Speech Enhancement Using Gradient Based Variable Step Size Adaptive Filtering Techniques

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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 practical application of the LMS algorithm, a key parameter is the step size. As is well known, if the step size is large, the convergence rate of the LMS algorithm will be rapid, but the steady-state mean square error (MSE) will increase. On the other hand, if the step size is small, the steady state MSE will be small, but the convergence rate will be slow. Thus, the step size provides a tradeoff between the convergence rate and the steady-state MSE of the LMS algorithm. An intuitive way to improve the performance of the LMS algorithm is to make the step size variable rather than fixed, that is, choose large step size values during the initial convergence of the LMS algorithm, and use small step size values when the system is close to its steady state, which results in Variable Step Size LMS (VSSLMS) algorithms. By utilizing such an approach, both a fast convergence rate and a small steady-state MSE can be obtained. By using this approach various forms of VSSLMS algorithms are implemented. Similar to in the case of the LMS algorithm, a variable step size algorithm is also necessary to obtain both fast convergence rate and small steady state MSE. In this paper various forms of VSSLMS algorithms, which are robust to high variance noise signals are implemented for the construction of adaptive noise cancellers (ANC). Finally we will apply these ANC structures for filtering speech signals. In order to measure the quality of these filters, SNR measurement is considered as quality factor.*

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

1. Introduction

In real time environment speech signals are corrupted by several forms of noise such as such as competing speakers, background noise, car noise, and also they are subject 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. Recently Jamal Ghasemi et.al [10] proposed a new approach for speech enhancement based on eigenvalue 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].

In practice, LMS is replaced with its Normalized version, NLMS. In practical applications of LMS filtering, a key parameter is the step size. If the step size is large, the convergence rate of the LMS algorithm will be rapid, but the steady-state mean square error (MSE) will increase. On the other hand, if the step size is small, the steady state MSE will be small, but the convergence rate will be slow. Thus, the step size provides a tradeoff between the convergence rate and the steady-state MSE of the LMS algorithm. The performance of the LMS algorithm may be improved by making the step size variable rather than fixed. The resultant approach with variable step size is known as variable step size LMS (VSSLMS) algorithm [13]. By utilizing such an approach, both a fast convergence rate and a small steady-state MSE can be obtained. Many VSSLMS algorithms are proposed during recent years [14]-[17]. In this paper, we considered the problem of noise cancellation in speech signals by effectively modifying and extending the framework of [1], using VSSLMS algorithms mentioned in [14]-[17]. For that, we carried out simulations on various real time speech signals contaminated with real noise. The simulation results show that the performances of the VSSLMS based algorithms are comparable with LMS counterpart to eliminate the noise from speech signals.

2. Adaptive Algorithms

In this paper we considered various speech signals contaminated with various forms of real noise to demonstrate the concept of adaptive noise cancellation. Figure 1 shows a block schematic of a real transversal FIR filter, here the input values are denoted by u(n), the filter order is denoted by M, and z^{-1} denotes a delay of one sample period. Adaptive filters utilize algorithms to iteratively alter the values of the impulse response vector in order to minimize a value known as the cost function. The cost function, ξ(n), is a function of the difference between a desired output and the actual output of the FIR filter. This difference is known as the estimation error of the adaptive filter, e(n) = d(n) - y(n).

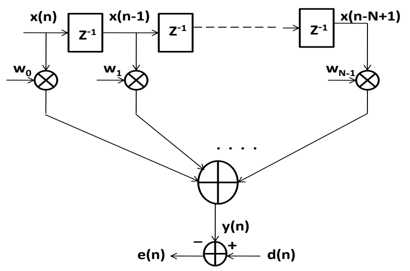

Figure 1: Block diagram of an transversal FIR adaptive filter.

2.1 Basic Adaptive Filtering Structure

Figure 2 shows an adaptive filter with a primary input that is noisy speech signal s_1 with additive noise n_1. While the reference input is noise n_2, which is correlated in some way with n_1. If the filter output is y and the filter error $e=(s_1+n_1)-y$, then

$$\begin{aligned} e^2 &= (s_1+n_1)^2 - 2y\,(s_1+n_1) + y^2 \\ &= (n_1-y)^2 + s_1^2 + 2\,s_1\,n_1 - 2y\,s_1. \end{aligned} \tag{1}$$

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

$$E[e^2]=E[(n_1-y)^2]+E[s_1^2] \tag{2}$$

Minimizing the MSE results in a filter error output that is the best least-squares estimate of the signal s_1. 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 y that is the best least-squares estimate of the signal s_1.

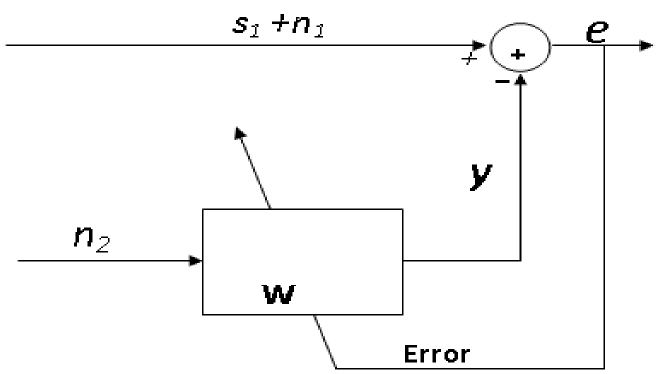

Figure 2: Adaptive Filter Structure.

2.2 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.

The error estimation e(n) is

$$e(n) = \mathbf{d}(n) - \mathbf{w}(n)\,\mathbf{\Phi}(n) \tag{4}$$

Coefficient updating equation is

$$\mathbf{w}(n+1) = \mathbf{w}(n) + \mu\,\mathbf{\Phi}(n)\,e(n), \tag{5}$$

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 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

$$\mathbf{w}(n+1) = \mathbf{w}(n) + \mu(n)\,\mathbf{\Phi}(n)\,e(n), \tag{6}$$

The variable step can be written as,

$$\mu(n) = \mu \,/\, [\,p + \mathbf{\Phi}^{\mathbf{t}}(n)\,\mathbf{\Phi}(n)\,] \tag{7}$$

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.

2.3 Gradient based variable step size (VSSLMS) LMS Algorithms.

In this paper we considered four types of gradient based VSSLMS algorithms for the implementation of adaptive noise cancellers based on [14]-[17].

2.3.1. Korni's VSSLMS algorithm:

In this algorithm the convergence factor μ is made time-varying in inverse proportion to the input power. As a result this algorithm is shown to be effective for a variety of applications.

$$W_i(n+1) = w_i(n)+\mu(n)e(n)x_i(n) \qquad 0 \le i \le N$$

Keep the μ(n) large before the algorithm converges and to reduce it as the algorithm converges. The purpose of the algorithm is to find the minimum of $e^{2,}$ e^2 being a quadratic function of $w_{i,}$ i=0,l,..., N. In other words, the algorithm solves the following simultaneous linear equations:

$$\frac{\partial e^2}{\partial wi} = 0 \qquad 0 \le i \le N \qquad (8)$$

Since

$$e(n) = d(n)-\sum_{i=0}^{M} W_i(n)x_i(n)$$

Where d(n) is the desired output, eq. (8) can be rewritten in vector form as

$$||eX|| = 0$$

Where ||.|| is the regular vector norm, and

$$X=[x_0, x_1,\ldots\ldots,x_M]$$

μ(n) should be bounded by

$$0 \le \mu(n) \le \mu'$$

and if the inputs are identically Gaussian distributed with power σ^2, we have

$$\mu'=1/((M+1)\sigma^2)$$

These discussions suggest a new convergence factor, expressed below:

$$\mu(n)= \mu'(1-e^{-\alpha||e(n)X(n)||}). \qquad (9)$$

Here, α > 0 is the damping parameter. In applications, the norm
||.|| can be replaced by the norm square $||.||^2$

When ||e(n)x(n)|| is large, μ(n)=μ', i.e., the algorithm is in its fast convergence state. After ||e(n)x(n)|| is greatly reduced, μ(n) will be very small, and the algorithm enters its misadjustment minimizing state. Decreasing ||e(n)x(n)|| causes the decreasing of μ(n)**.**Since the misadjustment is directly proportional to μ(n), the misadjustment is thus reduced [18]-[19].

In the case of a non-stationary input, the sudden change of the input induces ||e(n)x(n)|| to become large, which brings the algorithm back to the fast convergence state automatically. It must be pointed out that the "crossover point" of these two states-fast convergence state and misadjustment minimizing state-is governed by the damping parameter α . In fact, there is no clear cut "crossover point," since the exponential function is rather smooth. The larger the parameter α **,** the larger the fast convergence region will be. If α is taken as infinity, then this new algorithm degenerates into the conventional LMS algorithm. As a rule of thumb, α is to be set greater than unity. We note that μ(n) always keeps the algorithm stable.

2.3.2. Kwong's VSSLMS algorithm:

The LMS type adaptive algorithm is a gradient search algorithm which computes a set of weights w_k that seeks to minimize $E(d_k -X^T_kW_k)$The algorithm is of the form

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

Where

$$e_k = d_k + X^T_k W^*_k$$

and μ_k is the step size. In the standard LMS algorithm μ_k is a constant. In this μ_k is time varying with its value determined by the number of sign changes of an error surface gradient estimate. Here the new variable step size or VSS algorithm, for adjusting the step size μ_k yields :

$$\mu'_{k+1} = \alpha\mu_k + \gamma e^2_k \qquad 0 < \alpha < 1, \ \gamma > 0$$

and

$$\mu_{k+1} = \begin{cases} \mu_{max} & \text{if } \mu'_{k+1} > \mu_{max} \\ \mu_{min} & \text{if } \mu'_{k+1} < \mu_{min} \\ \mu'_{k+1} & \text{otherwise} \end{cases} \qquad (10)$$

where $0 < \mu_{min} < \mu_{max}$**.** The initial step size μ_0 is usually taken to be μ_{max}, although the algorithm is not sensitive to the choice. The step size μ_k , is always positive and is controlled by the size of the prediction error and the parameters α and γ. Intuitively speaking, a large prediction error increases the step size to provide faster tracking. If the prediction error decreases, the step size will be decreased to reduce the misadjustment. The constant μ_{max} is chosen to ensure that the mean-square error (MSE) of the algorithm remains bounded. A sufficient condition for μ_{max}

$$\mu_{max} \leq 2/(3\ \mathrm{tr}\ (R)) \quad (11)$$

μ_{min} is chosen to provide a minimum level of tracking ability. Usually, μ_{min} will be near the value of μ that would be chosen for the fixed step size (FSS) algorithm. α must be chosen in the range (0, 1) to provide exponential forgetting.

2.3.3. Mathew's VSSLMS algorithm:

Consider the problem of estimating the desired response signal *d(n)* as a linear combination of the elements of *X(n),* the N-dimensional input vector sequence to the adaptive filter. The popular least mean square (LMS) adaptive filter updates the filter coefficients in the following manner:

$$e(n) = d(n) - X^T(n)H(n)$$

and

$$H(n+1) = H(n) + \mu\, X(n)e(n)$$

Here, $(\cdot)^T$ denotes the matrix transpose of $(\cdot)$, *H(n)* is the coefficient vector at time *n*, and μ is the step-size parameter that controls the speed of convergence as well as the steady-state and/or tracking behavior of the adaptive filter. The selection of μ is very critical for the LMS algorithm. A small μ will ensure small misadjustments in steady state, but the algorithm will converge slowly and may not track the non-stationary behavior of the operating environment very well. On the other hand, a large μ will in general provide faster convergence and better tracking capabilities at the cost of higher misadjustments.

The adaptive step-size algorithm that will be eliminate the "guesswork" involved in selection of the step-size parameter, and at the same time satisfy the following requirements:

1) The speed of convergence should be fast.
2) when operating in stationary environments, the steady-state misadjustment values should be very small. and
3) when operating in non-stationary environments.

The algorithm should be able to sense the rate at which the optimal coefficients are changing and select step-sizes that can result in estimates that are close to the best possible in the mean-squared-error
sense. Our approach to achieving the above goals is to adapt the step-size sequence using a gradient descent algorithm so as to reduce the squared-estimation error at each time.

$$e(n) = d(n) - X^T(n)H(n)$$

$$\mu(n) = \mu(n-1) - \frac{\rho}{2}\frac{\partial}{\partial\mu(n-1)}e^2(n)$$

$$= \mu(n-1) - \frac{\rho}{2}\frac{\partial^T e^2(n)}{\partial H(n)} \cdot \frac{\partial H(n)}{\partial\mu(n-1)}$$

$$= \mu(n-1) + \rho e(n)e(n-1)X^T(n-1)X(n) \quad (12)$$

And

$$H(n+1) = H(n) - \frac{\mu(n)}{2}\frac{\partial e^2(n)}{\partial H(n)}$$

$$= H(n) + \mu(n)e(n)X(n) \quad (13)$$

In the above equations, ρ is a small positive constant that controls the adaptive behavior of the step-size sequence μ(n).

1) 2.3.4. Aboulnasr's VSSLMS algorithm:

The adaptation step size is adjusted using the energy of the instantaneous error. The weight update recursion is given by

$$W(n+1) = w(n) + \mu(n)e(n)X(n)$$

And updated step-size equation is

$$\mu(n+1) = \alpha\mu(n) + \gamma e^2(n) \quad (14)$$

where $0<\alpha<1, \gamma>0$, and μ(n+1) is set to or when it falls below or above these lower and upper bounds, respectively. The constant μ_{max} is normally selected near the point of instability of the conventional LMS to provide the maximum possible convergence speed. The value of μ_{max} is chosen as a compromise between the desired level of steady state misadjustment and the required tracking capabilities of the algorithm. The parameter γ controls the convergence time as well as the level of misadjustment of the algorithm. At early stages of adaptation, the error is large, causing the step size to increase, thus providing faster convergence speed. When the error decreases, the step size decreases, thus yielding smaller misadjustment near the optimum. However, using the instantaneous error *energy* as a measure to sense the state of the adaptation process does not perform as well as expected in the presence of measurement noise. The output error of the identification system is

$$e(n) = d(n) - X^T(n)W(n)$$

where d(n) is the desired signal is given by

$$d(n) = X^T(n)W^*(n) + \xi(n) \quad (15)$$

ξ(n) is a zero-mean independent disturbance, and $W^*(n)$ is the time-varying optimal weight vector. Substituting (3) and (4) in the step-size recursion, we get

$$\mu(n+1) = \alpha\mu(n) + \gamma\, V^T(n)X(n)X^T(n)V(n) + \gamma\xi^2(n) - 2\gamma\xi(n)V^T(n)X(n) \quad (16)$$

Where $V(n)=W(n)-W^*(n)$ is the weight error vector. The input signal autocorrelation matrix, which is defined as $R=E\{X(n)X^T(n)\}$, can be expressed as $R=Q\Lambda Q^T$, where Λ is the matrix of eigenvalues, and Q is the model matrix of

R. using $V'(n)=Q^TV(n)$ and $X'(n) = Q^TX(n)$, then the statistical behavior of $\mu(n+1)$ is determined.

$$E\{\mu(n+1)\}=\alpha E\{\mu(n)\}+\gamma(E\{\xi^2(n)\}+E\{V'^T(n)\ \Lambda V'(n)\})$$

where we have made use of the common independence assumption of $V'(n)$ and $X'(n)$. Clearly, the term $E\{V'^T(n)\ \Lambda V'(n)\}$ influences the proximity of the adaptive system to the optimal solution, and $\mu(n+1)$ is adjusted accordingly. However, due to the presence of $E\{\xi^2(n)\}$, the step-size update is not an accurate reflection of the state of adaptation before or after convergence. This reduces the efficiency of the algorithm significantly. More specifically, close to the optimum, $\mu(n)$ will still be large due to the presence of the noise term $E\{\xi^2(n)\}$. This results in large misadjustment due to the large fluctuations around the optimum. In this paper, a different approach is proposed to control step-size adaptation. The objective is to ensure large $\mu(n)$ when the algorithm is far from the optimum with $\mu(n)$ decreasing as we approach the optimum *even in the presence of this noise*. The proposed algorithm achieves this objective by using an estimate of the autocorrelation between e(n) and e(n-1) to control step-size update. The estimate is a time average e(n)e(n-1) of that is described as

$$p(n)=\beta p(n-1)+(1-\beta)e(n)e(n-1)$$

The use of p(n) in the update of $\mu(n)$ serves two objectives. First, the error autocorrelation is generally a good measure of the proximity to the optimum. Second, it rejects the effect of the uncorrelated noise sequence on the step-size update. In the early stages of adaptation, the error autocorrelation estimate $p^2(n)$ is large, resulting in a large $\mu(n)$. As we approach the optimum, the error autocorrelation approaches zero, resulting in a smaller step size. This provides the fast convergence due to large initial $\mu(n)$ while ensuring low misadjustment near optimum due to the small final $\mu(n)$ even in the presence of $\xi(n)$. Thus, the proposed step size update is given by

$$M(n+1)= \alpha\mu(n)+\gamma p(n)^2$$

The positive constant $\beta(0<\beta<1)$ is an exponential weighting parameter that governs the averaging time constant, i.e., the quality of the estimation. In stationary environments, previous samples contain information that is relevant to determining an accurate measure of adaptation state, i.e.,the proximity of the adaptive filter coefficients to the optimal ones. Therefore, β should be ≈ 1. For non stationary optimal coefficients, the time averaging window should be small enough to allow for forgetting of the deep past and adapting to the current statistics, i.e., $\beta<1$. The step size can be rewritten as

$$\mu(n+1)=\alpha\mu(n)+\gamma[E\{V^T(n)X(n)X^T(n-1)V(n-1)\}]^2. \qquad (17)$$

It is also clear from above discussion that the update of $\mu(n)$ is dependent on how far we are from the optimum and is not affected by independent disturbance noise. Finally, the considered algorithm involves two additional update equations compared with the standard LMS algorithm. Therefore, the added complexity is six multiplications per iteration. These multiplications can be reduced to shifts if the parameters α,β,γ, are chosen as powers of 2. A summary of step size update equation is shown in Table I.

Table I: Summary of all VSSLMS algorithms.

Name of the algorithm	Update of the step size
Karin's VSSLMS	$\mu(n)= \mu^1(1-e^{-\alpha\|e(n)X(n)\|})$ $\mu^1=1/((M+1)\sigma^2)$
Kwong's VSSLMS	$\mu^1_{k+1} = \alpha\mu_k + \gamma e^2_k$
Mathew's VSSLMS	$\mu(n) = \mu(n-1)+\rho e(n)e(n-1)X^T(n-1)X(n)$
Aboulnasr's VSSLMS	$\mu(n+1)=\alpha\mu(n)+\gamma[E\{V^T(n)X(n)X^T(n-1)V(n-1)\}]^2$

The performance of these algorithms compared from the convergence characteristics shown in figure 3. From the convergence curves it is clear that the performance of VSSLMS algorithms is better than the conventional LMS / NLMS algorithms. Among the four VSSLMS algorithms Aboulnsr's algorithm is better than the other. From the figure it is clear that the VSSLMS algorithms converge very slowly at the beginning, but speed up as the MSE level drops.

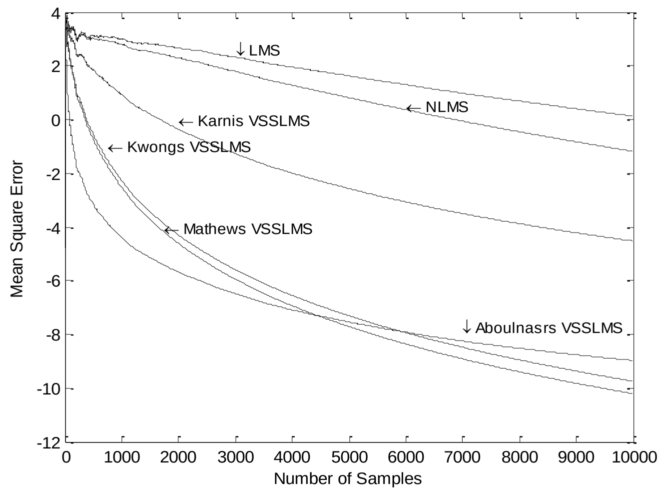

Figure 3: Convergence Characteristics of various algorithms.

3. Simulation Results

To show that VSS LMS algorithms are appropriate for speech enhancement we have used real speech signals and real noisy signals. These real speech signals are shown in figure 4. The sample-I is a practically recorded signal with 53569 samples. Sample-II is obtained from database and it has 68689 samples. Sample-III has 48136 samples, sample-IV is a real signal with 50000. These are shown in figure 4. In the figure *number of samples* is taken on *x-axis* and *amplitude* is taken on *y-axis*.

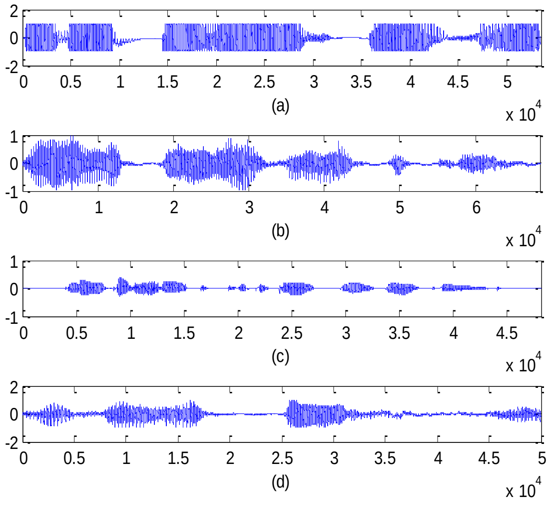

Figure 4: Real Speech Signals (a). Sample-I, (b). Sample-II,(c). Sample-III,(d). sample-IV.

To evaluate the performance of the adaptive algorithms and to prove the non-stationary tracking performance of the algorithms, both synthetic and real noises are taken. Some noises are shown in figure 5.

3.1 Characteristics of FIR filter

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 and impulse response of the considered FIR filter are shown in figure 6(a), 6(b) and 6(c) respectively.

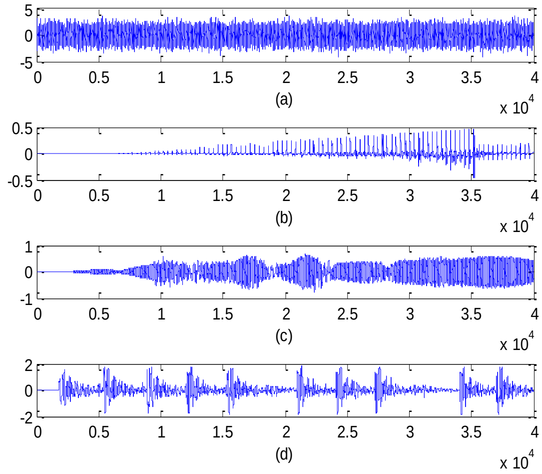

Figure 5: Synthetic and real noises used in this paper (a). Random noise (b). High voltage spark noise, (c). Speaker noise, (d). Battle field noise.

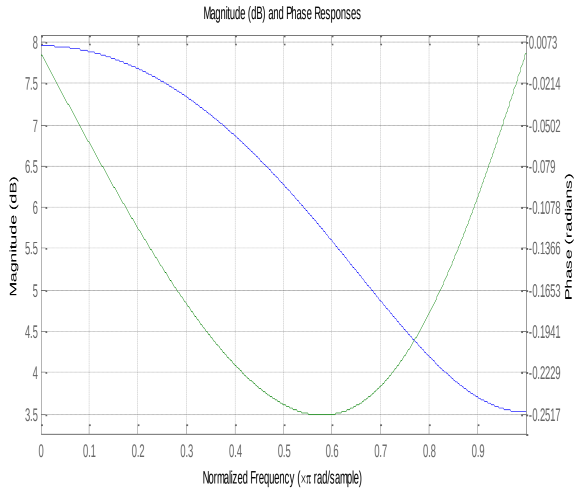

Figure 6(a): Magnitude and Phase response of the FIR filter.

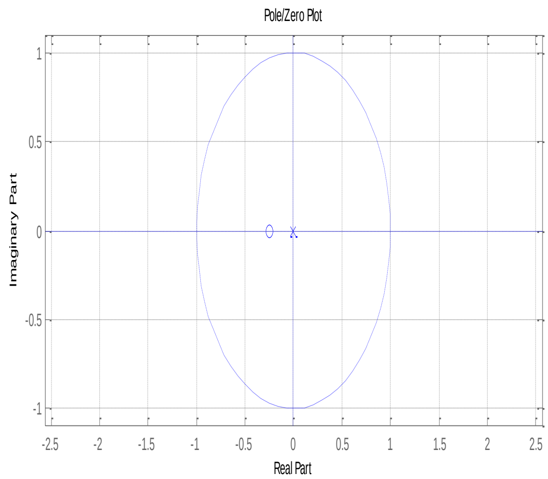

Figure 6(b): Pole Zero plot of the FIR filter.

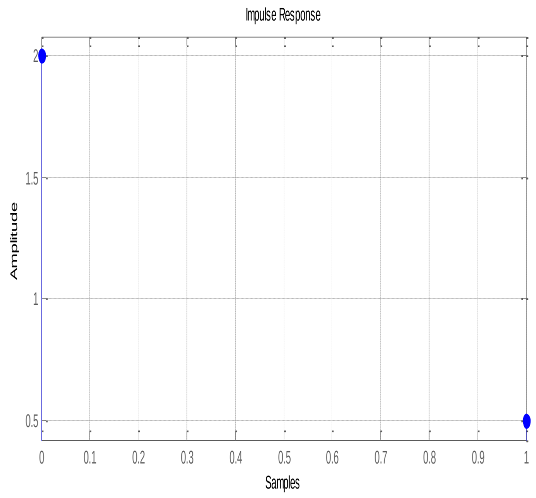

Figure 6(c): Impulse response of the FIR filter.

3.2. Simulation Results for Random Noise removal

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 2. 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 7 and 8. To evaluate the performance of the algorithms signal-to-noise (SNR) improvement is measured and tabulated in Table II.

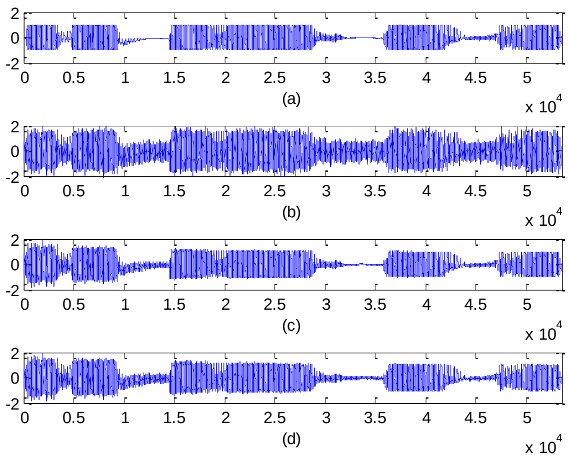

Figure 7: Typical filtering results of random noise removal (a) Original Speech Signal, (b) noisy signal, (c) recovered signal using LMS algorithm, (d) recovered signal using NLMS algorithm.

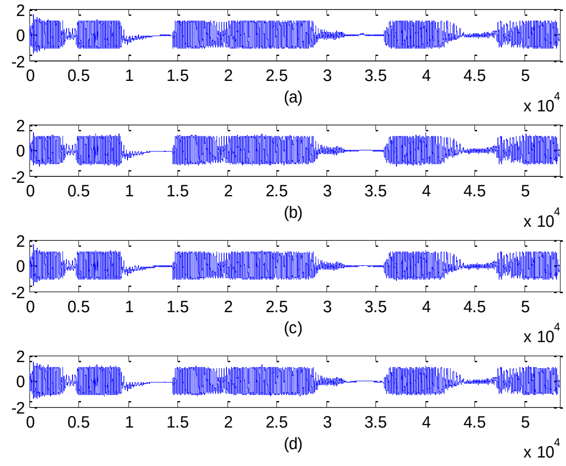

Figure 8: Typical filtering results of random noise removal (a) recovered signal using Karni's VSSLMS algorithm, (b) recovered signal using Kwongi's VSSLMS algorithm, (c) recovered signal using Mathew's VSSLMS algorithm, (d) recovered signal using Aboulnasr's VSSLMS algorithm.

3.3. 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 in put to the filter. The filtering results are shown in figures 9 and 10. The SNR contrast is shown in Table-II.

3.4. 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 figures 11 and 12. To evaluate the performance of the algorithms signal-to-noise (SNR) improvement is measured and tabulated in Table II.

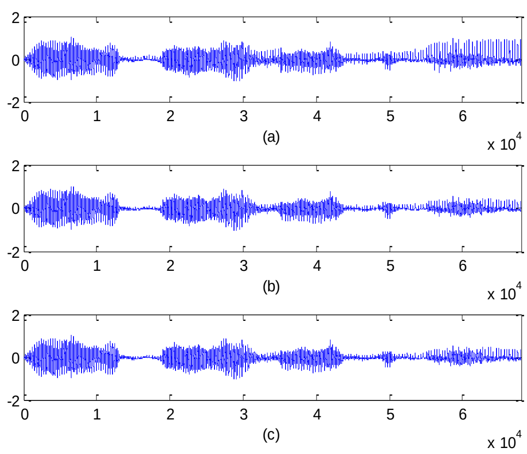

Figure 9: Typical filtering results of high voltage noiseremoval (a) Speech signal with high voltage noise,

(b) recovered signal using LMS algorithm, (c) recovered signal using NLMS algorithm.

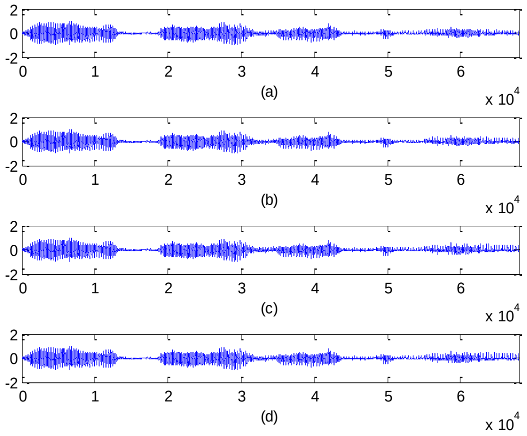

Figure 10**:** Typical filtering results of high voltage noise removal (a) recovered signal using Karni's VSSLMS algorithm, (b) recovered signal using Kwongi's VSSLMS algorithm, (c) recovered signal using Mathew's VSSLMS algorithm, (d) recovered signal using Aboulnasr's VSSLMS algorithm.

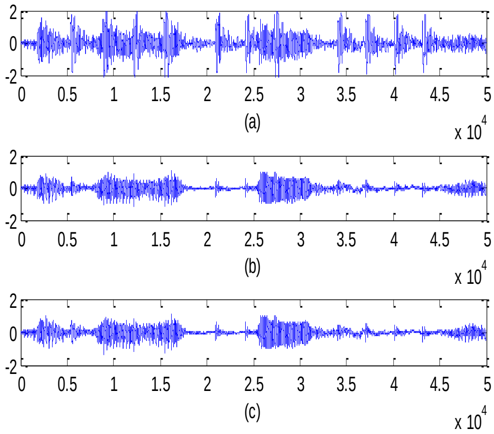

Figure 11**:** Typical filtering results of battle field noise removal (a) Speech signal with battle field noise, (b) recovered signal using LMS algorithm, (c) recovered signal using NLMS algorithm.

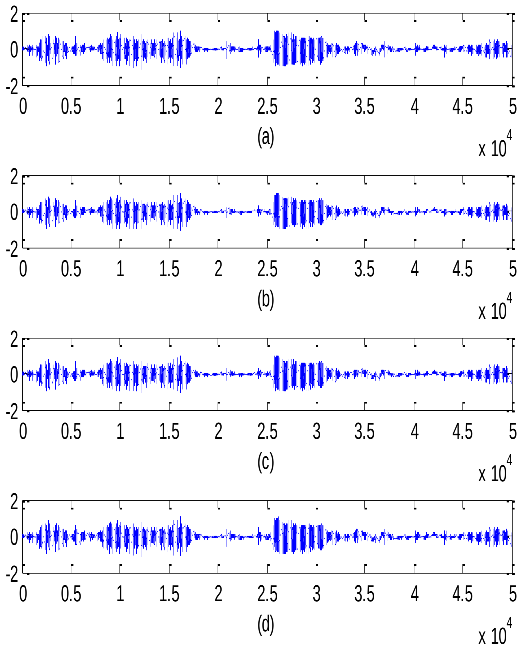

Figure 12**:** Typical filtering results of battle field noise removal (a) recovered signal using Karni's VSSLMS algorithm, (b) recovered signal using Kwongi's VSSLMS algorithm, (c) recovered signal using Mathew's VSSLMS algorithm, (d) recovered signal using Aboulnasr's VSSLMS algorithm.

3.5. Simulation Results for speaker noise removal

In this case speech signal contaminated with a loud speaker 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 figures 13 and 14. To evaluate the performance of the algorithms signal-to-noise (SNR) improvement is measured and tabulated in Table II.

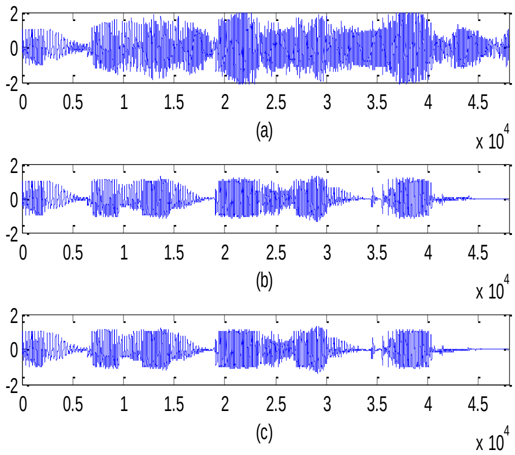

Figure 13**:** Typical filtering results of speaker noise removal (a) Speech signal with speaker noise, (b) recovered signal using LMS algorithm, (c) recovered signal using NLMS algorithm.

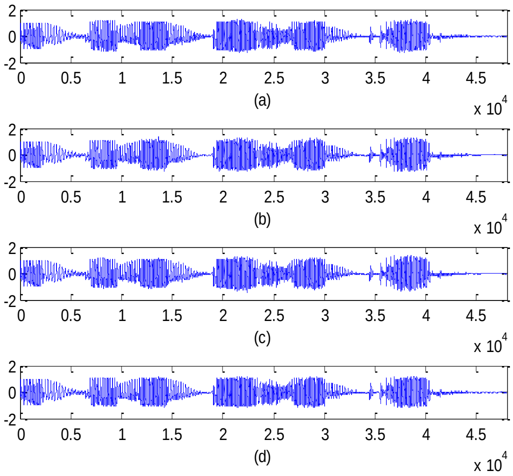

Figure 14: Typical filtering results of speaker noise removal (a) recovered signal using Karni's VSSLMS algorithm, (b) recovered signal using Kwongi's VSSLMS algorithm, (c) recovered signal using Mathew's VSSLMS algorithm, (d) recovered signal using Aboulnasr's VSSLMS algorithm.

Table II: SNR contrast of various algorithms.

Sample Number	SNR Imp. after LMS Filtering	SNR Imp. after NLMS Filtering	SNR Imp. after Karni's VSSLMS Filtering	SNR Imp. after Kwongs's VSS LMS Filtering	SNR Imp. after Mathew's VSS LMS Filtering	SNR Imp.after Aoulnasr's VSSLMS Filtering
Sample I	7.9095	6.3031	11.7786	11.9863	13.8720	15.7111
Sample II	8.2398	7.8904	11.9872	12.2897	13.5021	15.3921
Sample III	6.4891	6.6937	12.0739	12.9541	13.7289	14.9231
Sample IV	7.3642	7.7183	12.4923	13.1054	14.0625	15.8232

4. Conclusion

In this paper the problem of noise removal from speech signals using VSSLMS 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 VSSLMS algorithms is better than conventional LMS and NLMS algorithms in terms of SNR improvement and convergence rate. Hence these algorithms are acceptable for all practical purposes.

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