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Design of Adaptive Hybrid Windowing FIR Filter For Acoustic Noise Reduction in Underwater Communication

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Abstract

Reduction of ambient noise for underwater acoustic signal transmission has been considered as major problem over the past few decades. Among various filtering techniques to denoise acoustic signal, Adaptive filtering is the one of the most effective method which reconstruct the signal by minimizing Mean Square Error (MSE) and improve the Signal to Noise Ratio (SNR). In Conventional Adaptive Algorithm, filter Co-efficient are set to zero initially and they are updated by Adaptive algorithm which may increases the number of iteration to meet the requirement. By introducing Hybrid Window, we presents New Adaptive filter with three adaptive algorithms such as LMS, NLMS and RLS for denoising underwater signal which reduces the number of iteration into less than 100. It also provides MSE in order of 10^{-8} and improves the SNR in an average of 33.1167dB using LMS, 32.8128dB for NLMS and 33.6521dB for RLS. For the input SNR varies from -23.2681 to 8.0185, the proposed filter has a noise reduction of 65% more than the conventional Adaptive filter in an average for underwater noise source: Ocean gull noise, Ocean edge noise, Ocean lap noise, rainwater noise, rain roof noise, rain wind noise, rain thunder noise and seashore.

Keywords: Adaptive FIR Filter, denoising of acoustic signal, Hybrid window, Least Mean Square, Normalized Least Mean Square, Recursive Least Square, underwater communication

I. INTRODUCTION

In underwater communication, acoustic signals have been more effective than the radio frequency signals. Since the usable frequency range of underwater transmission is limited to low frequency and the radio signals have been highly attenuated due to its high frequency. Hence acoustic waves have been propagates over a very short distances. Therefore long distance communication has been established easily if acoustic signals were used for underwater communication [1]. But still underwater acoustic signal transmission is challenging task duo its limitation of frequency band and the transmission will be highly affected by ambient noise which are generated by wind, rainfall, breaking waves, seismic, human activities, marine animals and self-noise like noise radiated from ships and underwater vehicles [2]-[5]. The careful implementation of underwater acoustic systems may reduce the self-noise such as ship -radiated turbulence [6]. However, ambient noises are very difficult to avoid completely. Different methods have been developed and investigated for ambient noise reduction in the past few decades and various ambient noise source frequency ranges were shown in wenz curve [7].

This proposed work is focus on underwater ambient noise reduction using proposed variable Adaptive filter. Generally, noise reduction techniques have been developed based on the minimization of signal to noise ratio (SNR) such as wavelet based denoising technique for wind noise reduction with improved SNR of 7dB-10dB [8], various adaptive filter denoising methods were analyzed with modulated signal as reference signal to achieve a better SNR[9]. However, minimization of mean squares error (MSE) has not guarantee that smoothing the filter output [10]. Even wavelet soft thresholding (STH) techniques satisfies both criteria and it have been used for various application like Speech enhancement based on the multitaper spectrum [11], Digital communication and denoising of biological signal, it will not suitable for high frequency band noise. This problem has been improved by space domain wavelet transform that is Time Scale Filter (TSF), which provides smooth reconstruction in both time space and frequency space and achieved average noise reduction of 23.3%, 42.1% for rainfall noise and shrimp noise respectively [12] but the SNR is less than 20dB. The performance of Weiner filter and Adaptive filter for various ambient noise were analyzes and improved the SNR approximately 27 dB – 32 dB [13]. Two denoising techniques namely empirical mode Decomposition and Discrete wavelet transform have been developed for underwater acoustic signals and achieved the SNR of approximately 22dB [14]. Implementation of Welch, Bartlett and Blackman estimate methods for denoising the acoustic signal affected by wind driven noise have been developed [15] and achieved the SNR is about 42-51dB. In the previous work [9], [13], and [15], various adaptive filter algorithms such as LMS, NLMS, RLS and KLMS were implemented for noise reduction and compared their performance with different input signals.

In this work Variable Hybrid Windowing adaptive FIR filter with LMS, NLMS and RLS adaptation algorithm is proposed for denoising of underwater acoustic signal affected by the various ambient noises and their performance has been discussed in terms of SNR and MSE.

This brief is organized as follows. Section II describes the proposed adaptive filter with review of LMS, NLMS and RLS algorithm. Implementation of proposed structure for various ambient noise reductions using MATLAB are presented in section III. We discuss a performance comparison in section IV and finally our conclusion is given in section V.

II. PROPOSED ADAPTIVE FILTER

The proposed Adaptive filter consists of Hybrid windowing FIR filter with adjustable co-efficient and weight updating block used to adjust the filter coefficients is shown in Fig 1.

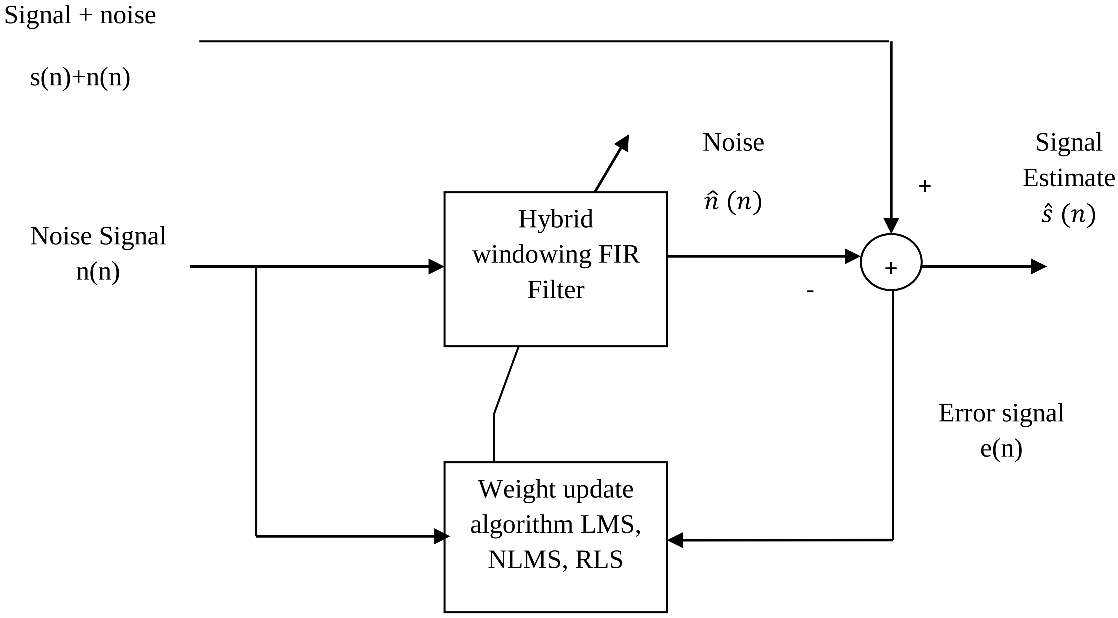


Fig 1. Block diagram of the proposed Adaptive filter

In the proposed work, noise estimate $\hat{n}\ (n)$ has been generated from the observation of input noise n(n) using linear model such as digital FIR filter which is subtracted from the desired signal d(n) which is consists of signal s(n) that is corrupted by noise yields error signal e(n) is also called as signal estimate $\hat{s}\ (n)$. The obtained error have been given to weight adaptation block for updating the filter co-efficients in order to minimize the difference between filter output and desired signal. This updating process continuous until the filter co-efficients converges to minimize the noise in the desired signal. Unlike, the existing method [13], the filter co-efficients are not set to initially zero which are computed using Hybrid window function and then they are updated using adaptation algorithm, as a result the convergence becomes fast and the number of iteration has been reduced.

The proposed hybrid window is a combination of Hamming and Blackman window which is

$$w(n) = \begin{cases} [0.54-0.46\cos(2\pi n/N-1)]*[0.42-0.5\cos(2\pi n/N-1) +0.08\cos(4\pi n/N-1)], & 0 \leq n \leq N-1 \\ 0, & \text{Otherwise} \end{cases} \quad (1)$$

$$w(n) = \begin{cases} [0.3418-0.4816\cos(2\pi n/N-1)+0.1582\cos(4\pi n/N-1) - 0.0184\cos(6\pi n/N-1)], & 0 \leq n \leq N-1 \\ 0, & \text{Otherwise} \end{cases} \quad (2)$$

The proposed Hybrid window achieved a maximum relative side lobe attenuation of -72.7 dB and their frequency response are shown in Fig 2.

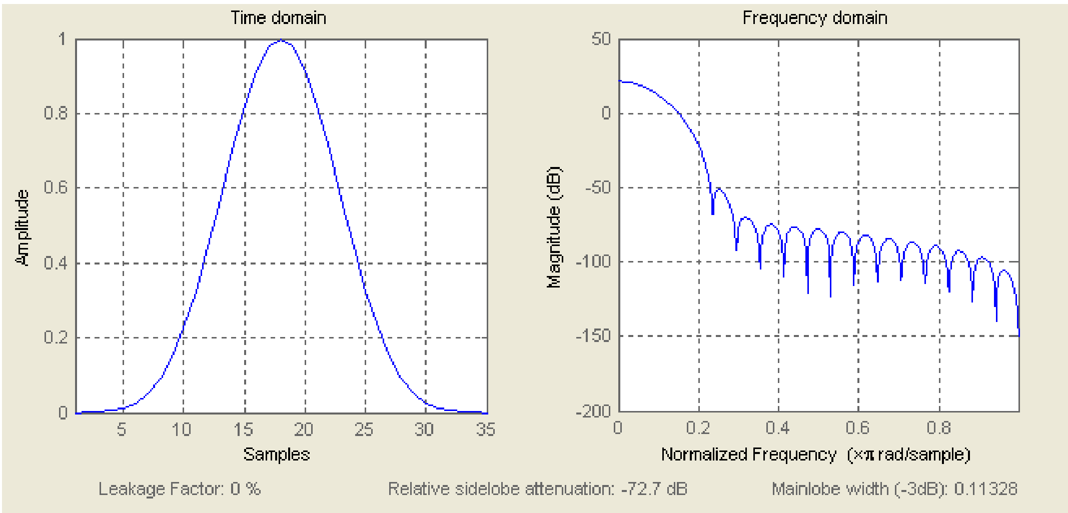


Fig 2. Hybrid Window Frequency Response

The filter co-efficients at n^{th} iteration is

$$h(n) = h_d(n) \times w(n) \quad (3)$$

where $h_d(n)$ is the desired impulse response of the filter

The output of Hybrid windowing FIR filter gives estimate of noise is

$$\hat{n}(n) = \sum_{k=0}^{N-1} h(k)x(n-k) \quad (4)$$

and the error signal or signal estimate is

$$e(n) \text{ or } \hat{s}(n) = d(n) - \hat{n}(n)$$
$$= s(n) + n(n) - \hat{n}(n) \quad (5)$$

II.I Adaptive Algorithm

Adaptive algorithms like LMS, NLMS and RLS are used to adjust the proposed filter co-efficients in order to minimize the noise in the signal estimate $\hat{s}\ (n)$.

II.I.I LMS Algorithm

The Least mean square algorithm have been developed from the steepest descent algorithm whose weight update equation is

$$h_{n+1} = h_n + \mu\ E[e(n)n^*(n)] \tag{6}$$

The practical limitation of this algorithm is that the $E[e(n)n^*(n)]$ is generally unknown for non- stationary process. Therefore, that must be replaced with an estimate such as the sample mean

$$\hat{E}[e(n)n^*(n)] = \frac{1}{L}\sum_{l=0}^{L-1} e(n-l)n^*(n-l) \tag{7}$$

Incorporating (7) into (6), the update for h_n becomes

$$h_{n+1} = h_n + \frac{\mu}{L}\sum_{l=0}^{L-1} e(n-l)n^*(n-l) \tag{8}$$

For one point sample mean (L=1)

$$\hat{E}[e(n)n^*(n)] = e(n)n^*(n) \tag{9}$$

and the simple form of weight vector update equation for LMS Algorithm is

$$h_{n+1} = h_n + \mu e(n)n^*(n) \tag{10}$$

The simplicity of the algorithm comes from the fact that the update for k^{th} co-efficient requires only one multiplication and one addition since the value for $\mu e(n)$ need only be computed once and it is used for all co-efficients. Therefore, LMS adaptive filter having N+1 co-efficients requires N+1 addition to update filter co-efficients. In addition, one addition is necessary to compute the error e(n) and one multiplication is needed to form the product $\mu e(n)$. Finally N+1 multiplication and N addition are necessary to calculate the output, y(n) of the adaptive filter. Therefore, a total of 2N+3 multiplications and 2N+2 additions per output are required.

II.I.II Normalized LMS

One of the difficulties in the design and implementation of the LMS adaptive filter is selection of step size μ. The LMS algorithm converges in the mean if $0 < \mu < \frac{2}{\lambda_{max}}$ and in the mean-square if $0 < \mu < \frac{2}{tr(R_X)}$. However, since R_X is generally unknown, then either λ_{max} or R_X has been estimated in order to use these bounds. One way around this difficult is to use the fact that $tr(R_X) = (N+1)E\ \{[|x(n)|^2]\}$.

Therefore, the condition for mean-square convergence have been replaced with

$$0 < \mu < \frac{2}{(N+1)E\{[|x(n)|^2]\}} \quad (11)$$

where E {[|x(n)|^2]} is the power in the process x(n). It has been estimate by Time average

$$\hat{E}\{|x(n)|^2\} = \frac{1}{N+1}\sum_{K=0}^{N}|x(n-k)|^2 \quad (12)$$

Sub (12) in (11), the step size for mean square convergence becomes,

$$0 < \mu < \frac{2}{x^H(n)x(n)} \quad (13)$$

In convenient form of varying step size is

$$\mu(n) = \frac{\beta}{x^H(n)x(n)} = \frac{\beta}{|x(n)|^2} \quad (14)$$

where β is a normalized step size with 0 < β < 2. Replacing μ in the LMS weight update (10) with $\mu(n)$ gives a normalized LMS algorithm

$$h_{n+1} = h_n + \frac{\beta}{|x(n)|^2}e(n)n^*(n) \quad (15)$$

In the LMS algorithm, the correction that is applied to h_n is proportional to the input vector x(n). Therefore, when x(n) is large, the LMS algorithm experiences a problem with gradiant noise amplification. With the normalization of the LMS step size by |x(n)|^2 in NLMS algorithm, however, this noise amplification problem is diminished. Although the NLMS algorithm bypass the problem when |x(n)| becomes too small and also NLMS requires additional computation to evaluate the normalized term |x(n)|^2. If this term is evaluated recursively as

|x(n+1)|^2 = |x(n)|^2 + |(x(n+1)|^2 - |x(n-N)|^2 then extra computation involves only two squaring operation, one addition and one subtraction.

II.I.III Recursive Least Squares

The difficulty of adaptive filtering such as LMS and NLMS is that they require knowledge of the auto correlation of the input process and cross correlation between the input and the desired output. An alternate approach, is to consider error measures that do not include statistical information about x(n) or d(n) and that may by computed directly from the data is known as Recursive Least Squares in which a least squares error is

$$\varepsilon(n) = \sum_{i=0}^{n}|e(i)|^2 \quad (16)$$

RLS weight update equation that minimize the least square error is

$$h_n = h_{n-1} + \alpha(n)g(n) \quad (17)$$

Where, $\alpha(n)$ is the difference between d(n) and the estimate of d(n)

$$\alpha(n) = d(n) - h_{n-1}^T x(n) \quad (18)$$

And $g(n)$ is the gain vector

$$g(n) = \frac{1}{\lambda + x^T(n)z(n)} z(n) \quad (19)$$

Where, $z(n) = p(n-1)x^*(n)$ (20)

$p(n)$ = inverse auto correlation matrix

λ = Exponential weight factor

Unlike the LMS algorithm, which requires on the order of N multiplication and addition, RLS algorithm requires on the order of N^2 operation, Specifically, the evaluation of $z(n)$ requires $(N+1)^2$ multiplications, computing the gain vector $g(n)$ requires 2(N+1) multiplications, finding the prier error $\alpha(n)$ requires another N+1 multiplications and the update of the inverse auto correlation matrix $p(n)$ requires $2(N+1)^2$ multiplications for total of $3(N+1)^2 + 2$ (N+1) and also similar number of additions. Therefore, RLS increases in computational complexity over LMS algorithm; however is an increase in performance.

III SIMULATION RESULT

The proposed noise reduction work has been implemented for different underwater noise sources such as ocean seagulls, ocean lap, ocean edge, rainfall, rain roof, rain thunder, rain wind and seashore and simulated using MATLAB. The recorded speech signal mixes with water noise such as ocean gulls noise which is measured in different ocean region are shown in Fig 3 and this background noise is removed by using proposed Hybrid filter with different adaptive algorithm are shown in Fig 4. Fig 5, 6 and 7 describes the comparison of Mean Square Error (MSE) in dB, Denoised output and Spectrogram for different adaptive algorithm when ocean gulls noise as input.

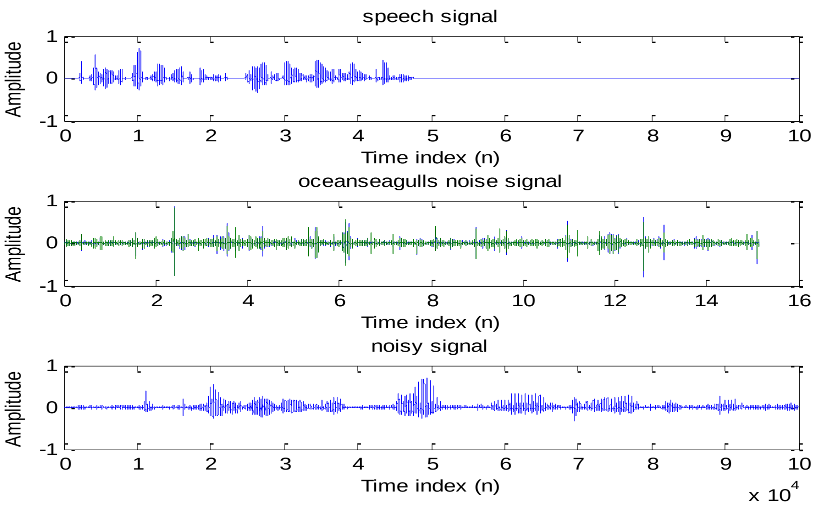
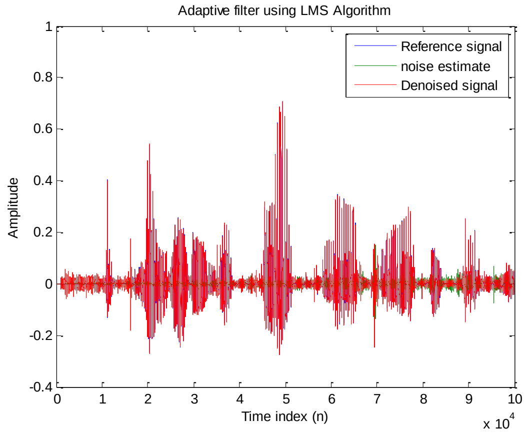
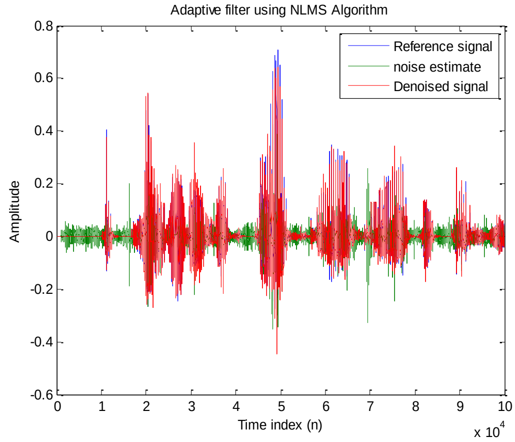


Fig 3. Speech signal, ocean sea gulls noise and mixed signal with noise signal



(a)



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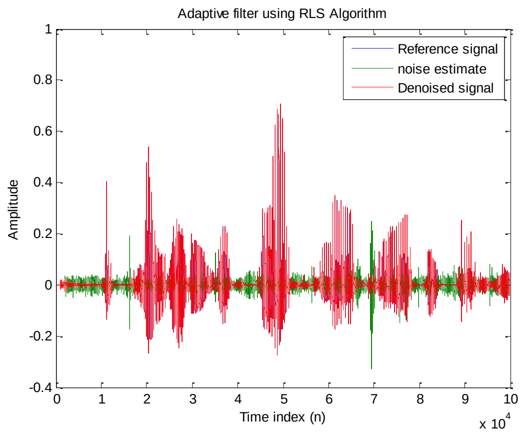


(c)

Fig 4. Comparison between denoised signal and the reference signal: (a) LMS algorithm (b) NLMS algorithm (c) RLS algorithm

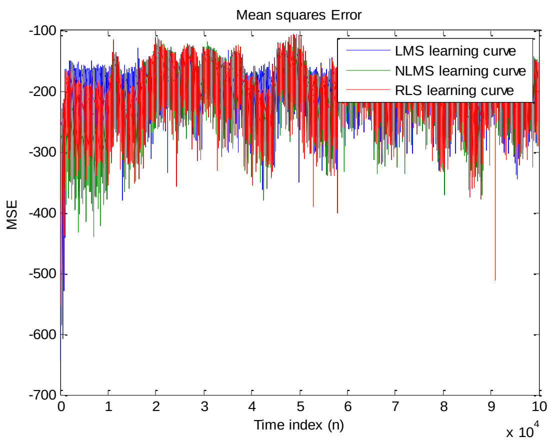


Fig 5. Comparison of MSE in dB

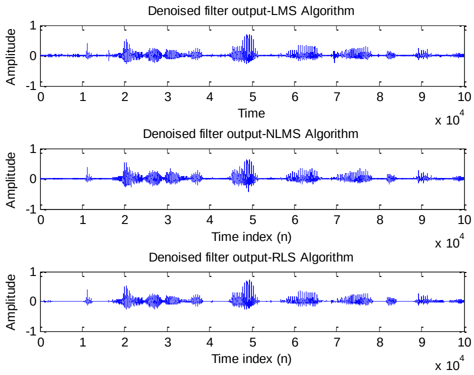


Fig.6. Comparison of Denoised output for Ocean Seagulls noise as input

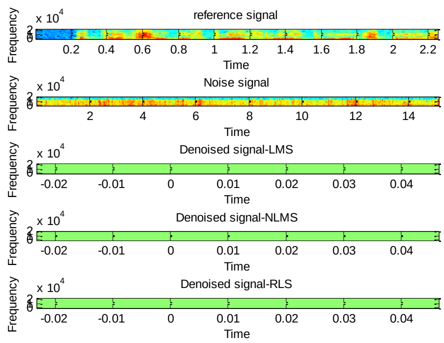


Fig.7. Spectrogram of speech signal, noise signal and denoised signal-LMS,NLMS RLS

The recorded speech signal mixes with water noise such as ocean edge noise which is measured in different ocean region are shown in Figure 8 and this background noise is removed by using proposed Hybrid filter with different adaptive algorithm are shown in Fig 9. The Fig 10, 11and 12 describes the comparison of Mean Square Error (MSE) in dB, Denoised output and Spectrogram for different adaptive algorithm when ocean edge noise as input.

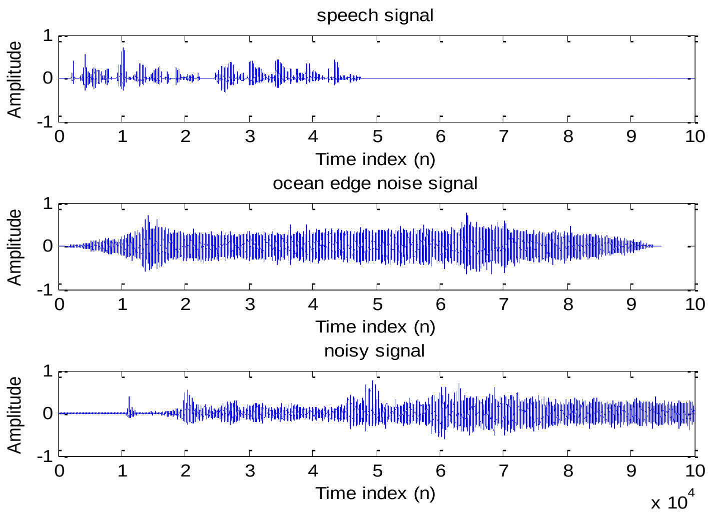
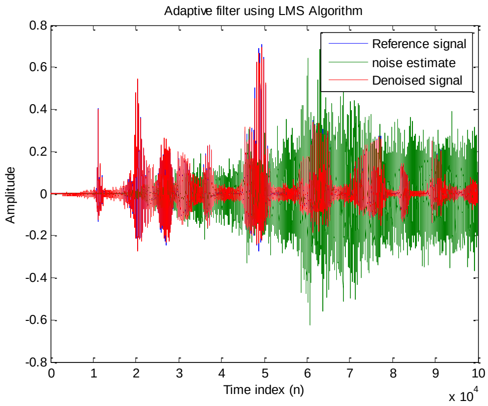
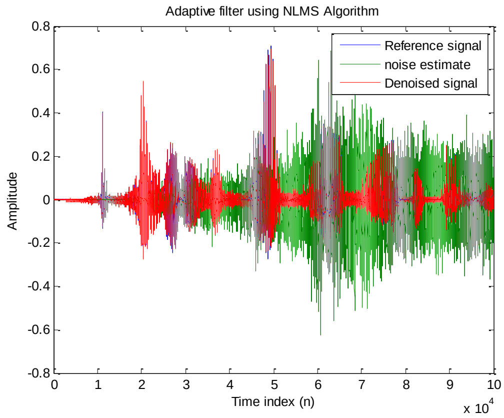


Fig 8. Speech signal, ocean edge noise and mixed signal with noise signal



(a)



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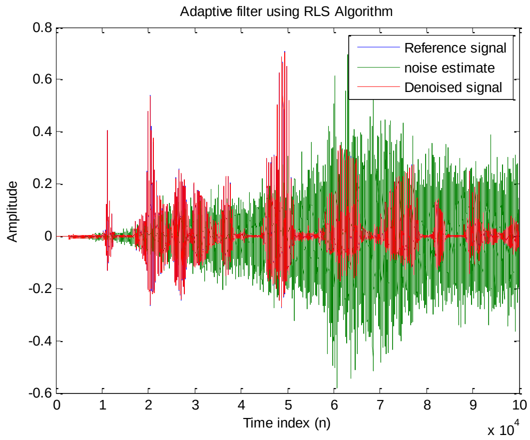


(c)

Fig 9. Comparison between denoised signal and the reference signal: (a) LMS algorithm (b) NLMS algorithm (c) RLS algorithm

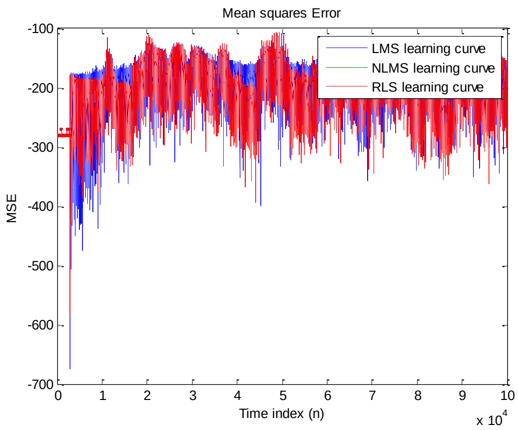


Fig 10. Comparison of MSE in dB

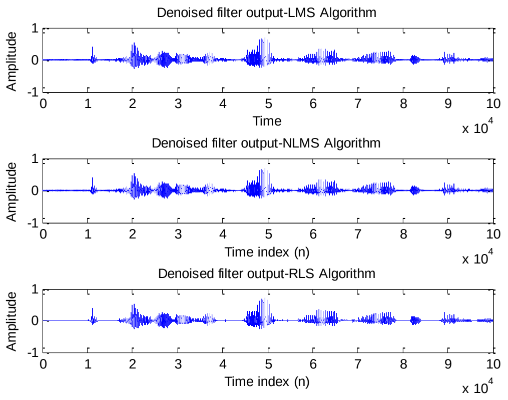


Fig 11. Comparison of Denoised output for Ocean edge noise as input

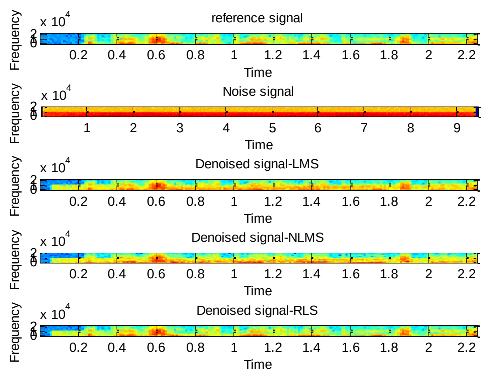


Fig 12. Spectrogram of speech signal, noise signal and denoised signal- LMS, NLMS, RLS

The recorded speech signal, Ocean lap noise and corresponding noisy signal are shown in Fig13 and the removable of background noise by using proposed Hybrid filter with different adaptive algorithm are shown in Fig 14. The comparison of Mean Square Error (MSE) in dB, Denoised output and Spectrogram for different adaptive algorithm when ocean lab noise as input are shown in Fig 15,16 and 17.

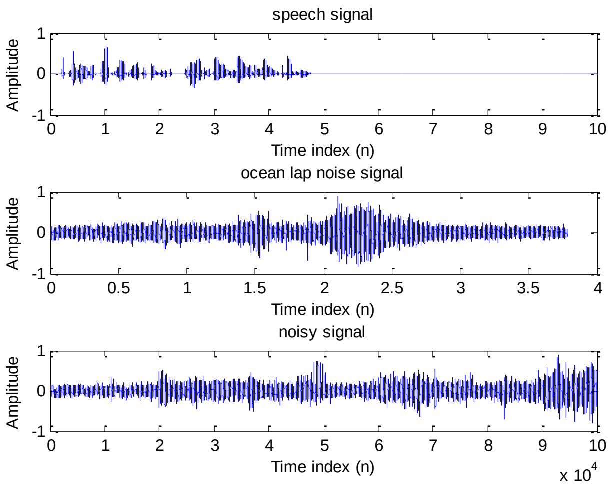
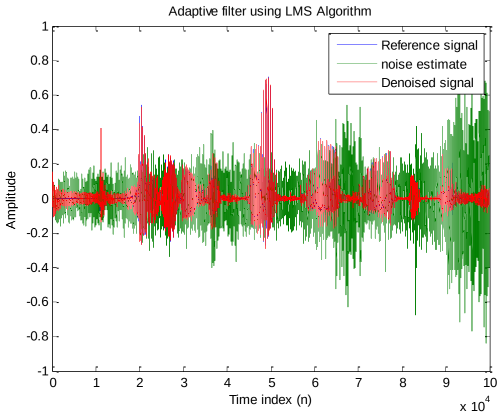
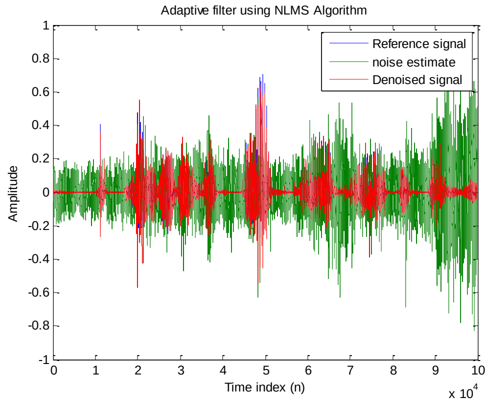


Fig 13. Speech signal, ocean edge noise and mixed signal with noise signal



(a)



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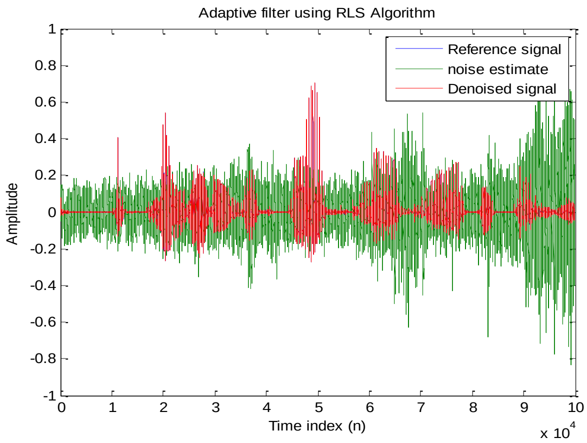


(c)

Fig 14. Comparison between denoised signal and the reference signal: (a) LMS algorithm (b) NLMS algorithm (c) RLS algorithm

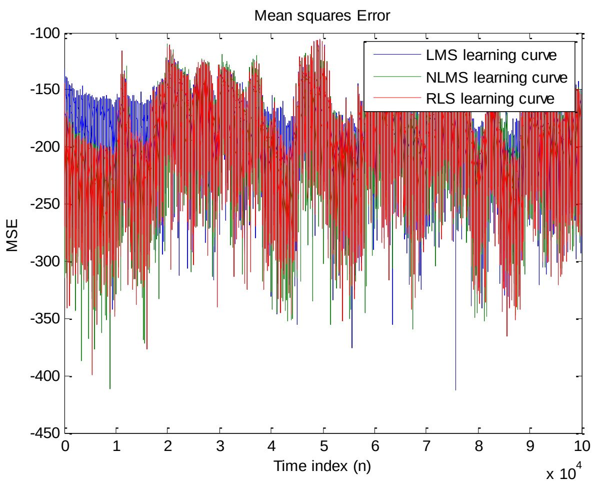


Fig 15. Comparison of MSE in dB

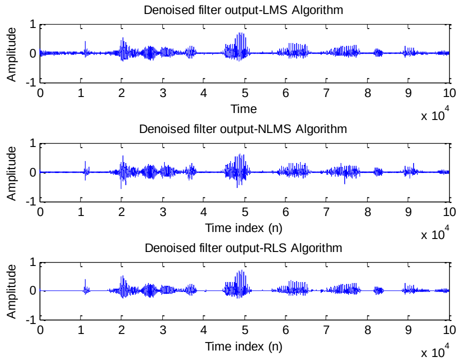


Fig 16. Comparison of Denoised output for Ocean Edge noise as input

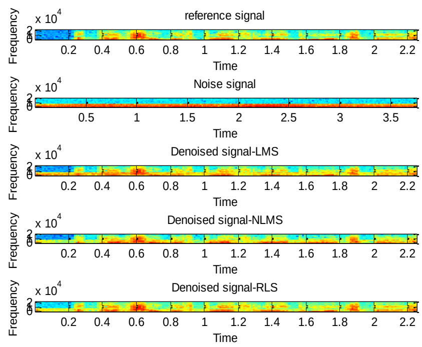


Fig 17. Spectrogram of speech signal, noise signal and denoised signal- LMS, NLMS, RLS

The recorded speech signal mixes with rain water noise are shown in Figure 18 and this background noise is removed by using proposed Hybrid filter with different adaptive algorithm are shown in Fig 19. The Fig 20, 21 and 22 describes the comparison of Mean Square Error (MSE) in dB, Denoised output and Spectrogram for different adaptive algorithm when rain water noise as input.

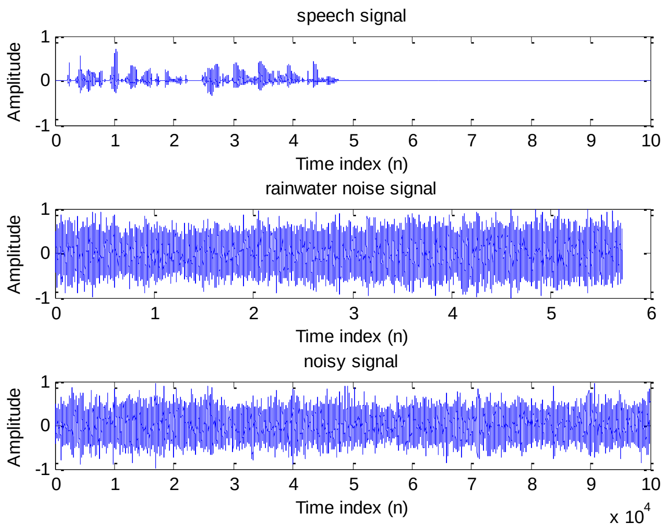
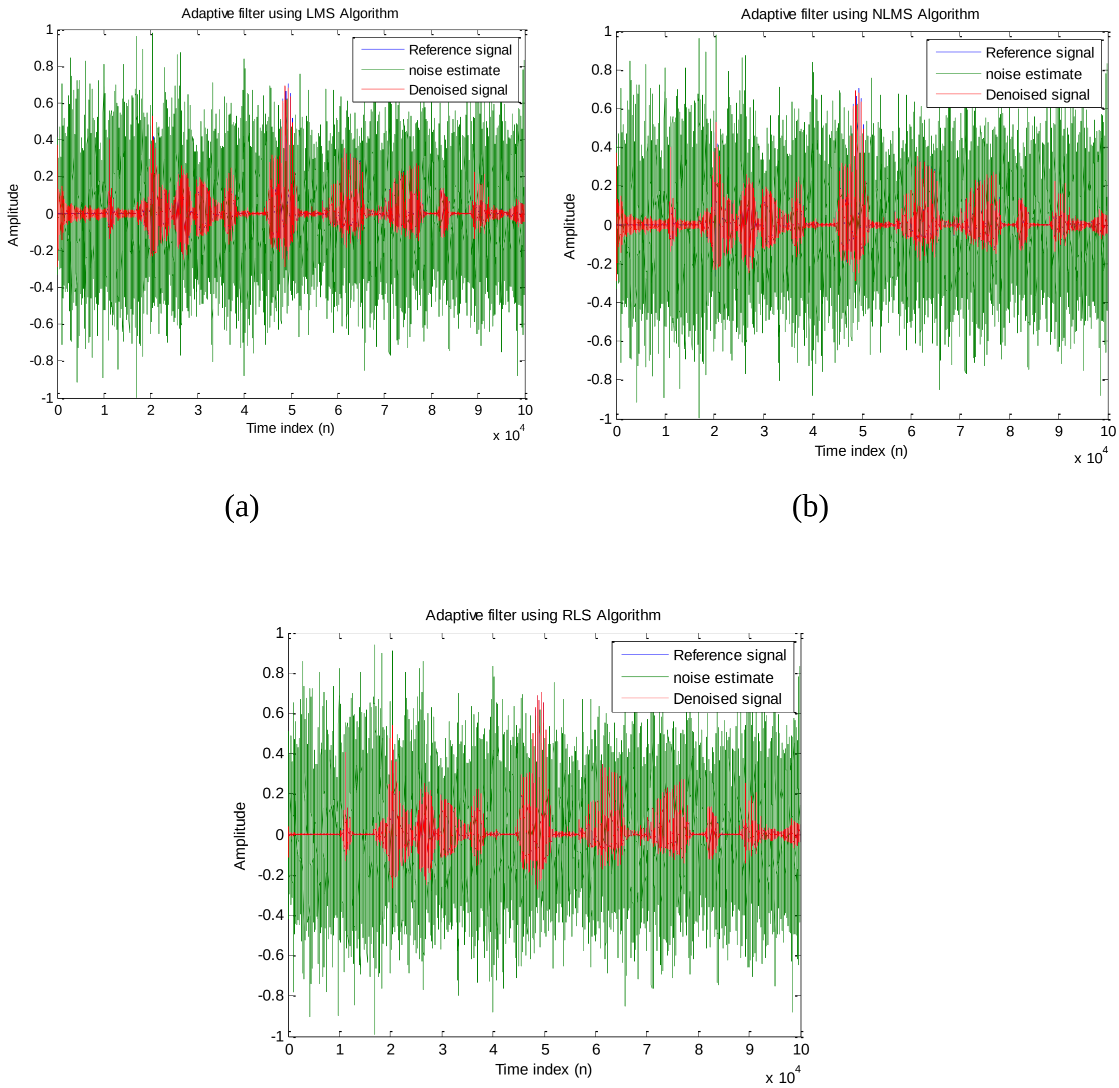


Fig 18. Speech signal, Rain waterfall noise and mixed signal with noise signal



(c)

Fig 19. Comparison between denoised signal and the reference signal: (a) LMS algorithm (b) NLMS algorithm (c) RLS algorithm

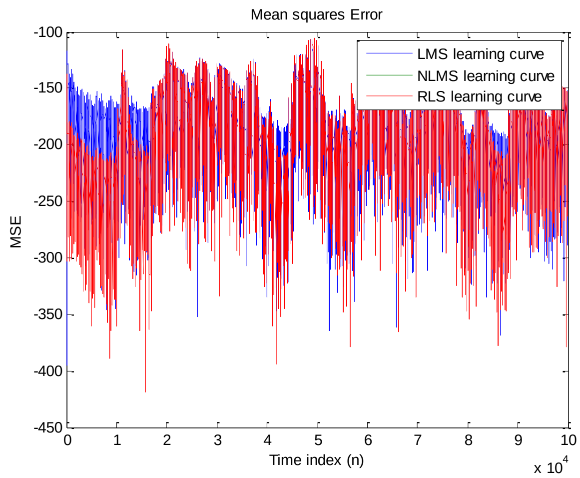


Fig 20. Comparison of MSE in dB

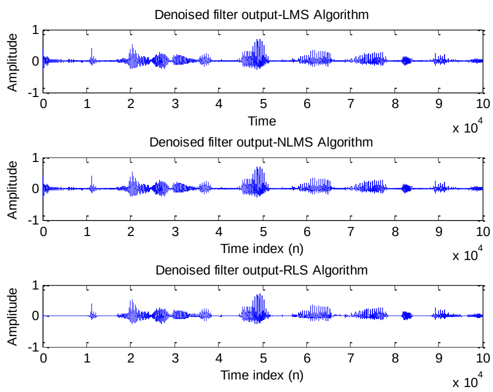


Fig 21. Comparison of Denoised output for Rain waterfall noise as input

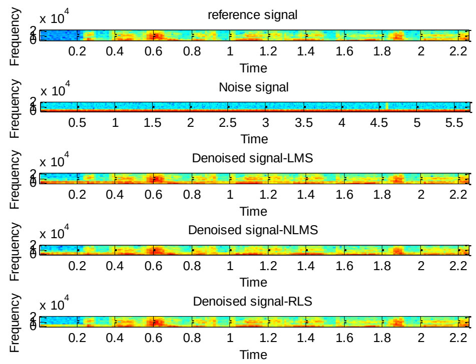


Fig 22. Spectrogram of speech signal, noise signal and denoised signal- LMS, NLMS, RLS

The recorded speech signal, rain roof noise and corresponding noisy signal are shown in Fig 23 and the rain roof noise cancellation in real environment by using proposed Hybrid filter with different adaptive algorithm are shown in Fig 24. The comparison of Mean Square Error (MSE) in dB, Denoised output and Spectrogram for different adaptive algorithm when rain roof noise as input are shown in Fig 25,26 and 27.

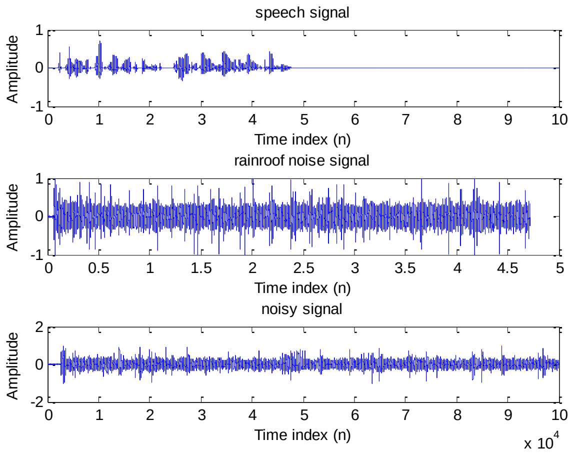
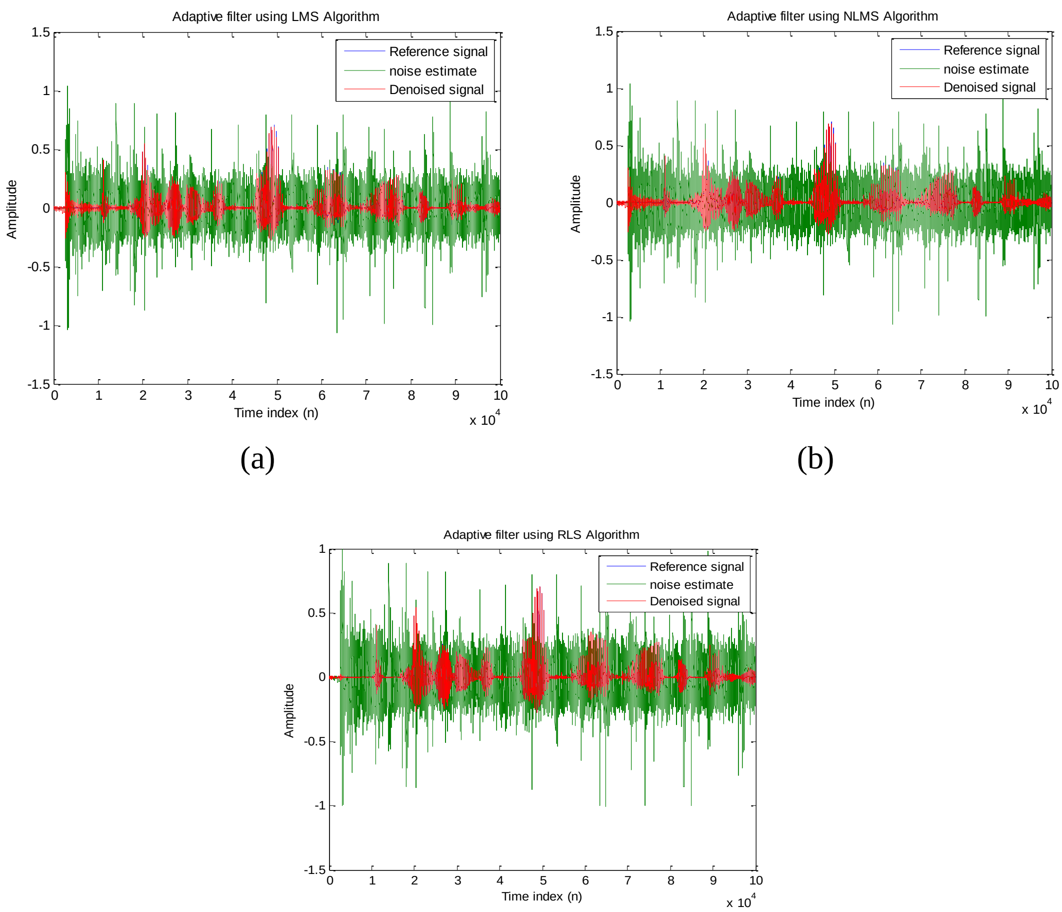


Fig 23. Speech signal, Rain roof noise and mixed signal with noise signal



(a) (b)

(c)

Fig 24. Comparison between denoised signal and the reference signal: (a) LMS algorithm (b) NLMS algorithm (c) RLS algorithm

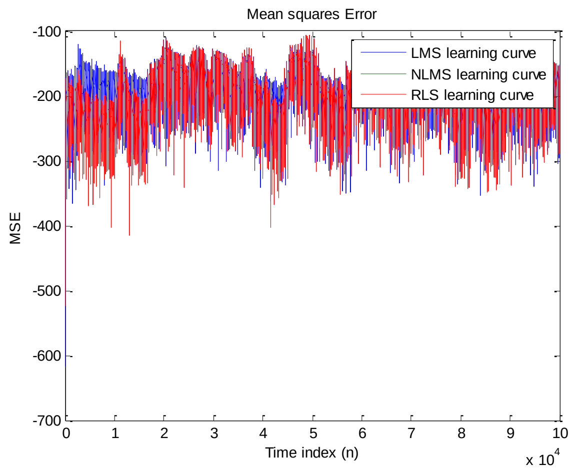


Fig 25. Comparison of MSE in dB

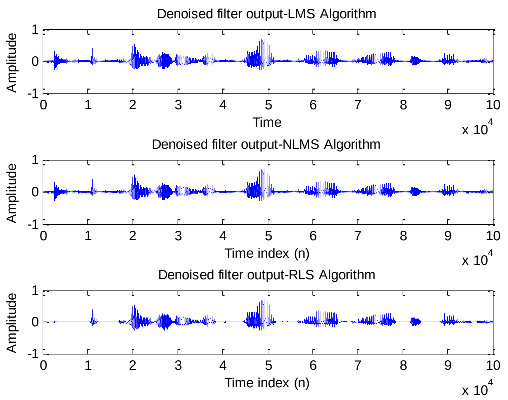


Fig 26. Comparison of Denoised output for Rain roof noise as input

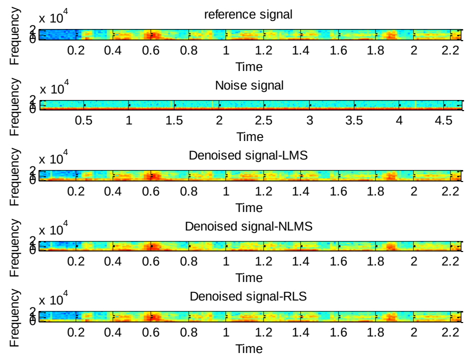


Fig 27. Spectrogram of speech signal, noise signal and denoised signal- LMS, NLMS, RLS

The recorded speech signal mixes with rain wind noise are shown in Figure 28 and this background noise is removed by using proposed Hybrid filter with different adaptive algorithm are shown in Fig 29. The Fig 30, 31 and 32 describes the comparison of Mean Square Error (MSE) in dB, Denoised output and Spectrogram for different adaptive algorithm when rain wind noise as input.

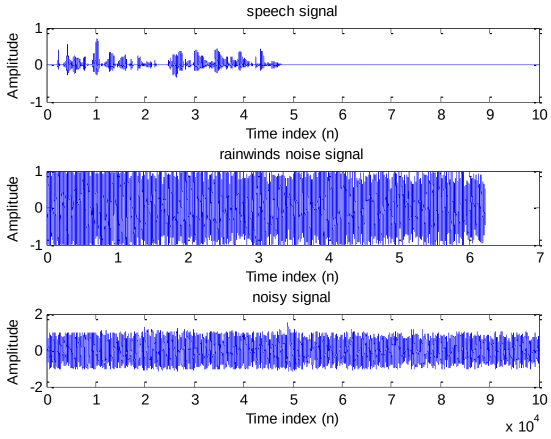
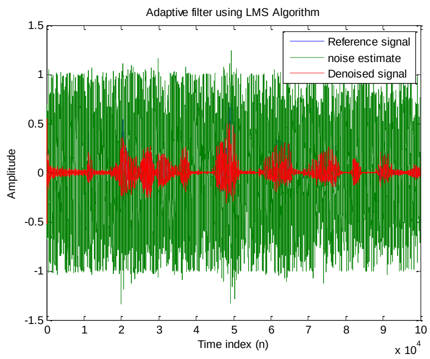
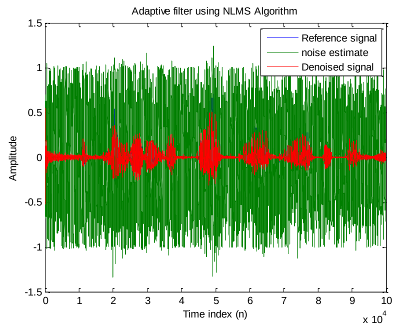


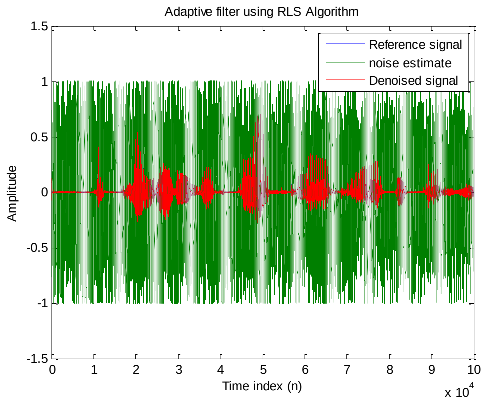
Fig 28. Speech signal, Rain wind noise and mixed signal with noise signal



(a)



(b)



(c)

Fig 29. Comparison between denoised signal and the reference signal: (a) LMS algorithm (b) NLMS algorithm (c) RLS algorithm

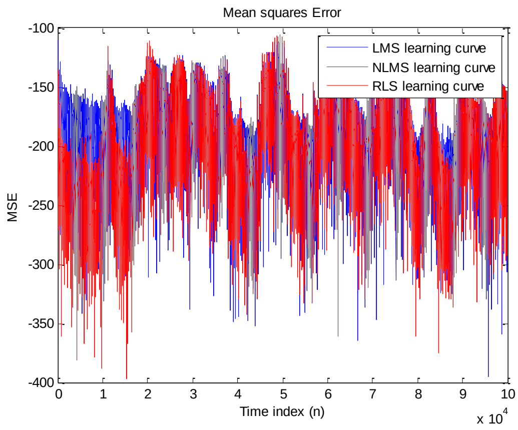


Fig 30 Comparison of MSE in dB

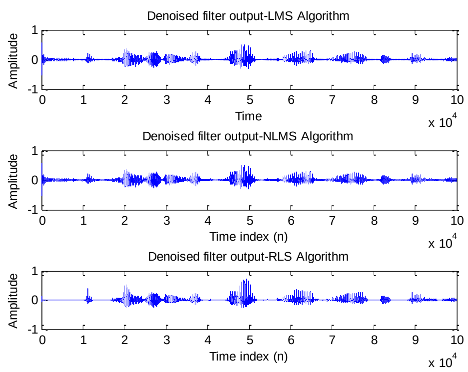


Fig 31. Comparison of Denoised output for Rain wind noise as input

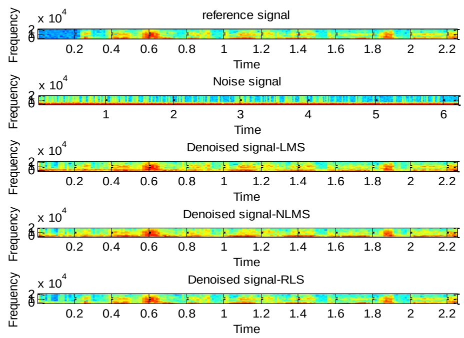


Fig 32. Spectrogram of speech signal, noise signal and denoised signal- LMS, NLMS, RLS

The recorded speech signal mixes with rain thunder and Seashore noise are shown in Fig 33,38 respectively and these background noise are removed by using proposed Hybrid filter with different adaptive algorithm are shown in Figure 34,39 respectively. Fig 35 & 40, 36 & 41 and 37 & 42 describes the comparison of Mean Square Error (MSE) in dB, Denoised output and Spectrogram for different adaptive algorithm when rain thunder and Seashore noise as inputs.

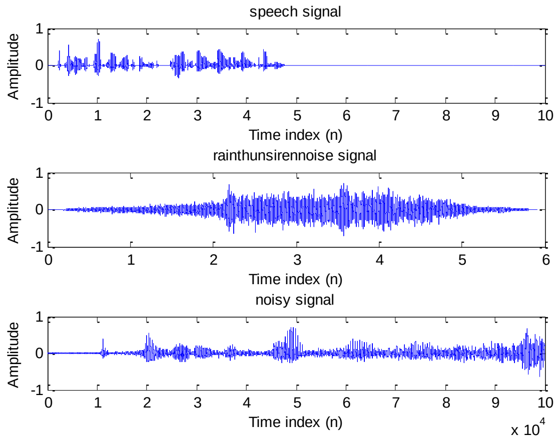
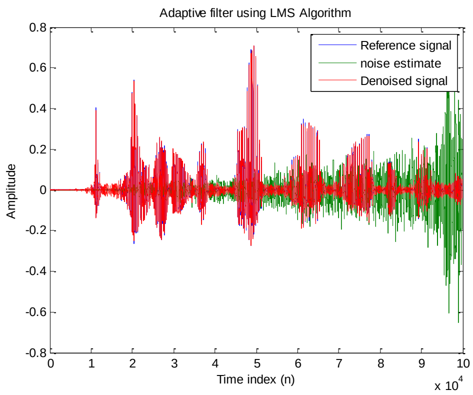
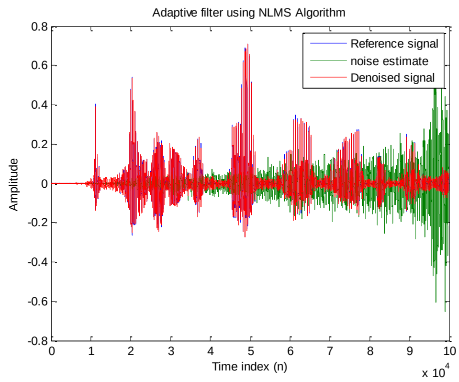


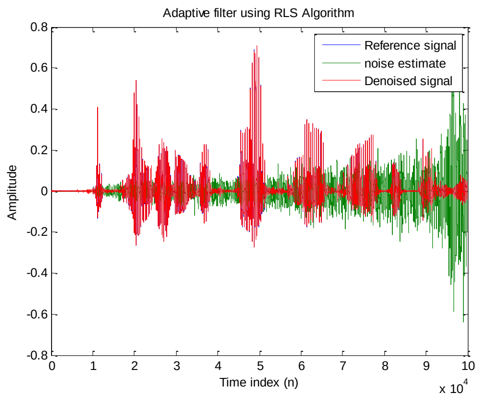
Fig 33. Speech signal, Rain Thunder noise and mixed signal with noise signal



(a)



(b)



(c)

Fig 34. Comparison between denoised signal and the reference signal: (a) LMS algorithm (b) NLMS algorithm (c) RLS algorithm

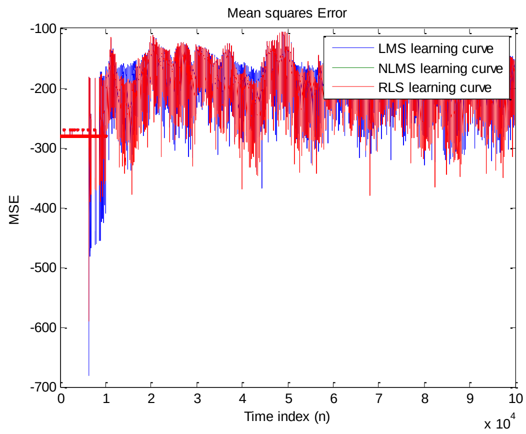


Fig 35. Comparison of MSE in dB

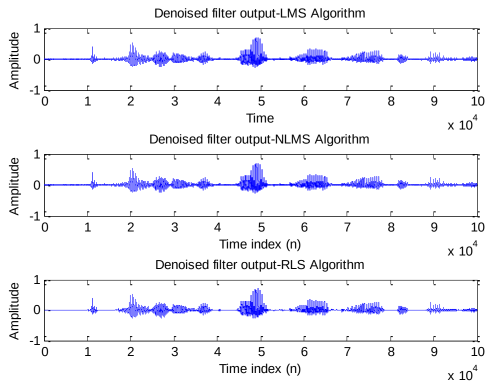


Fig 36. Comparison of Denoised output for Rain Thunder noise as input

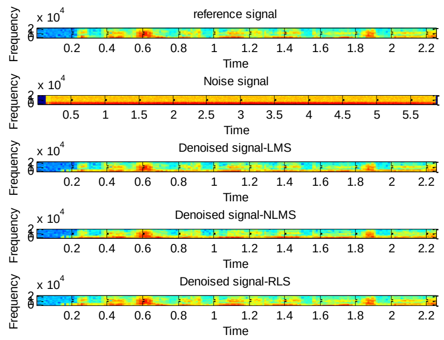


Fig 37. Spectrogram of speech signal, noise signal and denoised signal- LMS, NLMS, RLS

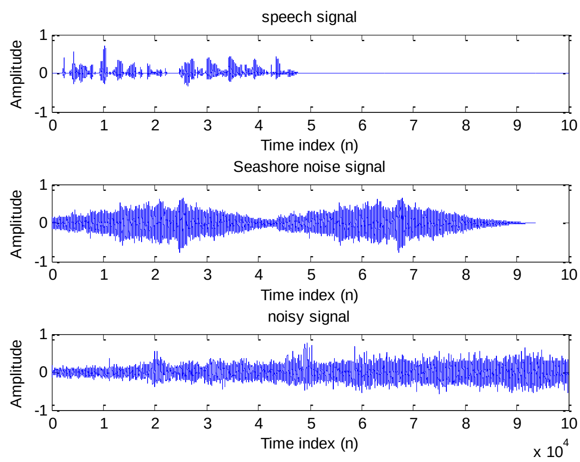
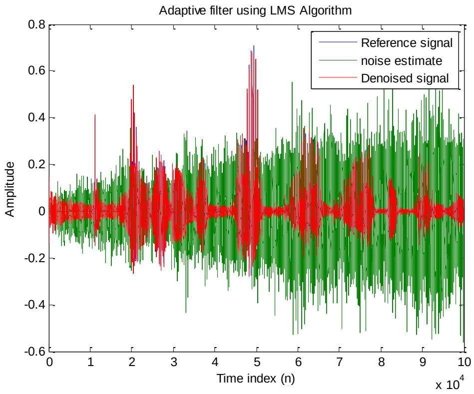
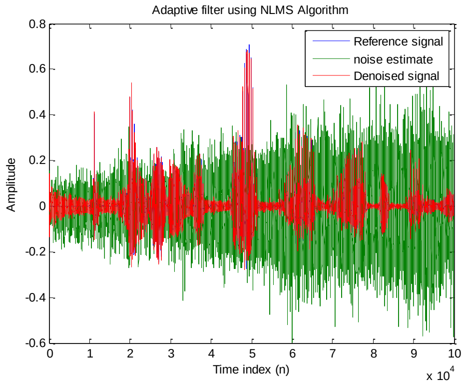


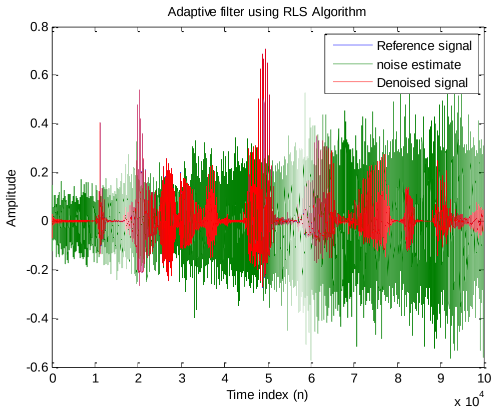
Fig 38. Speech signal, Seashore noise and mixed signal with noise signal



(a)



(b)



(c)

Fig 39. Comparison between denoised signal and the reference signal: (a) LMS algorithm (b) NLMS algorithm (c) RLS algorithm

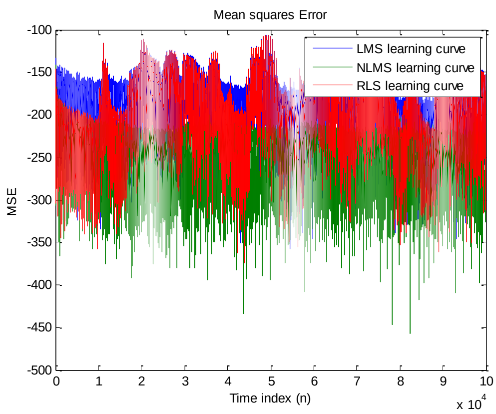


Fig 40. Comparison of MSE in dB

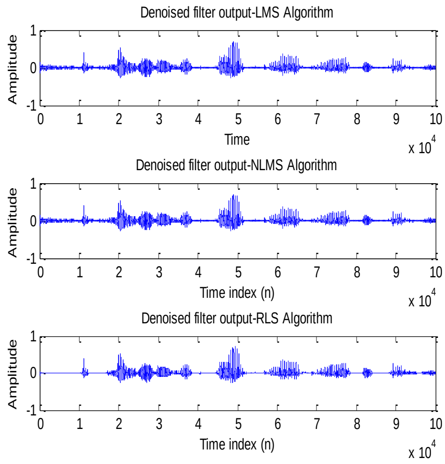


Fig41. Comparison of Denoised output for Seashore noise as input

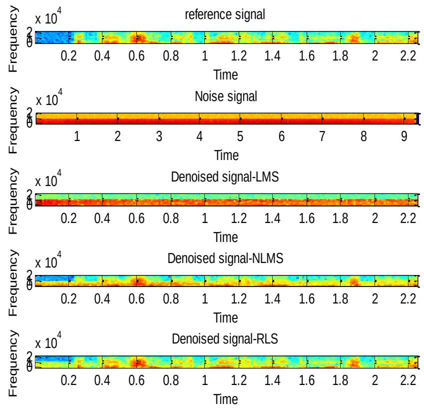


Fig 42. Spectrogram of speech signal, noise signal and denoised signal- LMS, NLMS, RLS

III PERFORMANCE COMPARISON

Table I shows the SNR in dB which is measured at input and output of the filter for different noise. With the different input SNR ranging from -23.2681 to 8.0183 dB, our proposed method improves the output SNR in an average of 33.1167dB, 32.8128dB, 33.6521dB for LMS, NLMS and RLS respectively and for Existing Adaptive filter [13], they are 11.59dB, 11.4621dB and 30.276dB. The results proved that the proposed LMS and RLS method gives almost same output SNR and they are superior to NLMS as well as method [13]. For rainfall water noise, the output SNR obtained by TSF [12] in an average is 11.4 dB with the input SNR varying from -52.6 to 8.7 dB. Therefore our proposed method gives 65% more noise reduction compared to [13] and [12].

Table I. Performance Comparison of Adaptive filter in terms of SNR

Different Noises	Method	SNR in dB before filtering (input)	SNR in dB after filtering (output)		
			LMS	NLMS	RLS
Ocean gull Noise	Existing [13]	1.9104	10.736	10.721	27.413
	Proposed	8.0183	20.5412	30.1613	24.7504
Ocean edge noise	Existing [13]	1.4360	10.7137	10.6505	32.8803
	Proposed	-9.0095	26.818	26.6842	26.83
Ocean lap Noise	Existing [13]	-0.5102	10.7697	10.7441	27.9213
	Proposed	-6.7942	33.2391	27.7384	34.4708
Rain water Noise	Existing [13]	-6.1655	10.8147	10.4040	29.5624
	TSF [12]	-52.6 to 8.7	11.4		
	Proposed	-16.1069	24.192	24.1911	24.2105
Rain roof Noise	Proposed	-12.5481	23.6489	23.6412	23.6688
Rain wind Noise	Proposed	-23.2681	34.4335	22.4599	34.7809
Rain thunder Noise	Proposed	-5.6784	22.9133	22.9123	22.9488
Seashore	Proposed	-30.5898	5.3367	4.5654	4.6149

Fig 5,10,15,20,25,30,35 and 40 describes the Mean Square Error in dB for different input noise and it is in the order of 10^{-8} as well as number of iteration required to meet the desired output is in the range of 50-100 which is very less. Since our proposed hybrid windowing FIR filter coefficients are not set to zero initially which are designed by Hybrid window function. Figure 6,11,16,21,26,31,36 and 41 describes the reconstruction of expected signal using different adaptive algorithm which are very closer than [13] and [12]. Since MSE is very less compared to [13] & [12].

V. CONCLUTION

We have proposed a Hybrid windowing Adaptive FIR filter designed to reconstruct underwater acoustic signal from various ambient noise source such as Ocean gull noise, Ocean edge noise, Ocean lap noise, rainwater noise, rain roof noise, rain wind noise, rain thunder noise and seashore. A Hybrid window technique was applied on proposed Adaptive filter to reduce the number of iteration into less than 100 for denoising the underwater acoustic signal. The Proposed filter provides high degree of reconstruction with significantly improved SNR in an average of 33.1167dB, 32.8128dB, 33,6521dB using LMS, NLMS and RLS respectively and also provides minimum MSE in order of 10^{-8}. For the input SNR varies from -23.2681 to 8.0185, the proposed filter has a noise reduction of 65% more than the conventional Adaptive filter in an average for various underwater noise sources. The proposed work was simulated using MATLAB and their results were compared with conventional adaptive filter. The simulation results proved that the proposed Adaptive filter with LMS and RLS provides better performance than NLMS in reducing the MSE and improved the SNR but RLS requires larger number of computation as a result system cost is high. Therefore adaptive filter with LMS is more suitable for denoising of underwater acoustic signal.

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