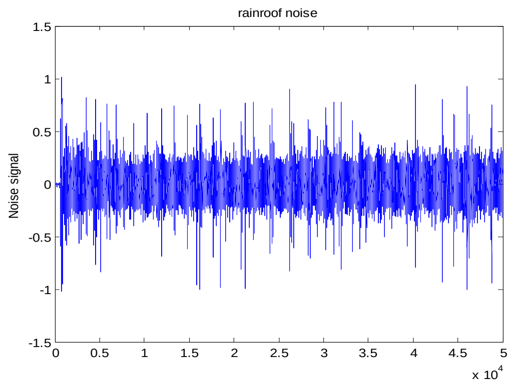

Fig 9 : Rain Roof Noise

Figure 9 shows the noise that is produced due to rain, which describes the noise that is occurred during rain at the roof of the room. Figure 10 describes the comparison of different variable filters for rain roof noise cancellation in real time environment.

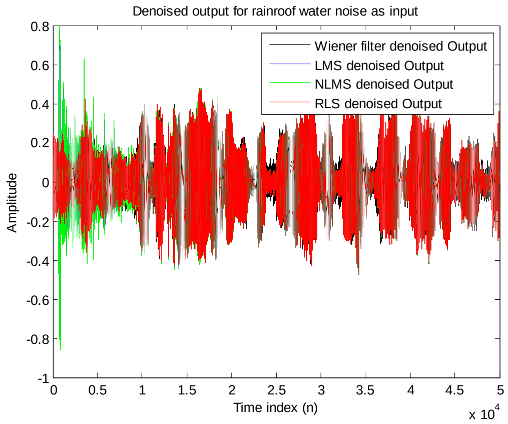

Fig 10: Comparison of Denoised Output for Rain Roof Noise as input

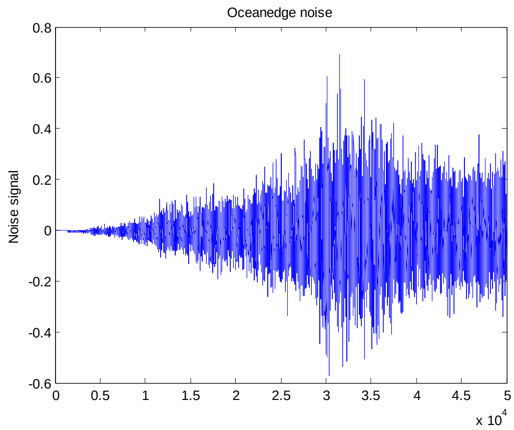

Fig 11: Ocean Edge Noise

Figure 11 describes the water noise which is produced at different ocean regions that shows the noise produced at ocean edge.

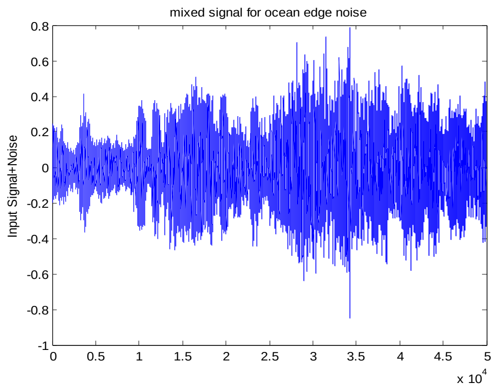

Fig 12: Mixed signal with Ocean Edge Noise

Figure 12 describes the mixed signal that is produced due to the combination of a real time acoustic signal along with different ocean noises respectively. Figure 12 shows the mixed signal when ocean edge noise as the input noise.

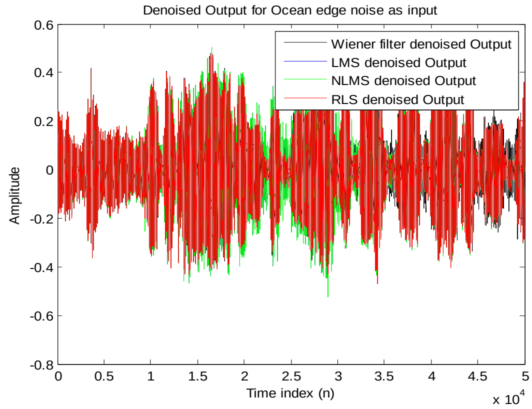

Fig 13: Comparison of Denoised Output for Ocean Edge Noise as input

Figure 13 shows the comparison of different variable filters for ocean edge noise cancellation in real time environment.

7. CONCLUSION AND FUTURE SCOPE

At the initial stage, this paper presents different noises in under water communication, wiener filter theory, wiener filter problem, solution to optimal filtering, adaptive filtering, adaptive algorithm, study of wiener filter and adaptive filter for noise reduction etc. Among many underwater communication noises, at present, we have worked on rain roof and ocean edge noises using wiener and adaptive filters. Wiener filter provides better performance for noise cancellation but it requires large number of computations i.e., complexity and cost of the system is high, so adaptive filter is the alternate approach for removal of noise with moderate complexity and cost. The proposed work is simulated in MATLAB, analyzed and proven better than all the previous techniques. As the future work, the work is to extend by implementing minimization of different other noises like ocean lap noise, ocean gull noise, etc and the performance to be compared.

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