Analysis on Extraction of Modulated Signal Using Adaptive Filtering Algorithms against Ambient Noises in Underwater Communication

S. S. Murugan and S. Prethivika
SSN College of Engineering/Department of ECE, Chennai, India
Email: sakthivels@ssn.edu.in, prethivi1993@gmail.com

V. Natrajan
Department of Instrumentation Engineering, MIT Campus, Anna University, Chennai, India
Email: natraj@mitindia.edu

***Abstract*—Acoustic signals on transmission in underwater channels are often prone to corruption by ambient noises, wind interference and other random sources of disturbance. Adaptive filters can be used to extenuate the effects of ambient noise in acoustic signals. An effective technique for denoising the degraded modulated acoustic signals using adaptive filters has been proposed. Adaptive techniques, such as Least Mean Square (LMS), Normalized Least Mean Square (NLMS), and Kalman Least Mean Square (KLMS) have been analyzed based on their performance, with the help of characteristics like Signal to Noise Ratio (SNR) and Mean Square Error (MSE) for various wind speeds ranging from 2m/s to 6m/s. From the simulation, it is observed that the KLMS filter converges to the desired useful signal faster than the other adaptive filter techniques. This result is further supported by the fast converging Mean Square Error (MSE) signal of KLMS compared to the other adaptive filter techniques discussed.**

***Index Terms*—adaptive filters, mean square error, signal to noise ratio, underwater acoustic signal**

I. Introduction

Underwater signal transmission is generally facilitated through acoustic signals. Electromagnetic waves, used in terrestrial communication are highly attenuated under water. Hence they cannot be used for underwater communication. As acoustic signals are low frequency, low power signals they are more prone to corruption due to various sources of disturbance. Therefore, the need for denoising becomes imminent.

Among the various sources of disturbance, the effect of ambient noise on acoustic signal is highly significant. Ambient noises are used to refer to the background noises in any underwater environment. These ambient noises mask the information transmitted in an underwater channel. Therefore the detection and cancellation of the ambient noises is essential to enhance the Signal to Noise Ratio (SNR) of the acoustic signal.

Literature surveys on ambient noise characteristics show that noise from different sources occupy different frequency bands [1]. The variation in their Power Spectral Density has also been studied. Various contributions in this field concentrate on denoising of acoustic signals using wavelets.

In this paper, the various adaptive filters based denoising techniques for wind driven ambient noise and their corresponding effect on SNR are discussed. The main focus is on LMS, NLMS and KLMS algorithms [2] and their performance has been analysed using characteristics like MSE.

II. Adaptive Filtering

Adaptive filters are basically digital filters which can alter their co-efficients based on different adaptive algorithms. These algorithms are generally used when no prior information about the signal is available and if the signal is time variant. These algorithms use a feedback in the form of weight update equations which alters the transfer function to match the changing parameters. A typical adaptive FIR traversal filter is shown in Fig. 1.

A. Structure of Adaptive Filter

Adaptive filtering algorithms generally consists of two processes namely,

1. Filtering
2. Adaptation

Filtering is used to generate an output signal from a given output and generation of an error signal by comparing the output with a desired response while Adaptation is used to adjust the filter co-efficient in order to minimise the desired cost function. These two processes constitute the weight update part of the algorithm and are implemented by the feedback loop. The order of the filter determines the number of samples processed per iteration.

The input signal to the adaptive filter is $x(n)$ which is the additive sum of the desired signal $d(n)$ and the interfering ambient noise $v(n)$ as given in (1)

$$x(n) = d(n) + v(n) \tag{1}$$

Manuscript received July 7, 2014; revised September 15, 2014.

doi: 10.12720/ijsps.3.1.25-29

The linear traversal filter is a Finite Impulse Response (FIR) filter of order p whose co-efficient are given by (2)

$$w(n) = [w(0)\ w(1),\ w(2)\ \dots\ w(P)]^T \quad (2)$$

The error signal $e(n)$ or cost function is given by the difference between the desired signal $d(n)$ and the estimated signal $\hat{d}(n)$ which can be expressed as

$$e(n) = d(n) - \hat{d}(n) \quad (3)$$

The linear traversal filter estimates the desired signal by convolving the input signal with the impulse response is given by

$$\hat{d}(n) = w(n)x(n) \quad (4)$$

The linear traversal filter updates the filter coefficients during every time instant which can be mathematically expressed as follows.

$$W(n+1) = w(n) + \Delta w(n) \quad (5)$$

$\Delta w(n)$ is a correction factor for the filter co-efficient.

The adaptive algorithm generates this correction factor based on the input and error signals. The efficiency of the filter depends upon the accurate design of the weight update equation.

III. Adaptive Algorithms

A. LMS Algorithm

LMS algorithm [3] is one among the stochastic gradient algorithms. Equation (6) gives the weight update relation for updating the filter tap-weights so that the error $e(n)$ can be minimized.

$$w(n+1) = w(n) + \mu x(n)e(n) \quad (6)$$

where μ is the step-size. It must be chosen between $0<\mu<2/Tr(R)$ for the proper convergence of the algorithm. $Tr(R)$ denotes the trace of R, where R is the autocorrelation matrix of $x(n)$. Pure LMS algorithms are sensitive to scaling of its input $x(n)$, it was difficult to calculate the step size μ to maintain the stability of the LMS algorithm from the analysis. Hence an improvement is necessary to minimize the error $e(n)$ from the existing LMS algorithm which can be carried out by normalizing the power of the input using NLMS algorithm.

B. NLMS Algorithm

In NLMS algorithm [4], [5], the tap-weight vector at iteration n+1 is "normalized" with respect to the squared Euclidean norm of the tap-input vector $x(n)$ at iteration n. The recursive relation for updating the tap-weight vector is given by (7)

$$w(n+1) = w(n) + \frac{\mu x(n)e(n)}{\varepsilon + \|x(n)\|^2} \quad (7)$$

C. KLMS Algorithm

KLMS [6] is a new normalized Kalman based LMS algorithm which has advantages over the LMS and NLMS algorithms [7]-[9]. The step size control in KLMS shows good convergence properties over a large range of signal input powers. The weight update equation for KLMS algorithm is given as,

$$w(n+1) = w(n) + \frac{x(n)e(n)}{P(n) + \frac{q_v(n)}{\sigma_w^2(n)}} \quad (8)$$

where $q_v(n)$ is, the auto correlation of the interfering is is ambient noise, $\sigma_w^2(n)$ is the state noise variance and $p(n)$ is the product of the hermitian of reference signal and the reference signal.

IV. Results and Discussion

A. Data Collection

The data is collected at the depths of 5 and 20m using a self made fixture containing two hydrophones at Bay of Bengal, Chennai. The sampling frequency used for collecting the data is 50kHz. The spectral characteristics of the collected data and a model for wind noise are analyzed in [1] and it has been observed that the wind noise dominates up to a frequency of 6kHz.

B. Performance Analysis

The performance analysis of the adaptive algorithms is done using the noise data whose wind speed is 4.23m/s. A sinusoidal signal, FSK modulated signal, ASK modulated signal and burst signal are considered as different cases of reference signals during simulation. The amplitude of the reference signals are chosen such that they remain buried within the interfering ambient noise. The noisy signal is obtained by combining the reference signal with the noise data. The input given to the adaptive filter is the noisy signal.

It is observed that for the LMS algorithm, the output convergence takes more time and hence the MSE takes more time to converge. With NLMS algorithm, the MSE is reduced and converges faster than LMS algorithm. For KLMS algorithm, the output convergence is rapid and the mean square error is also very minimal. Hence it can be verified that KLMS algorithm exhibits better performance compared to LMS and NLMS algorithms in reconstructing the corresponding reference signals from the noisy signal.

It is also inferred that the KLMS algorithm achieves better improvement in output SNR compared to LMS and NLMS algorithms for varying input SNR. In particular for the low SNR regions, the performance of the KLMS algorithm is the best when compared to other adaptive algorithms. It is also clearly evident that KLMS algorithm has a better performance with an improvement of 50-60dB on an average. As ambient noises dominate the underwater acoustic signal, the SNR at the input of the adaptive filter at the receiving side will be very low. Thus KLMS algorithm based adaptive filters at the receiver end are best suited for reconstructing the buried low frequency acoustic signals against various ambient noises.

Simulation results show that for KLMS algorithm, the time taken by MSE to converge to approximately zero is very small, i.e., after 150 iterations. Comparatively, the MSE convergence is very slow for NLMS and LMS algorithms, and it takes more than 5000 and 32000 iterations, respectively. The total number of iterations carried out is 32000 and it is clear that LMS requires even more number of iterations to converge to zero. It is observed that MSE has not been achieved zero by LMS algorithm even after maximum number of iteration considered.

TABLE I. PERFORMANCE COMPARISON OF THE KLMS, NLMS AND LMS ADAPTIVE ALGORITHMS

S. No	Parameter	KLMS	NLMS	LMS
1	SNR Improvement (dB)	41.41	31.18	22.81
2	Convergence (No. of Iterations)	100-125	4500-5000	More than 32000
3	Convergence time (sec)	7.5×10^{-3}	3×10^{-2}	More than 6 $\times10^{-1}$
4	MSE achieved	Negligible	Very low	High

Table I shows the comparison between LMS, NLMS and KLMS in terms of SNR, convergence factors and MSE. Hence it is inferred that KLMS algorithm outperforms other algorithms as it can achieve an average improvement in SNR of 41.44 dB whereas it is a mere 31.18 and 22.81 dB improvement for NLMS and LMS respectively.

C. *Comparison of KLMS, NLMS and LMS Algorithms*

Fig. 1 gives a pictorial representation of the basic structure of an adaptive FIR transversal filter.

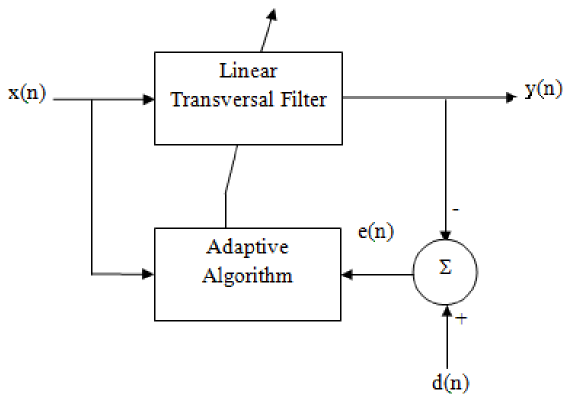

Figure 1. Basic structure of adaptive FIR traversal filter

Table I summarizes the performance of the three algorithms, in terms of SNR improvement, convergence in retrieving the required signal with the number of iterations, the time taken, and the MSE achieved for a wind speed of 2m/s ambient noise data.

Fig. 2 and Fig. 3 provide the comparison between LMS, NLMS and KLMS algorithms for a sinusoidal reference signal using time domain and spectrogram representation. Similarly, Fig. 4, Fig. 5, Fig. 6 and Fig. 7 describe the time domain and spectrogram representation for FSK modulated reference signal and ASK modulated reference signal, respectively. Fig. 8 and Fig. 9 provide the time domain and spectrogram representation for ASK modulated input signal and burst input signal.

For the various reference signals discussed, the time domain representation illustrates the MSE comparison of the various adaptive filtering techniques. The spectrogram depiction portrays a pictorial representation of the transmitted, error and recovered signals.

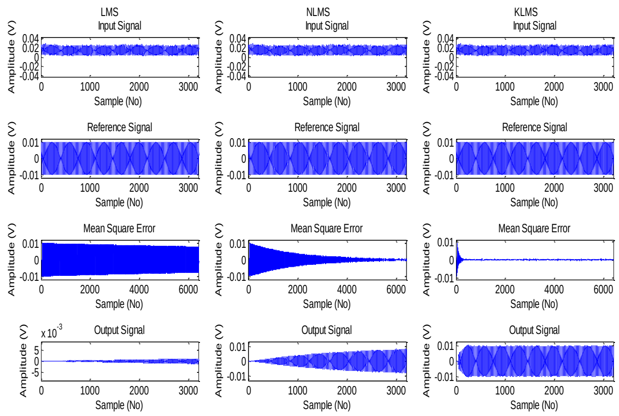

Figure 2. MSE - comparison of LMS, NLMS and KLMS algorithms for a sinusoidal input signal

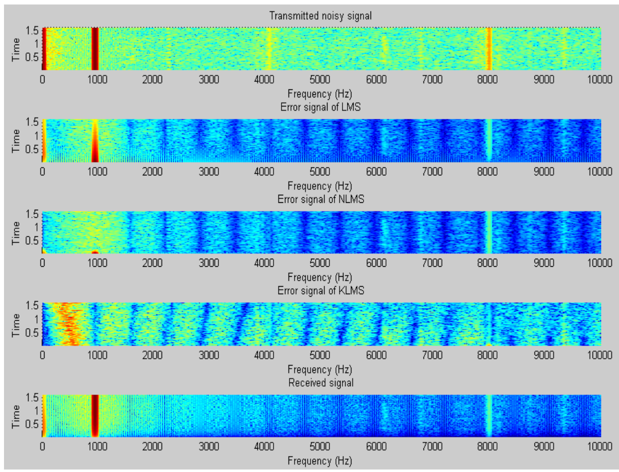

Figure 3. Spectrogram for LMS, NLMS and KLMS for a sinusoidal input showing the transmitted, error and recovered signals

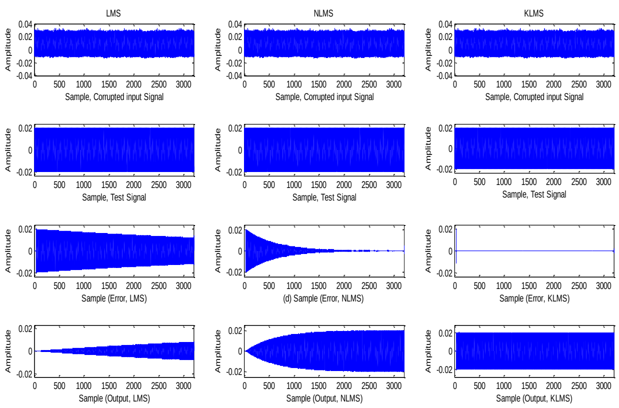

Figure 4. MSE - comparison of LMS, NLMS and KLMS algorithms for a FSK modulated input signal

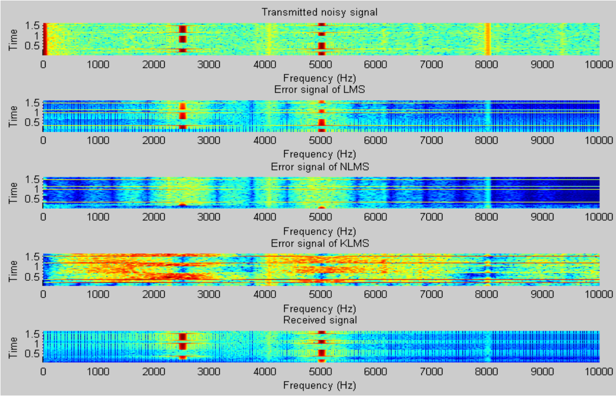

Figure 5. Spectrogram for LMS, NLMS and KLMS for a FSK modulated input showing the transmitted, error and recovered signals

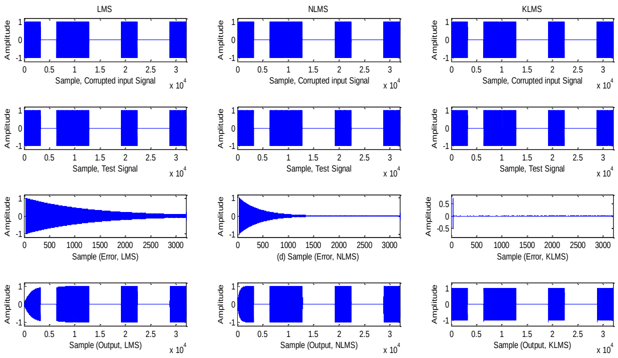

Figure 6. MSE - comparison of LMS, NLMS and KLMS algorithms for a ASK modulated input signal

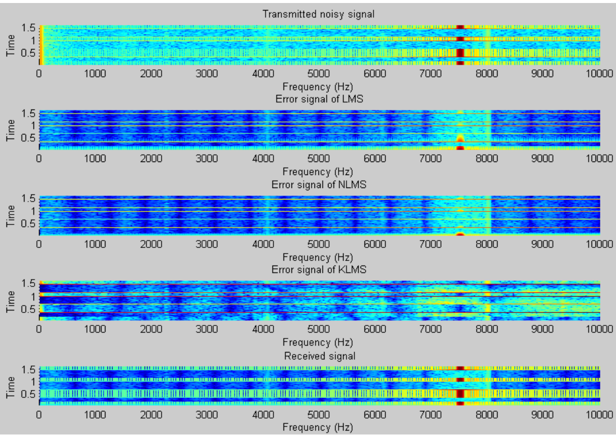

Figure 7. Spectrogram for LMS, NLMS and KLMS for a ASK modulated input showing the transmitted, error and recovered signals

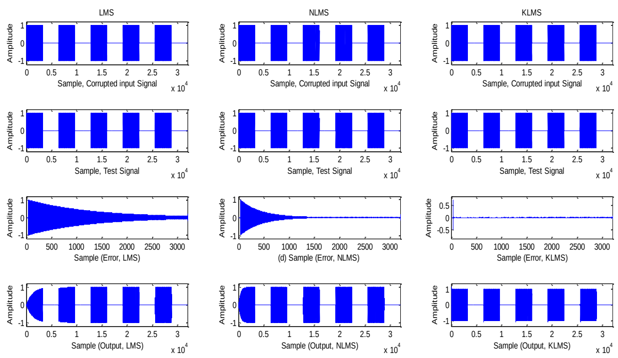

Figure 8. MSE - comparison of LMS, NLMS and KLMS algorithms for a burst input signal

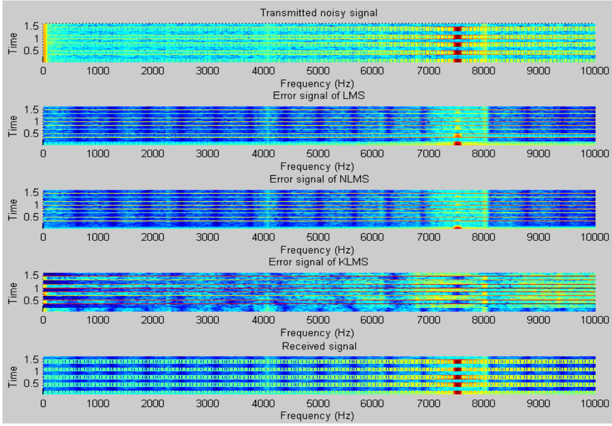

Figure 9. Spectrogram for LMS, NLMS and KLMS for a FSK modulated input showing the transmitted, error and recovered signals

V. Conclusion

In this paper, the performance of various adaptive filter based denoising techniques like LMS, NLMS and KLMS have been analyzed for various input reference signals like sinusoidal signal, FSK modulated signal, ASK modulated signal and burst sequence. It is inferred that the KLMS algorithm adapts faster and reconstructs the desired signal very quickly when compared to LMS and NLMS. KLMS thereby achieves maximum convergence in minimum number of iterations. It is also found that the MSE for KLMS algorithm is the least compared to NLMS and LMS. High output SNR for low frequency, low SNR can also been achieved by KLMS technique. Thus KLMS algorithm can be used for effectively denoising all kinds of low frequency acoustic signals in underwater communication.

VI. Future Work

The analysis of performance for various reference signals discussed in this paper can be extended to other denoising techniques like wavelet decomposition and empirical mode decomposition (EMD). Implementation of EMD based denoising techniques in a real time underwater wireless sensor network is also proposed as future research.

References

[1] R. J. Urick, *Ambient Noise in the Sea*, Peninsula Publishing, 1984.

[2] S. S. Murugan, V. Natarajan, and S. Radha, "Adaptive algorithm testing to determine best adaptive filtering approaches for denoising signals affected by wind noise," *Sea Technology*, vol. 53, no. 7, pp. 42-45, 2012.

[3] J. Sanubari, "A new variable step size method for the LMS adaptive filter," in *Proc. 2004 IEEE Asia-Pacific Conference on Circuits and Systems*, Taiwan, Dec. 6-9, 2004.

[4] Eweda, "A new performance measure of the normalized LMS adaptive filter," in *Proc. IEEE International Conference on Signal Processing and Communications (ICSPC 2007)*, Dubai, United Arab Emirates, Nov. 24-27, 2007.

[5] P. A. C. Lopes and J. B. Gerald, "New normalised LMS algorithm Based on the Kalman filter," in *Proc. IEEE International Symposium on Circuits and Systems*, 2007, pp. 117-120.

[6] S. S. Murugan and V. Natarajan, "SNR and MSE analysis of KLMS algorithm for underwater acoustic communication," *Journal of Marine Engineering and Technology*, vol. 11, no 3, pp. 3-8, 2012.

[7] S. S. Murugan, V. Natarajan, and S. Radha, "Analysis of NLMS and KLMS algorithm for underwater acoustic communications," *Fluctation Noise Letter*, vol. 11, no 4, 2012.
[8] S. Haykin, *Adaptive Filter Theory*, Prentice-Hall, Inc., 1996.
[9] J. G. Prokais and D. K. Manolakis, *Digital Signal Processing - Principles, Algorithms and Applications*, Pearson Education, 2006.

S. Sakthivel Murugan completed his B.E from Madras University and M.Tech from Pondicherry University. His area of research is Underwater Acoustic Signal Processing. He has more than 13 years of teaching and 4 years of research experience. He has published research papers in more than 10 International journals and presented 23 International and national conference papers. He is also a life member in Ocean society of India

Dr. V. Natarajan has done his doctorate in the field of security and cryptography in Anna University, Chennai. He is currently working in water marking cryptography and security system in underwater communication. He has more than ten years of experience in the field of research. To his credit, he has guided many research projects. He is currently an Associate professor at MIT campus, Anna University, Chennai, India and has more than 20 years of experience in teaching.

Prethivika S. is currently pursuing her Bachelor's degree in Electronics and Communication Engineering at SSN College of Engineering, Chennai, India.