International Journal of Electrical and Electronic Engineering & Telecommunications

ISSN 2319 – 2518 www.ijeetc.com
Vol. 3, No. 2, April 2014

Research Paper

ADAPTIVE FILTER FOR AUDIO SIGNAL ENHANCEMENT USING LEAKY AND NON LEAKY ALGORITHMS

Harmanpreet Kaur[1]*, Kirandeep Kaur[1] and Rajesh Mehra[1]

*Corresponding Author: Harmanpreet Kaur, ✉ harmanpreetz14@gmail.com

In this paper, an adaptive filter has been designed and simulated for enhancing an audio signal. The designed filter is based on Block LMS algorithm wherein a comparison has been made for enhancement of audio signal buried in both periodic sinusoidal and FM modulated noise. The enhancement has been perfomed using leaky and non leaky algorithms by varying the convergance rate. The performance has been evaluated using Signal to Noise Ratio (SNR) for each.

Keywords: Adaptive filters, Adaptive line enhancer, FM modulated noise, Block LMS algorithm

INTRODUCTION

Noise cancellation has recently gained much popularity as a method to eliminate noise contained in useful signals (Sambur 1978; and Widrow *et al.*, 1985). This technique has been applied in various communication and industrial appliances, such as hands-free phones, machineries, and transformers (Hernandez, 2003; and Wu *et al.*, 2010). In addition, noise cancellation has been implemented in biomedical signal and image processing, echo cancellation, and speech enhancement (Sasaoka *et al.*, 2009; Ahmad *et al.*, 2011; and Kim *et al.*, 2011). In acoustics applications, noise from the surrounding environment severely reduces the quality of speech and audio signals. Therefore, an adaptive noise cancellation system is used to suppress noise and enhance speech and audio signal quality. Adaptive filters determine the input signal and decrease the noise level in the system output. The parameters of the adaptive filter can be adjusted automatically and require almost neither prior signal information nor noise characteristics.

An Adaptive filter has the property that its frequency response is adjustable automatically to improve its performance in accordance with some criterion, allowing the filter to adapt to changes in the input signal characteristics.

[1] National Institute of Technical' Training & Research Chandigarh, UT, India.

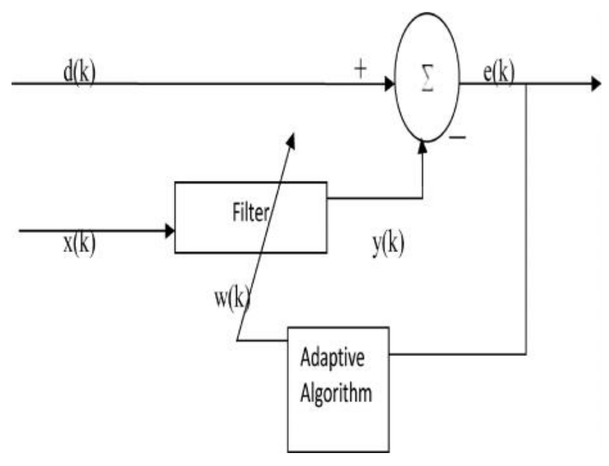
Usually the criterion is the estimated mean squared error or the correlation. The adaptive filters are time-varying since their parameters are continually changing in order to meet a performance requirement. In this sense, an adaptive filter can be interpreted as a filter that performs the approximation step on-line. Usually the definition of the performance criterion requires the existence of a reference signal that is usually hidden in the approximation step of fixed-filter design.

Adaptive filters is used when it is necessary for the filter characteristics to be variable, adapted to changing conditions; when there is spectral overlap between the signal and noise or if the band occupied by the noise is unknown or varies with time. The use of conventional filters in the above cases would lead to unacceptable distortion of the desired signal (Ifeachor, 2004).

The general set up of adaptive filtering environment is shown in Figure 1, where k is the iteration number, $x(k)$ denotes the input signal, $y(k)$ is the adaptive filter output, and $d(k)$ defines the desired signal. The error signal $e(k)$ is calculated as $d(k) – y(k)$. The error is then used to form a performance function or objective function that is required by the adaptation algorithm in order to determine the appropriate updating of the filter coefficients. The minimization of the objective function implies that the adaptive filter output signal is matching the desired signal in some sense (Vijaykumar, 2007).

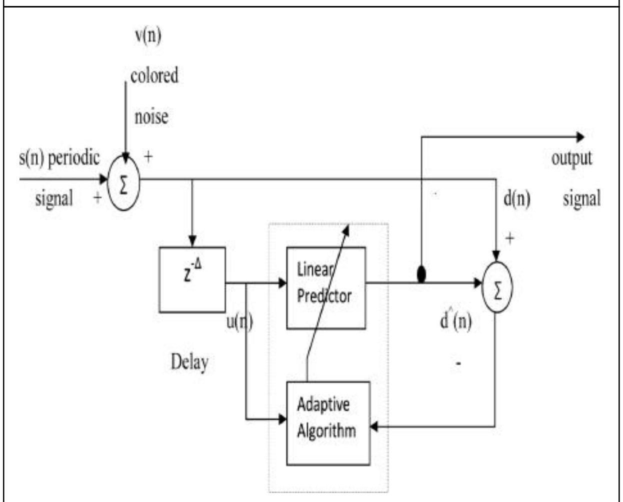
There are four major types of adaptive filtering configurations; adaptive system identification, adaptive noise cancellation, adaptive linear prediction, and adaptive inverse system. All 4 systems have the same general parts; an input $x(n)$, a desired result $d(n)$, an output $y(n)$, an adaptive transfer function $w(n)$, and an error signal $e(n)$. In addition to these parts, the system identification and the inverse system configurations have an unknown linear system $u(n)$ that can receive an input and give a linear output to the given input.

Figure 1: General Setup of Adaptive Filter



Adaptive Line Enhancer (ALE): The ALE is a special form of adaptive noise canceller that is designed to suppress the wide-band noise component of the input, while passing the

Figure 2: Adaptive Line Enhancer



narrow-band signal component with little attenuation.

The input signal $d(n)$ is formed of the desired signal $s(n)$ which is periodic, i.e., narrow-banded, and the disturbing noise $v(n)$ which is colored, i.e., wide-banded. The predictor output $\hat{d}(n)$ is subtracted from the input signal $d(n)$ to produce the estimation error $e(n)$. This estimation error is, in turn, used to adaptively control the predictor. The predictor input $u(n)$ equals $d(n - \Delta)$, which is the input signal delayed with samples. The delay has to be chosen such that the noise in the original input signal d(n) and in the delayed predictor input $d(n - \Delta)$ ... $d(n - \Delta - M)$, where M is the filter length, is uncorrelated, so that it can be suppressed by the linear predictor. This linear predictor is a FIR flter whose tap weights are controlled by the adaptive algorithm.

The adaptive filter responds by forming a transfer function equivalent to that of a narrow-band filter centered at the frequency of the sinusoidal components. The noise component of the delayed input is rejected, while the phase difference of the sinusoidal components is readjusted so that they each other at the summing junction, producing a minimum error signal composed of the noise component of the instantaneous input data alone. Signal s_n, is available which is contaminated by noise.

Suppose the Signal x_n Consists of Two Parts: A narrowband component that has long-range correlations such as a sinusoid, and a broadband component which will tend to have short-range correlations. One of these could represent the desired signal and the other an undesired interfering noise. Pictorially the autocorrelations of the two components could look as follows. Where k_{NB} and k_{BB} are effectively the self-correlation lengths of the narrowband and broadband components, respectively; beyond these lags, the respective correlations die out quickly. Suppose the delay Δ is selected so that

$$k_{BB} \leq \Delta \leq k_{NB} \qquad ...(1)$$

Since Δ is longer than the effective correlation length of the *BB* component, the delayed replica $BB(t - \Delta)$ will entirely uncorrelated with the *BB* part of the main signal. The adaptive filter will not be able to respond to this component. On the other hand, since Δ is shorter than the correlation length of the *NB* component, the delayed replica $NB(t - \Delta)$ that appears in the secondary input will still be correlated with the *NB* part of the main signal, and the filter will respond to cancel it (Dhull, 2011).

ADAPTIVE ALGORITHMS

Attaining the best performance of an adaptive filter requires usage of the best adaptive algorithm with a fast convergence rate and low computational complexity. The LMS algorithm is the most commonly used adaptive algorithm. Other adaptive algorithms that have been applied and developed to speed up the adaptive process include the Normalized LMS (NLMS), RLS, and the APA.

Least Mean Square Algorithm: The most widely used adaptive filtering technique is a version of the LMS algorithm, initially proposed by Widrow and Hoff (Widrow *et al.*, 1960). The LMS is based on the steepest descent method, a gradient search technique to determine filter coefficients that minimize the mean square prediction of a transversal filter.

The derivation of the LMS algorithm can be summarized as below.

$$y(n) = x^T(n).w(n) \qquad ...(2)$$

$$e(n) = d(n) - x^T(n).w(n) \qquad ...(3)$$

where the output of an adaptive transversal filter $y(n)$ and the error signal $e(n)$ are given by (2) and (3), respectively.

In these equations, $x(n)$ is the input signal vector, and $w(n)$ is the weight vector of the adaptive transversal filter. Here, the equations use the current estimate of the weight vector. The weight update recursion of the conventional LMS algorithm is given by

$$w(n+1) = w(n) + «e(n)x(n) \qquad ...(4)$$

where « is the step size parameter controlling the convergence rate within its suitable range. The step size value affects the convergence behavior of an LMS filter; a too low value of « leads to extremely long convergence time of the algorithm, whereas a too high value of « causes the algorithm to diverge, thus degrading the error performance of the adaptive filter. Therefore, choosing a suitable value for the step size is necessary when implementing the LMS algorithm as an adaptive filter. The main reason for the LMS algorithms popularity in adaptive filtering is its computational simplicity, making it easier to implement (Aboulnasr, 1997; Mader *et al.*, 2000; and Sasaoka *et al.*, 2008).

NLMS and LEAKY LMS Algorithm: The main drawback of the conventional LMS is the difficulty in choosing a suitable value for the step size parameter that guarantees stability. Therefore, the NLMS has been proposed to overcome this problem in controlling the convergence factor of LMS through modification into a time-varying step size parameter. The NLMS converges faster than the conventional LMS because it employs a variable step size parameter aimed at minimizing the instantaneous output error (Haykin, 2002; and Sergio Ramirez Diniz, 2008). The NLMS is defined as an extension of the LMS due to its step size parameter that is inversely proportional to the actual input signal energy. The value of ì has to be set within 0 and 2 (Douglas *et al.*, 1994).

For Leaky LMS algorithm,

$w(n + 1) = (1 - «¥)\, w(n) + «e(n)\, x(n)$, ¥ is a small constant.

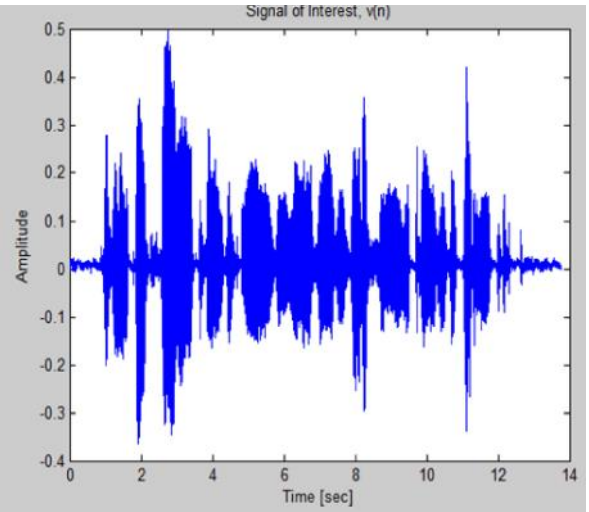
(1 – «¥) is also called Leakage factor. The value of the leakage factor is typically close to 1. The advantage of the leaky LMS algorithm compared to the LMS algorithm is that it avoids the drift of the weights. The disadvantage of the leaky LMS is its “bias”, i.e., $E\{w(n)\} \to W_0$.

Block LMS Algorithm: This algorithm is similar to the well-known Least-Mean Square (LMS) algorithm, except that it employs block coefficient updates instead of sample-by-sample coefficient updates. It also runs efficiently in MATLAB when the block lengths are more than a few samples. The Block LMS algorithm needs an initial coefficient vector W_0, a block length N, and a step size value *mu* (also denoted as « and called convergence rate).

ALE DESIGN AND SIMULATION

The comparative analysis is done by comparing the simulation results of different models which are fed with same input audio

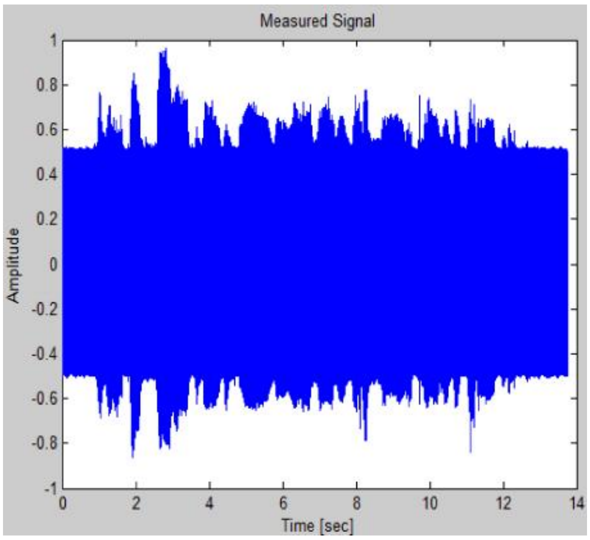
Figure 3: Input Audio Signal



signal but are based on adaptive filters with different LMS algorithms, different types of noises and convergence rates. Here, we describe the simulation modeling used for the generating the analysis. The audio signal of interest is first loaded and plotted in time axis.

A periodic noise signal—a sinusoid with a frequency of 1000 Hz is generated and added to our audio signal. The signal thus obtained

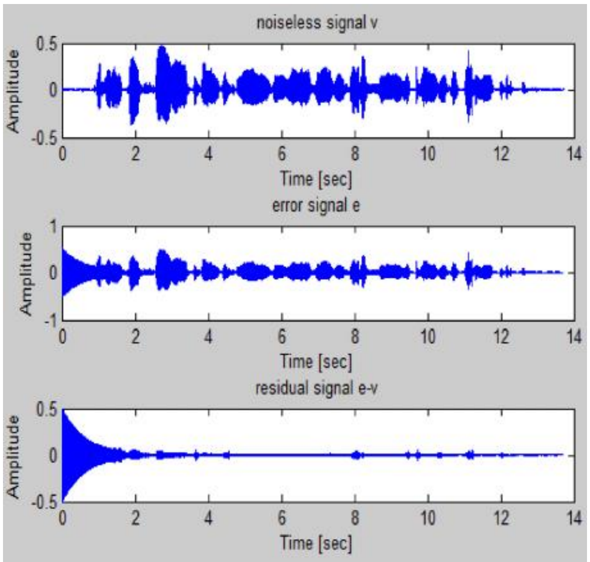
Figure 4: Noise Corrupted Input Signal



has the amplitude-time plot as Measured signal:

Applying non leaky Block LMS algorithm for a convergence rate of 0.0001. The output signal $y(n)$ should largely contain the periodic sinusoid, whereas the error signal $e(n)$ should contain the musical information. The residual signal (difference signal) sounds like a hollow and quieter version of the original music once the adaptive filter has converged. That is why we don't hear it; it simply changes the frequency content of the music a little bit. Remember, a linear filter cannot totally separate signals that are overlapped in frequency, so we can expect some errors in the output. We won't listen to the adaptive filter output $y(n)$; it sounds like a 1000 Hz tone subtracted from this same small residual signal.

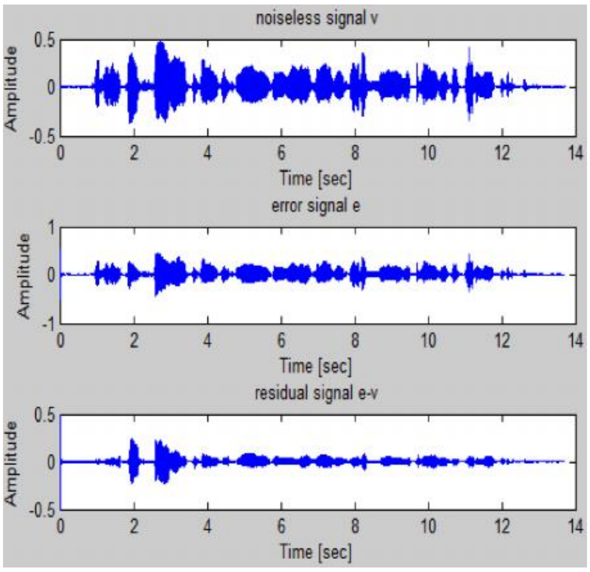
Figure 5: ALE Results for Step Size 0.0001



We can refine the step size now and find the mean and mean-square step size bounds. In our signal we have found the maximum step size values as 0.4820 and 0.1607 respectively.

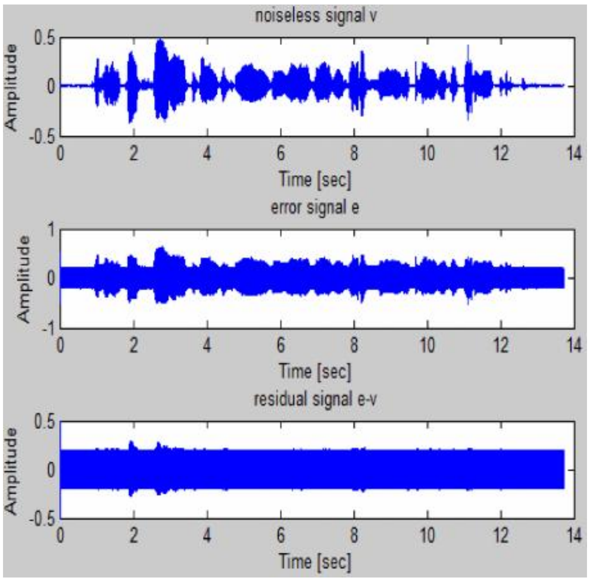
Therefore we can use another value 0.005 safely and compare the results.

Figure 6: ALE Results for Step Size 0.005



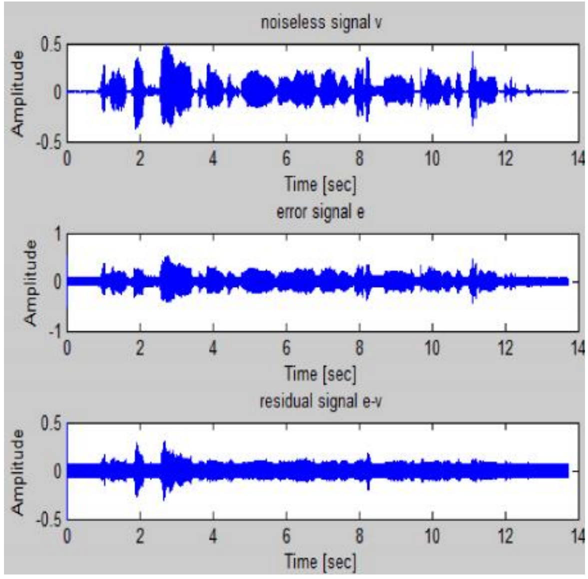
We shall now demonstrate the effect of Leaky BLMS with a leak equal to 0.80. However we will keep the step size equal to 0.005.

Figure 7: ALE Results for Step Size 0.005 with Leak of 0.80



Increasing step size to 0.02, brings us closer to the non leaky algorithm plot for step size equal to 0.0001.

Figure 8: ALE Results for Step Size 0.02 with Leak 0.80



SNR of noisy signal $s(n)$ is –14.3021 dB. SNR of Filtered output of ALE (in dB) can be tabulated for all of the above periodic noise corrupted audio signals. A percentage decrease of 64% is observed for leaky BLMS as compared to non leaky one.

Table 1: SNR for Audio Signal Buried in Periodic Noise

Step Size	Non Leaky BLMS in dB	Leaky BLMS in dB
0.0001	4.1232	0.1694
0.005	7.0381	1.7360
0.02	4.9614	3.8653

Removing a pure sinusoid from a sinusoid plus music signal is not that difficult a task provided the frequency of the offending sinusoid. A simple two-pole, two-zero notch filter can perform this task. So we make the problem a bit harder by adding an FM-modulated sinusoidal signal as our noise source. We will begin with a step size of 0.005 in case of FM modulated noise.

Figure 9: ALE Results for Step Size 0.005

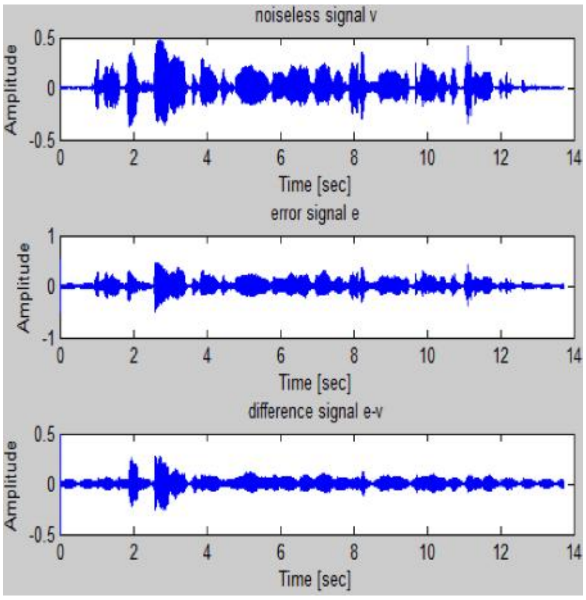
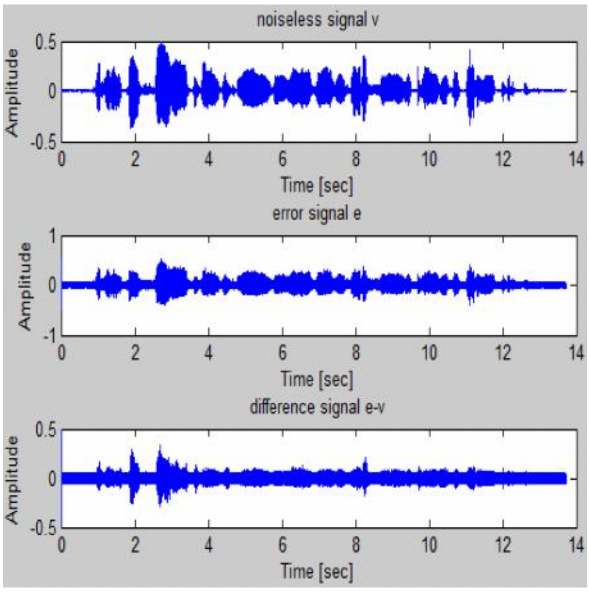
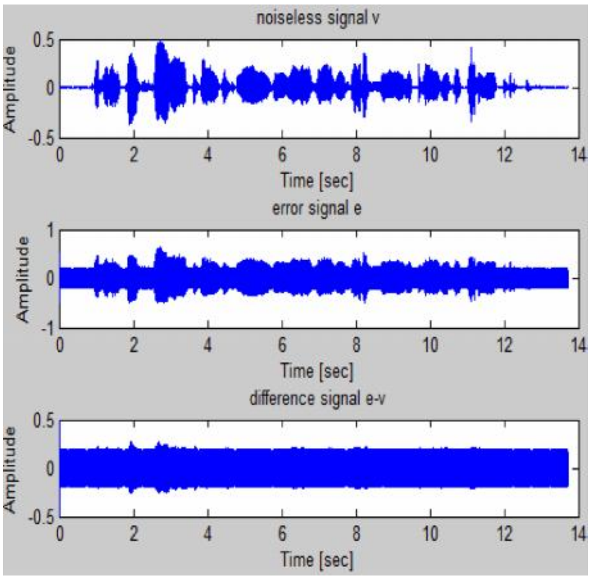


Figure 10: ALE Results for Step Size 0.009



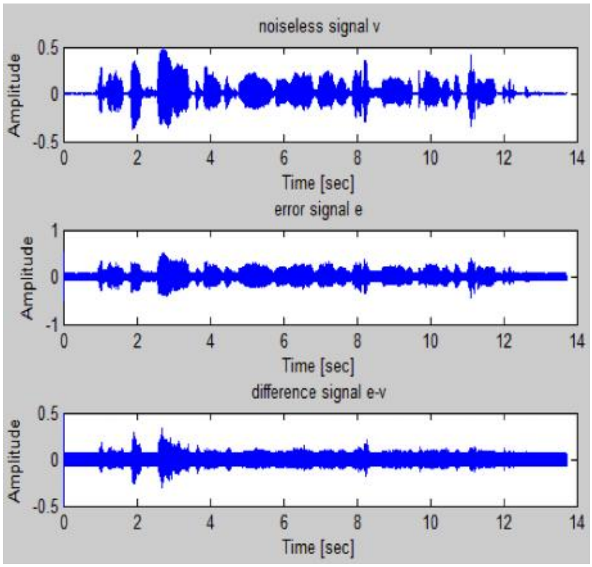
Now we shall implement leaky BLMS algorithm with a step size of 0.005 with a leak of 0.80.

Figure 11: ALE Results for Step Size 0.005 with a Leak of 0.80



In order to get a plot closer to non leaky algorithm result for step size 0.05, we increase step size to about 0.02.

Figure 12: ALE Results for Step Size 0.02 with Leak 0.80



A percentage decrease of 58.5% is observed for leaky BLMS as compared to non leaky one.

Table 2: SNR for Audio Signal Buried in FM Modulated Noise

Step Size	Non Leaky BLMS in dB	Leaky BLMS in dB
0.005	5.8860	0.9074
0.009	5.7163	1.7366
0.02	4.0927	3.8659

CONCLUSION

This paper provides a performance analysis of enhancement of audio signal corrupted by periodic sinusoidal noise as well as an FM modulated noise using Adaptive Line Enhancer.SNR findings show that for FM modulated noisy audio signal the convergence rate is higher than that for periodic noise buried audio signal. The SNR for non leaky LMS is about 60% higher than leaky LMS for same convergence rate. The convergence rate can however be increased to bring SNR closer to NLMS. The leaky LMS has its own advantage that it prevents coefficient overflow.

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