Filtering Non-Stationary Noise in Speech Signals using Computationally Efficient Unbiased and Normalized Algorithm

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Abstract - Extraction of high resolution information signals is important in all practical applications. The Least Mean Square (LMS) algorithm is a basic adaptive algorithm has been extensively used in many applications as a consequence of its simplicity and robustness. In this paper we present a novel adaptive filter for de-noising the speech signals based on unbiased and normalized adaptive noise reduction (UNANR) algorithm. The UNANR model does not contain a bias unit, and the coefficients are adaptively updated by using the steepest-descent algorithm. The adaptive filter essentially minimizes the mean-squared error between a primary input, which is the noisy speech, and a reference input, which is either noise that is correlated in some way with the noise in the primary input or a signal that is correlated only with speech in the primary input. To measure the ability of the proposed implementation, signal to noise ratio improvement (SNRI) is calculated. The results show that the performance of the UNANR based algorithm is superior to that of the LMS and conventional Normalized LMS (NLMS) algorithms in noise reduction

Keywords: Adaptive filtering, LMS algorithm, MSE, Noise cancellation, Speech enhancement.

I. INTRODUCTION

In real time environment speech signals are corrupted by several forms of noise such as competing speakers, background noise, car noise, and also they are subjected to distortion caused by communication channels; examples are room reverberation, low-quality microphones, etc. In all such situations extraction of high resolution signals is a key task. In this aspect filtering come in to the picture. Basically filtering techniques are broadly classified as non-adaptive and adaptive filtering techniques. In practical cases the statistical nature of all speech signals is non-stationary; as a result non-adaptive filtering may not be suitable. Speech enhancement improves the signal quality by suppression of noise and reduction of distortion. Speech enhancement has many applications; for example, mobile communications, robust speech recognition, low-quality audio devices, and hearing aids.

Many approaches have been reported in the literature to address speech enhancement. In recent years, adaptive filtering has become one of the effective and popular approaches for the speech enhancement. Adaptive filters permit to detect time varying potentials and to track the dynamic variations of the signals. Besides, they modify their behavior according to the input signal. Therefore, they can detect shape variations in the ensemble and thus they can obtain a better signal estimation. The first adaptive noise cancelling system at Stanford University was designed and built in 1965 by two students. Their work was undertaken as part of a term paper project for a course in adaptive systems given by the Electrical Engineering Department. Since 1965, adaptive noise cancelling has been successfully applied to a number of applications. Several methods have been reported so far in the literature to enhance the performance of speech processing systems; some of the most important ones are: Wiener filtering, LMS filtering [1], spectral subtraction [2]-[3], thresholding [4]-[5]. On the other side, LMS-based adaptive filters have been widely used for speech enhancement [6]–[8]. In a recent study, however, a steady state convergence analysis for the LMS algorithm with deterministic reference inputs showed that the steady-state weight vector is biased, and thus, the adaptive estimate does not approach the Wiener solution. To handle this drawback another strategy was considered for estimating the coefficients of the linear expansion, namely, the block LMS (BLMS) algorithm [9], in which the coefficient vector is updated only once every occurrence based on a block gradient estimation. A major advantage of the block, or the transform domain LMS algorithm is that the input signals are approximately uncorrelated. In the recent past Jamal Ghasemi et.al [10] proposed a new approach for speech enhancement based on eigen value spectral subtraction, in [11] authors describes usefulness of speech coding in voice banking, a new method for voicing detection and pitch estimation. This method is based on the spectral analysis of the speech multi-scale product [12]. Recently in [16] Karthik et.al demonstrated speech enhancement using variable step size LMS (VSSLMS) algorithms, in [17] Rahman et.al presented speech filtering using variable step size least mean fourth based treatment.

In this paper we present a novel unbiased and normalized adaptive noise reduction (UNANR) system to suppress non stationary noise in speech signals using the frame work of [15] - [17]. The UNANR learning rate demonstrate that the adaptive noise-reduction system that includes the UNANR model can effectively eliminate random noise in speech recordings, leading to a higher SNR improvement than that with the same system using the popular least-mean-square (LMS) filter. To prove the ability of UNANR we compared its functioning with LMS and NLMS based realizations.

II. ADAPTIVE ALGORITHMS

A. Basic Adaptive Filter Structure

Figure 1 shows an adaptive filter with a primary input i(n), that is noisy speech signal *S(n)* with additive noise *C(n)*. While the reference input is noise *r(n)*, which is correlated in some way with *C(n)*. If the filter output is *f(n)*, the output of the summer O(n) is nothing but the error signal and it is written as, filter error $e = \{S(n) + C(n)\} - f(n)$, then

$$\begin{aligned} e^2 &= \{S(n) + C(n)\}^2 - 2 f(n) \{S(n) + C(n)\} + f(n)^2 \\ &= \{C(n) - f(n)\}^2 + S(n)^2 + 2 S(n) C(n) - 2 f(n) S(n) \end{aligned} \quad (1)$$

Since the signal and noise are uncorrelated, the mean-squared error (MSE) is

$$E[e^2] = E[\{C(n) - f(n)\}^2] + E[S(n)^2] \quad (2)$$

Minimizing the MSE results in a filter error output that is the best least-squares estimate of the signal *S(n)*. The adaptive filter extracts the signal, or eliminates the noise, by iteratively minimizing the MSE between the primary and the reference inputs. Minimizing the MSE results in a filter error output *f(n)* that is the best least-squares estimate of the signal *S(n)*.

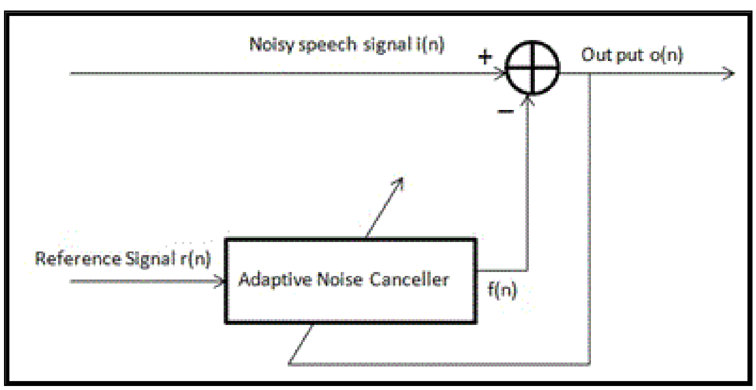

Figure 1: Adaptive Filter Structure.

B. Conventional LMS Algorithms

The LMS algorithm is a method to estimate gradient vector with instantaneous value. It changes the filter tap weights so that e(n) is minimized in the mean-square sense. The conventional LMS algorithm is a stochastic implementation of the steepest descent algorithm. It simply replaces the cost function $\xi(n) = E[e^2(n)]$ by its instantaneous coarse estimate.

Coefficient updating equation for LMS is given by,

$$\mathbf{w}(n+1) = \mathbf{w}(n) + \mu\, \mathbf{i}(n)\, e(n), \quad (3)$$

Where μ is an appropriate step size to be chosen as $0 < \mu < \frac{2}{tr\,R}$ for the convergence of the algorithm.

Normalized LMS (NLMS) algorithm is another class of adaptive algorithm used to train the coefficients of the adaptive filter. This algorithm takes into account variation in the signal level at the filter output and selecting the normalized step size parameter that results in a stable as well as fast converging algorithm. The weight update relation for NLMS algorithm is as follows

$$\mathbf{w}(n+1) = \mathbf{w}(n) + \mu(n)\, \mathbf{i}(n)\, e(n), \qquad (4)$$

The variable step can be written as,

$$\mu(n) = \mu \,/\, [\, p + \mathbf{i}^t(n)\, \mathbf{i}(n)\,] \qquad (5)$$

Here μ is fixed convergence factor to control maladjustment, μ(*n*) is nonlinear variable of input signal, which changes along with p. The step diminishes and accelerates convergence process. The parameter p is set to avoid denominator being too small and step size parameter too big.

The advantage of the NLMS algorithm is that the step size can be chosen independent of the input signal power and the number of tap weights. Hence the NLMS algorithm has a convergence rate and a steady state error better than LMS algorithm.

C. The unbiased and normalized adaptive noise reduction system

The UNANR model of the system performs the function of adaptive noise estimation. The UNANR model of order M, as shown in Figure 2, is a transversal, linear, finite impulse response (FIR) filter. The response of the filter f(n) at each time instant (sample) n can be expressed as,

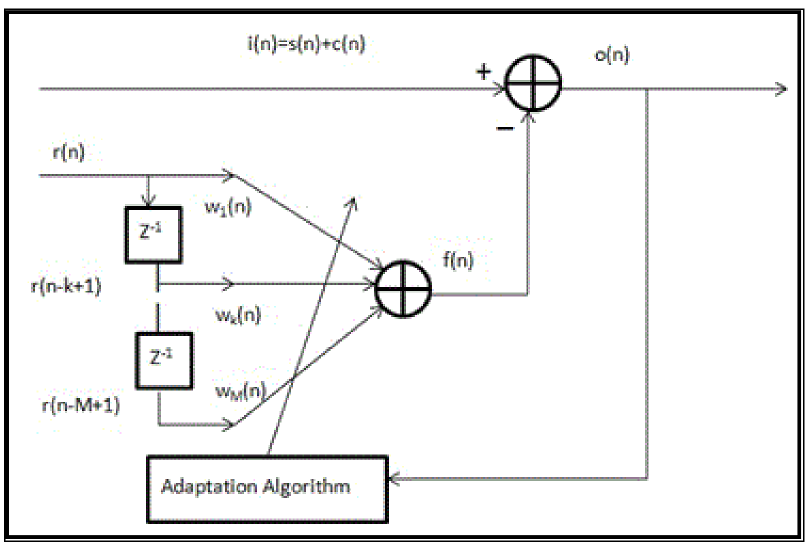

Figure.2: Detailed structure of the UNANR model.

$$f(n) = \sum_{m=1}^{M} w_m(n) r(n-m+1) \qquad (6)$$

Where $w_m(n)$ represents the UNANR coefficients, and r(n − m + 1) denotes the reference input noise at the present (m = 1) and preceding m − 1, (1 < m ≤ M), input samples. In order to provide unit gain at DC, the UNANR coefficients should be normalized such that

$$\sum_{m=1}^{M} w_m(n) = 1 \qquad (7)$$

The adaptation process of the UNANR model is designed to modify the coefficients that get convolved with the reference input in order to estimate the noise present in the given speech signal. To provide the estimated speech signal component, ŝ(n), at the time instant n, the output of the adaptive noise-reduction system subtracts the response of the UNANR model f (n) from the primary input i(n), i.e.,

$$\hat{s}(n) = o(n) = i(n) – f(n) \tag{8}$$

where the primary input includes the desired speech component and the additive white noise, i.e.,

$$i(n) = s(n) + c(n). \tag{9}$$

Squaring both sides of (9) yields

$$\hat{s}^2(n) = i^2(n) + f^2 (n) – 2i(n)f (n) \tag{10}$$

$$= [s(n) + c(n)]^2 + f^2(n) − 2[s(n) + c(n)]f (n)$$

$$= s^2(n) + 2s(n)u(n) + u^2(n) + f^2(n)$$

$$−2[s(n) + c(n)]f (n). \tag{11}$$

Different from the MMSE criterion, the goal of the UNANR coefficient adaptation process is considered to be the minimization of the instantaneous error ε(n) between the estimated signal power $\hat{s}^2(n)$ and the desired signal power $s^2(n)$, i.e.,

$$\varepsilon(n) = \hat{s}^2(n) – s^2(n) = c^2(n) + 2s(n)c(n) + f^2(n)$$

$$– 2[s(n)+c(n)]f(n) \tag{12}$$

Such a goal can be achieved by optimizing the UNANR coefficients according to the steepest-descent algorithm [13]. The process of convergence in the multidimensional coefficient space follows a deterministic search path provided by the negative gradient direction as

$$-\nabla w_k\, \varepsilon(n) = -\frac{\partial f^2(n)}{\partial w_k} + 2\,\frac{\partial[s(n)+c(n)]f(n)}{\partial w_k}$$

$$= -2r(n-k+1)\sum_{m=1}^{M} w_m(n)r(n-m+1) - 2\, i(n)r(n-k+1)$$

$$= -2r(n-k+1)\left[\sum_{m=1}^{M} w_m(n)r(n-m+1) - i(n)\right] \tag{13}$$

By substituting (8) and (13) into the standard steepest descent algorithm [13], we may derive the UNANR adaptation rule as

$$w_k(n+1) = w_k(n) - \eta\nabla w_k\, \varepsilon(n)$$

$$= w_k(n) - 2\eta r(n-k+1)\left[\sum_{m=1}^{M} w_m(n)r(n-m+1) - i(n)\right]$$

$$= w_k(n) + 2\eta r(n-k+1)\sum_{m=1}^{M} w_m(n)r(n-m+1) \tag{14}$$

Where η (η > 0) represents the learning rate that indicates the search magnitude in the negative gradient direction.

Before the UNANR model provides its response f (n +1) referring to (13), at each time instant n + 1, the estimated coefficients $\widehat{w}_k(n + 1)$ should be normalized so as to meet the requirement of (14). The UNANR coefficient normalization formulation is given by

$$\widehat{w}_k(n + 1) = \frac{w_k(n+1)}{\sum_{k=1}^{M} w_k(n+1)}$$

III SIMULATION RESULTS

To show that UNANR algorithm is appropriate for speech enhancement we have used real speech signals with noise. In the figure *number of samples* is taken on *x-axis* and *amplitude* is taken on *y-axis*. The convergence curves for various algorithms is shown in Figure 3.

For the implementation of adaptive noise canceller we have chosen a second order FIR filter. The considered filter is a direct form II stable filter. The numerator length is two, denominator length is three, number of multipliers are two, number of adders is one, number of states are two, multiplications per input sample are two, additions per input sample is one. The transfer function of the filter is given by,

$$H(z) = 2Z^2 – 5Z+2 \;/\; 2Z^2(Z-1).$$

The magnitude – phase response, pole-zero plot of the considered FIR filter are shown in Figure 4(a) and 4(b).

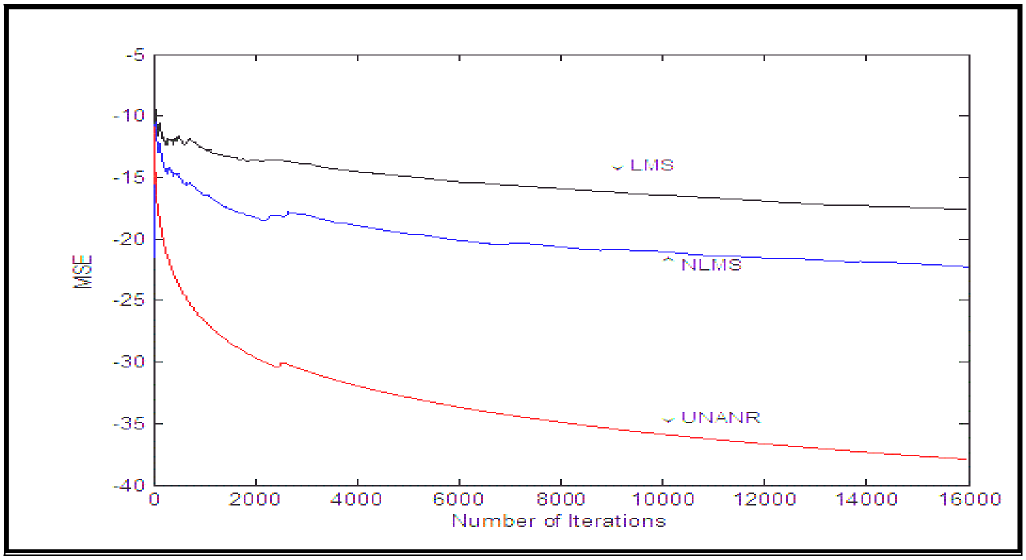

Figure 3: convergence curves for various algorithms.

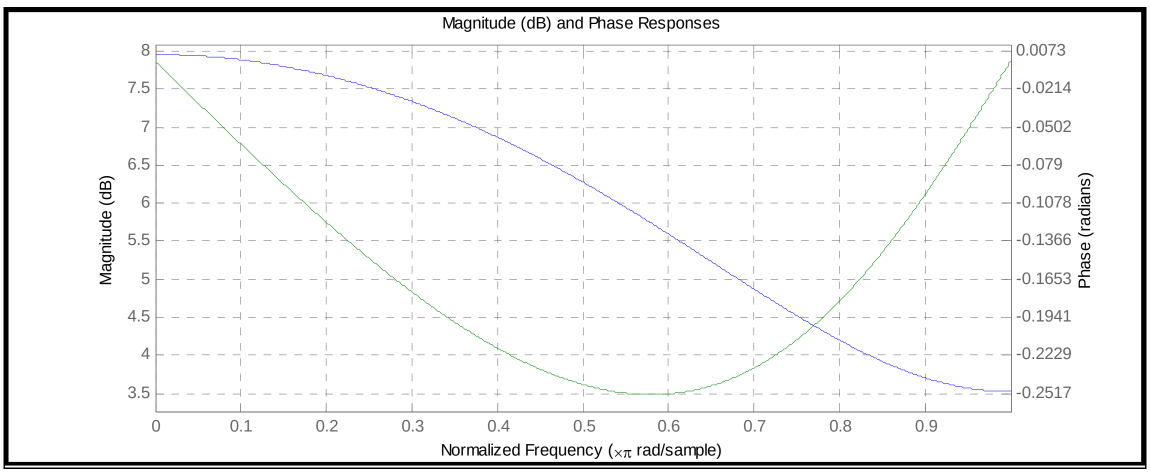

Figure 4(a): Magnitude and Phase response of the FIR filter.

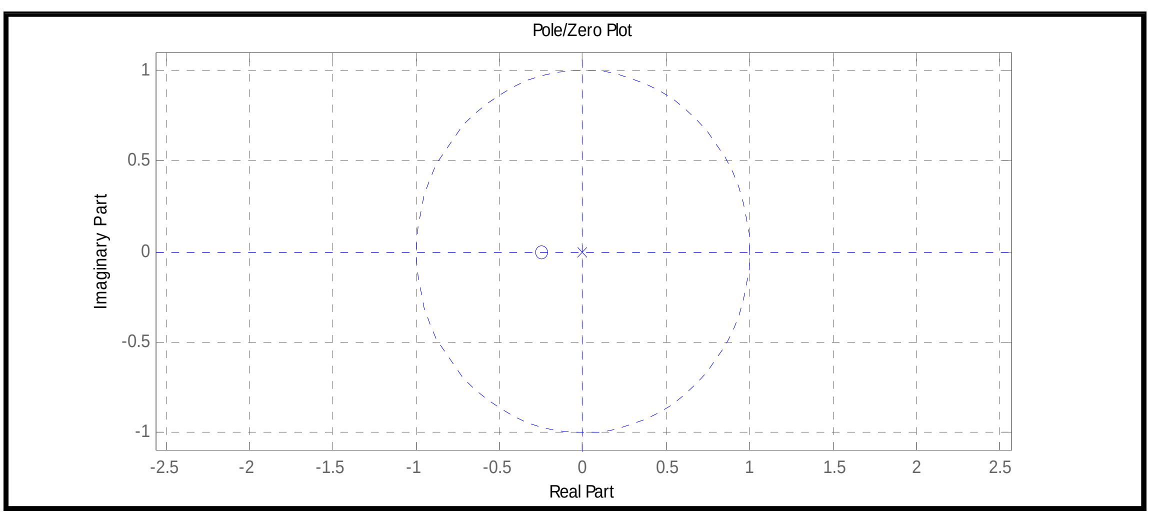

Figure 4(b): Pole Zero plot of the FIR filter.

A. Simulation Results for Helicopter noise

As a first step in adaptive noise cancellation application, the speech signal corresponding to sample-I is corrupted with random noise and is given as input signal to the adaptive filter shown in Figure 1. As the reference signal must be somewhat correlated with noise in the input, the random noise signal is given as reference signal. The filtering results are shown in Figures 5 and 6. To evaluate the performance of the algorithms SNRI is measured and tabulated in Table II.

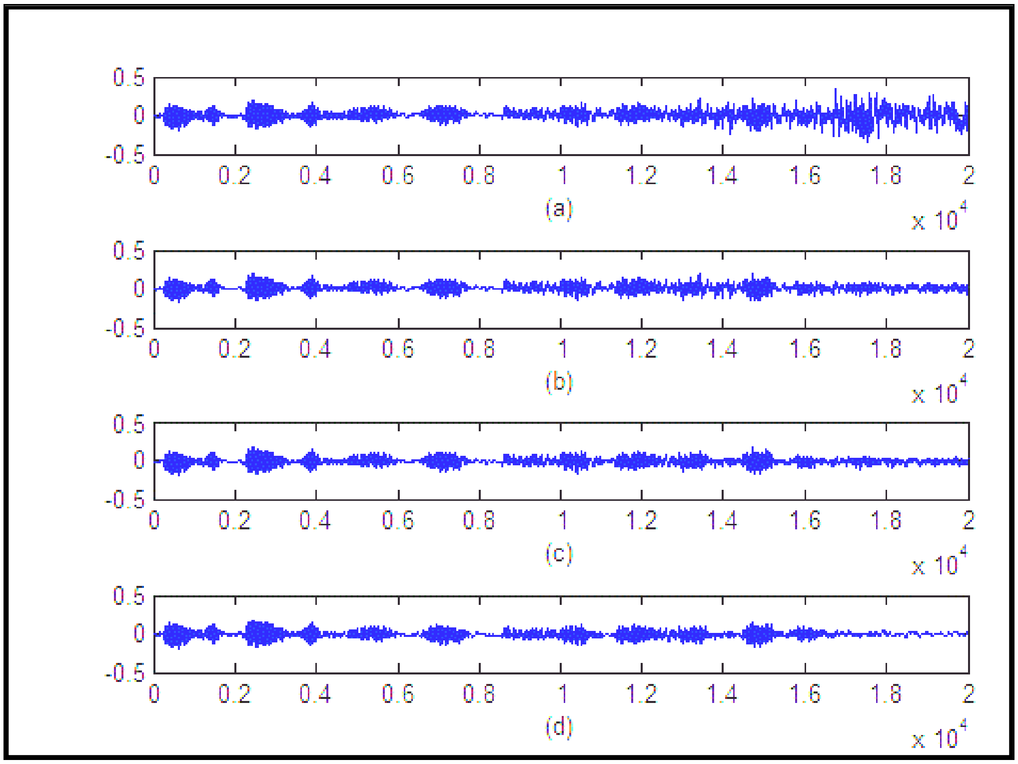

Figure 5: Typical filtering results of helicopter noise removal (a) Speech Signal with real noise, (b) recovered signal using LMS algorithm, (c) recovered signal using NLMS algorithm, (d) recovered signal using UNANR algorithm.

B. Adaptive cancellation of real high voltage murmuring

In this experiment a speech signal corresponding to sample-II contaminated with high voltage murmuring is given as input to the filter. The filtering results are shown in Figures 9 and 10. The SNRI contrast is shown in Table-II.

C. Simulation Results for battle field noise removal

In this experiment the speech signal contaminated with a real battle field noise (gun firing noise predominates in this noise) is given as input to the adaptive filter shown in Figure 2. As the reference signal must be somewhat correlated with noise in the input, the noise signal is given as reference signal. The filtering results are shown in Figure 7. To evaluate the performance of the algorithms SNRI is measured and tabulated in Table II.

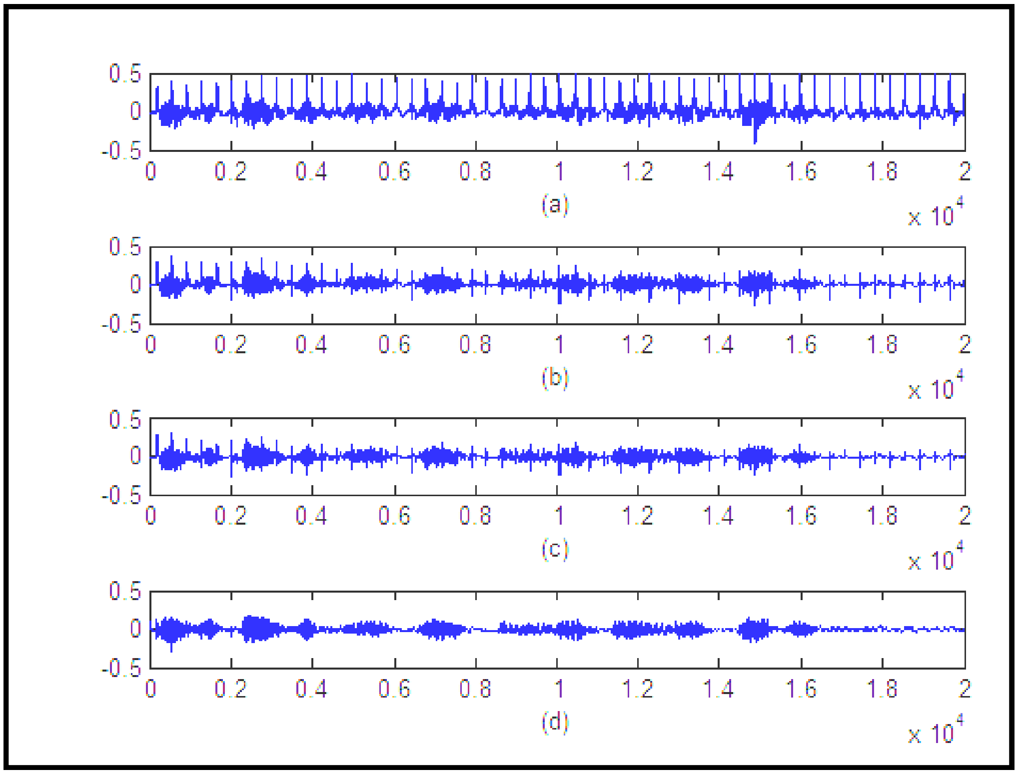

Figure 6: Typical filtering results of high voltage noise removal (a) Speech Signal with real noise, (b) recovered signal using LMS algorithm, (c) recovered signal using NLMS algorithm, (d) recovered signal using UNANR algorithm.

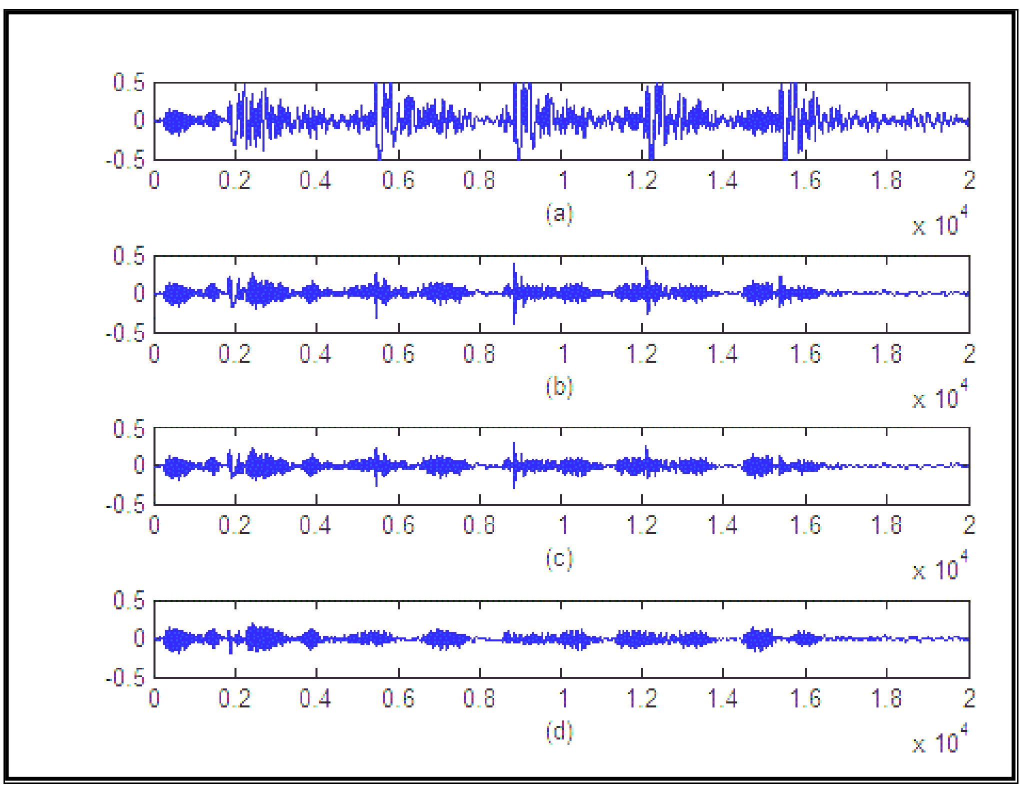

Figure 7: Typical filtering results of battle field noise removal (a) Speech Signal with real noise, (b) recovered signal using LMS algorithm, (c) recovered signal using NLMS algorithm, (d) recovered signal using UNANR algorithm.

Table II: SNR Improvement after filtering with LMS, NLMS and UNANR algorithms.

Sample Number	**LMS Filtering**	**NLMS Filtering**	**UNANR Filtering**
Sample I	4.1895	6.2603	10.5804
Sample II	6.8848	8.4071	14.6986
Sample III	4.2488	5.4370	12.0910

IV CONCLUSION

In this paper the problem of noise removal from speech signals using UNANR based adaptive filtering is presented. For this, the same formats for representing the data as well as the filter coefficients as used for the LMS algorithm were chosen. As a result, the steps related to the filtering remains unchanged. The proposed treatment, however exploits the modifications in the weight update formula for all categories to its advantage and thus pushes up the speed over the respective LMS-based realizations. Our simulations, however, confirm that the ability of UNANR algorithms is better than conventional LMS and NLMS algorithms in terms of SNR improvement and convergence rate. Hence these algorithm is acceptable for all practical purposes.

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