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An Adaptive Algorithm based Speech Processing technique for Clinical and Speech Therapy Applications

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Abstract: In all practical scenarios the extraction of noise free speech signals is an essential task. Many undesired noises are added with the desired speech signal during the transmission. The noises should be eliminated at the destination point. To eliminate the noises the basic widely used type of adaptive algorithm that is Least Mean Square (LMS) algorithm used in several practical applications due to its robustness and simplicity. Step-size is an important parameter in the LMS algorithm. For rapid step size, rate of convergence will be fast, but rise in mean square error (MSE) is main disadvantage. Apart from that, MSE will be small for the smaller step size, but convergence rate will be quit slowly. Hence, step size gives a tradeoff between rate of convergence and MSE. Performance of the algorithm is increased with variable step size parameter. With the variable step size parameter, we developed several variants of LMS algorithm; they are data variable LMS (DVLMS), error variable LMS (EVLMS), time variable LMS (TVLMS) and step variable LMS (SVLMS) algorithms. In these variants, step size is not fixed and it varies based on error signal at a particular instant. With these techniques improves the quality of the signal, the MSE will be decreased and the signal to noise ratio (SNR) also will be improved for speech signal. Several Adaptive noise elimination (ANE) techniques are developed based on these LMS variants and the performance of these ANEs is analyzed, the proposed schemes are well suited for clinical scenarios in speech therapy applications.

1. Introduction

From the decades Speech enhancement (SE) attracted front-end speech processing system. Speech signal enhancement in the random noise situations is the challenging task in speech processing. The SE deals with enhancing the quality of speech signals which are contaminated by undesired noise. Generally, SE is used as preprocessing step in speech processing to enhance the performance of the system in non-stationary noisy situations. Main aim is to eliminate noisy signal from speech input signals so that quality of speech signal is improved in applications lsuch as mobile communications, automatic speech recognition, in-car communication, voice coders, teleconference systems hearing aids and forensics [1], [2]. In [3] the authors presented a circular statistics-based speech enhancement technique that describes Kalman filtering based on modulation-domain to extract speech phase, in addition to large spectrum of noise and speech signals. In this technique, the speech phase posterior is used to establish an improved speech phase spectrum for restoration of speech signals. The nonlinear step models of Kalman filter updated under the consideration of noise and speech signal then they are added in the domain of Fourier transform complex short-time. In [4] $H\infty$ filtering technique is developed for speech enhancement system which contains adaptive in time domain as well as frequency domain beam formers to produce a noise free and undisturbed speech signal and enhances the rate of recognition in vehicle applications. Hardware is also developed for Microphone array data acquisition for the speech enhancement system. In [5] the authors presented adaptive center weighted average filter and empirical mode decomposition for speech filtering process. The mechanism lies in integrating frame class in conventional filtering process using empirical mode decomposition and adaptive center weighted average filter. By empirical mode decomposition signal is divided into frames and then each frame is divides into a finite number of intrinsic mode functions. The number of intrinsic mode functions depends on type of the signal whether it is voiced or unvoiced. To recognize frames as voiced frames an energy criterion is used, whereas a stationary index discriminates among the unvoiced frames and transient sequences.

In [6] proposed a particle filter technique for speech enhancement. To show non-Gaussian statistics and inter-frame dependencies spectral amplitudes are utilized, but, closed-form solutions are established by incorporating these properties makes intractable. By using Laplace distribution, speech spectral amplitudes are modeled as autoregressive method in particle filter technique. During transmission of speech signals in practical applications several desired signals are contaminated with noisy signals. To enhance the resolution of speech signals speech enhancement using several adaptive noise elimination (ANE) techniques are used. Perceptual quality and intelligibility of speech noise signals are improved with speech enhancement techniques. The general phenomenon in speech enhancement is generating noisy free speech signal by eliminating undesired noise. Filtering techniques are used for reducing the noise. Generally, there are two categories in filtering techniques, non-adaptive filtering and adaptive filtering [7]. The noise components can be eliminated by using estimation of noise characteristics in the conventional filtering. Hence prior knowledge of noise is required for non-adaptive filtering techniques such as Filtering techniques such as Infinite Impulse Response (IIR) filtering, Notch filter, Finite Impulse Response (FIR) filtering [8] etc. In practical scenarios we can’t predict the nature of noise. In non-adaptive filtering the weights of the filter are fixed irrespective of the amount of noise contamination. This leads to desire information loss due to the inaccuracy in filtering. Therefore, non-adaptive filtering techniques are not preferable in different noise environment. These drawbacks can be overcome by adaptive filtering [9] techniques. The key notation in the adaptive filtering is weights of the filter are varying from iteration to iteration related to the noise contamination in the output of the filter. So many such filtering techniques are available to change the filter weights [10]-[12]. Least Mean Square (LMS) adaptive algorithm is basic adaptive algorithm. In [13]-[15] adaptive solutions for signal processing are described based on the LMS adaptive algorithm. In updating filter weights of adaptive algorithm, step size is mainly considered. Steady state convergence rate [16]-[19] of the filter depends on step size parameter. A reference signal which is correlated noise contamination is required to perform adaptive filtering [20]-[25] operation. By varying step size parameter, we developed several ANEs to eliminate the noise and to increase the adaptive filter’s performance. The interested parameters in any technique are signal to noise ratio improvement (SNRI). convergence rate, minimum residual error, and computational complexity. To obtain better features we considered several methods to vary the step-size of adaptive algorithm instantly. The step size variants are data variable, error variable, time variable and step variable techniques. These are combined with LMS algorithm and results Data Variable LMS (DVLMS), Error Variable LMS (EVLMS), Time Variable LMS (TVLMS) and Step Variable LMS (SVLMS) algorithm. Several Speech Enhancement Units (SEUs) are developed based on these techniques. The performance of these SEUs is determined based on SNRI, Rate of convergence, computational complexity and computation complexity.

2. Adaptive algorithms for Speech Enhancement

Discrete Wavelet Transform

For analyzing signals, Wavelet transform is commonly used technique. The wavelet transform has the main advantage in providing the temporal and spectral knowledge about the signal, that means, for higher frequencies the wavelet transform provides well temporal resolution and for lower frequencies it provides well frequency resolution. Therefore, for analyzing multi resolution signals, wavelet transform is used. For a signal y(t), wavelet transform [26] is expressed as follows:

$$y(t) = \sum_{m} a_{Mm} \emptyset_{Mm} + \sum_{l=1}^{M} \sum_{m} d_{lm} \emptyset_{lm}(t) \quad (1)$$

Here aMm is approximate coefficient and dlm represents detail coefficients. By using these coefficients, the signal y(t) can be retrieved for M levels of decomposition and it is expressed as follows

$$y(t) = A_M(t) + \sum_{l=1}^{M} D_l\,(t) \quad (2)$$

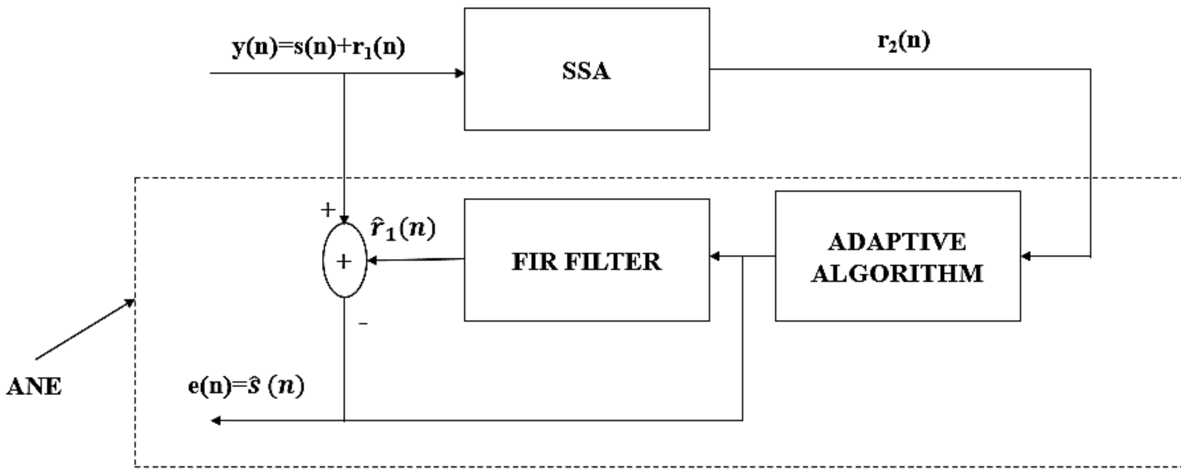

Fig: 1

3. Discrete Wavelet Transform Adaptive Noise Elimination (DWT-ANE)

The reference signal is generated using DWT-ANE, db4 mother wavelet from the contaminated speech signal. Wavelet decomposition is performed on input speech signal for seven decomposition levels to determine the coefficients. Then, soft thresholding technique is applied for the coefficients of least three levels and the newly derived coefficients are used in wavelet reconstruction process to generate reference signal for ANE. Finally, the signal which is correlated to noise components is generated and it is used as reference signal which is subtracted from the corrupted input speech signal at the output of ANE to generate actual speech signal $\hat{s}(n)$. In the DWT-ANE, the type of wavelet decomposition and the decomposition levels are mostly based on spectral characteristics and morphology of the source of interest. This is the main drawback of this technique. To overcome this problem, we developed SSA-ANE mechanism which is not dependent on the signal of interest morphology.

4. Singular Spectrum Analysis

The SSA is a subspace-based method and it is used for climatic and geophysics time series analysis. SSA comprises of four basic steps: embedding, decomposition, grouping, and reconstruction. In embedding, the contaminated speech signal vector y is represented as multivariate data matrix with L rows and J columns. Trajectory matrix Y with $L \times J$ dimensions is produced and it is expressed as,

$$Y = \begin{bmatrix} y\,(1) & y\,(2) & \dots & y\,(J) \\ y\,(2) & y\,(3) & \dots & y\,(J+1) \\ \vdots & \vdots & \vdots & \vdots \\ y\,(L) & y\,(L+1) & \dots & y\,(N) \end{bmatrix} \tag{3}$$

Here $J = N - L + 1$ and L represents size of window. Window size is based on L > fs / f condition, here, sampling frequency is represented with fs, f represents signal frequency. All elements in anti-diagonal parts of the Y matrix are identical.

In the decomposition step the **Y** matrix is decomposed into L trajectory matrices, $\mathbf{Y}_1, \mathbf{Y}_2, \ldots, \mathbf{Y}_L$. The covariance matrix $\mathbf{C} = \mathbf{Y}\mathbf{Y}^T$ is determined. For the covariance matrix the eigenvalues are $\lambda_1, \lambda_2, \ldots \lambda_L$ and eigenvectors are $\mathbf{v}_1, \mathbf{v}_2, \ldots, \mathbf{v}_L$. The eigenvalues are arranged in the form of $\lambda_1 \geq, \ldots, \geq \lambda_L \geq 0$ and also the respective eigenvectors $\mathbf{v}_1, \mathbf{v}_2, \ldots, \mathbf{v}_L$. The i^{th} trajectory matrix $\mathbf{Y}_i$ can be represented as

$$Y_i = \sqrt{\lambda_i}\, v_i u_i^T \qquad i \in \{1,2,\ldots,L\} \tag{4}$$

where $u_i = Y^T v_i / \sqrt{\lambda_i}$. By substitution of $\mathbf{u}_i$ in the above equation, the matrix $\mathbf{Y}_i$ is expressed in terms of eigenvectors **C** matrix and it is expressed as

$$Y_i = v_i v_i^T Y \tag{5}$$

The term $v_i v_i^T$ denotes the i^{th} subspace component.

The Y matrix is projected onto that subspace that leads to generate trajectory matrix for i^{th} signal of **y**. The actual trajectory matrix Y can be reproduced by using

$$Y = \sum_{i=1}^{L} Y_i \tag{6}$$

In the grouping step, the trajectory matrices $\mathbf{Y}_i$ are portioned into d categories, based upon the eigenvalues here the condition is $d < l$. Let $K = \{k_1, \ldots, k_q\}$ indicates the indices relating to the q eigenvalues of the signal. Then the K^{th} trajectory matrix can be expressed as $\hat{Y}_K = \sum_{l=k_1}^{k_q} Y_l$. The d disjoint subsets are formed by grouping the L eigenvalues *i.e.* $K_1, K_2, \ldots, K_d$, then the **Y** can be expressed as

$$Y = \sum_{m=1}^{d} \hat{Y}_{K_m} \tag{7}$$

In reconstruction step, estimated trajectory matrix *i.e.* $\hat{Y}_I$, is maps into single channel signal, here I is eigenvalue indices. For instance, let $\hat{Y}_{k_j}$ is a component of $\hat{Y}_I$ at k^{th} row and j^{th} column, a single channel signal is generated by averaging all the components of k and j in anti-diagonal parts of $\hat{Y}_I$.

5. Extraction of Reference Signal for ANE

Identifying subspace of the signal is the significant step in SSA [27]. In our proposed method, based on the eigenvalues the subspace of a signal can be recognized. A novel grouping criterion is used which is based upon the eigenvector's local variations. The local variations m_v of an eigenvector $\boldsymbol{v} = [v(1), v(2), \ldots, v(L)]$ having L samples can be expressed as

$$m_v = \frac{\sqrt{\frac{\sum_{j=1}^{L-1} z^2(j)}{L-1}}}{\sqrt{\frac{\sum_{j=1}^{L} v^2(j)}{L}}} \tag{8}$$

here, $z(j) = v(j) - v(j-1)$ represents the successive samples difference in v. The local mobility for every eigenvector is calculated to determine the subspace of noise. Then threshold is selected based on prior knowledge like maximum noise frequency after that the arguments are determined for the respective eigenvectors. Then the trajectory matrices are determined using (5). A single channel signal for noise vector $r_2 = [r_2(1), r_2(2), \ldots, r_2(N)]$ is constructed using trajectory matrix, in N bit register buffer it is stored after generation and combining of by all noise trajectory matrices then it applied as reference signal for noise cancellation in ANE.

6. SSA-ANC

In this the contaminated speech signal **y** and SSA generated noise signal $\mathbf{r}_2$ are given as primary and reference inputs for ANC to eliminate the noise in the contaminated speech signal. Adaptive filter updates its filter weights by taking $\mathbf{r}_2$ samples and estimates $\hat{r}_1(n)$signal. At every instant of time *n*, from speech signal y(n) contaminated signal $\hat{r}_1(n)$ is subtracted, then it produces actual speech signal $\hat{s}(n)$. This phenomenon is performed for all the data blocks individually. To get actual speech signal amount of time taken is considered as sum of time taken from parallel to serial converter, serial to parallel converter and ANC operating time. For practical applications the proposed technique is more advantageous since the time taken for getting actual speech signal is significantly lesser than that of the of the speech signal sampling interval.

The block diagram representation of SSA based adaptive filtering technique is shown in figure 1. ANE comprises of FIR filter and a weight update algorithm. Here several strategies are proposed for weight updating of FIR filter. For this purpose, LMS adaptive filter is considered with filter length of *M*. The input for the SSA as well as adaptive filter is contaminated speech signal y(n). y(n) is combination of original speech signal s(n) and noise signal $r_1(n)$. The output of SSA is reference signal $r_2(n)$ it is correlates of contaminated signal y(n) with noise components. Let the impulse response of the FIR filter is p(n), output is q(n), and e(n) is error signal generated in ANE. If we use LMS technique in the adaptive weight update then the weight updating can be expressed as

$$p(n+1) = p(n) + sy(n)e(n) \tag{9}$$

In (9), $p(n) = [p_0(n)\, p_1(n) \ldots p_{M-1}(n)]^t$ represents the weight vector of size M at n^{th} time instance, $y(n) = [y(n)\, y(n-1) \ldots y(n-M+1)]^t$ represents input sequence, $e(n) = y(n) - p^t(n) r_2(n)$ and ‘s’ is the step-size parameter.

Step size parameter exhibits major role in the practical application of an adaptive. For large step size the convergence rate will be fast, but the MSE is going to be raised and if it is small then MSE will be reduced, but the convergence rate is slow. Hence, step size is the key parameter in the performance of the filter. For improving performance of adaptive filter algorithm, step size is considered as variable value rather than constant step size value i.e., in adaptive filter algorithm at the initial stage, ‘s’ value should be large, later when adaptive algorithm reaches its steady state ‘s’ value should be small, that leads to Variable Step Size (VSS) algorithms. Therefore, VSSLMS algorithm is developed by incorporating the variable step size strategy in the weight updating process of LMS adaptive algorithm. To increase the convergence rate and noise eliminating capability of the adaptive filter, ‘s’ should be upgraded continuously in an efficient manner. In the speech processing applications, the amount of noise contamination may change rapidly. Hence, variable step size methods are better than the fixed. Based on this phenomenon, we developed a set of novel adaptive algorithms with reference to data variable (DV), error variable (EV), time variable (TV) and step variable (SV) techniques to eliminate the noise in ANE. By incorporating these four variants with LMS algorithm that gives DVLMS, EVLMS, TVLMS and SVLMS adaptive algorithms. In DVLMS the variable step size inversely related the total expected energy of weights of input vector. Generally, DVLMS algorithm converges more than that of LMS, this is due to the variable convergence utilization to minimize of output error. In this technique the step-size is varying according to squared norm of input data vector *y(n)*. The weight updating of DVLMS adaptive algorithm can be expressed as,

$$p(n+1) = p(n) + s(n)y(n)e(n) \tag{10}$$

Where *s(n)* is represented by,

$$s(n) = \frac{s}{u + y^t(n)y(n)}$$

The parameter *u* is chosen in such a way that it avoids the denominator becoming too small that leads to larger step size.

In the EVLMS with respect to error vector, step size is normalized. Number of iterations are the size of the error vectors. In this technique the step-size is varying according to squared norm of the error vector *e(n)*. Signal distortion can be significantly reduced with this algorithm. In EVLMS the step size is chosen individually, it does not depend on filter weights and the signal power. Hence this technique has better performance than that of LMS. The weight updating of EVLMS adaptive algorithm can be expressed as,

$$p(\,n+1) = p(\,n) + s_e(\,n)y(\,n)e(\,n) \tag{11}$$

Where $s_e(n)$ is error normalized variable step size parameter, and it expressed as,

$$s_e(n) = \frac{s}{u + e^t(n)e(n)}$$

It is very crucial to set the step size for the signals which are indeterminate manner, for this purpose a time varying step size model of LMS algorithm is developed using decaying function. The weight updating of EVLMS adaptive algorithm can be represented as,

$$p(n+1) = p(n)+s \times y(n) \times e(n) \tag{12}$$

At each iteration the step size can be vary based on the following expression,

$$s(n) = \alpha(n) \times s(0)$$

In the above expression the decaying factor $\alpha(n) = C(1/(1 + b^n \times d))$. C, b and d are positive parameters used to determine the value of $\alpha(n)$. In each iteration the $\alpha(n)$is multiplied by the step size. The TVLMS algorithm exhibits better convergence rate than LMS algorithm with fixed step size parameter and also eliminate the noise efficiently.

In a situation such as gradient noise is contaminated with the desired speech signal, the weights of the adaptive filter are changing in a random manner instead of terminating on Weiner solution. To solve such difficulties SVLMS algorithm is developed by adding a fourth step to the LMS technique. The weight updating of EVLMS adaptive algorithm is expressed as,

$$p(\,n+1) = p(\,n) + s_s(\,n)z(\,n)r(\,n) \tag{13}$$

Then the updated step size parameter is represented as,

$$s_s(n+1) = s_s(n) + \rho \times s(n) \times e(n) \times \gamma(n)$$

Hereρ represents a low positive constant and $\gamma(n)$ is expressed as partial derivative of $p(n)$ with respect to $s(n)$.

$$\gamma(n) = \frac{\delta p(n)}{\delta s(n)}$$

SVLMS exhibits faster convergence rate than the LMS algorithm. This is due to the step size of current iteration depends on the input and error vectors of previous iteration.

7. Results

The proposed algorithm convergence characteristics are shown in the fig.2.The convergence rate is the rate at which system converges to its resultant state. Generally, main requirement of adaptive systems is fast convergence rate. other performance characteristics does not influence the convergence rate. But there will be a trade-off with other performance characteristics, i.e., the increase in other performance characteristics with decreased convergence performance and vice versa. Let us consider, with increased convergence rate its stability of the system is decreased and the system becomes more diverge to give proper solution. On the other side the adaptive system achieves more stability with decrease in convergence rate. Using SVLMS algorithm it's clear that it achieves faster converges when compared to other adaptive algorithms.

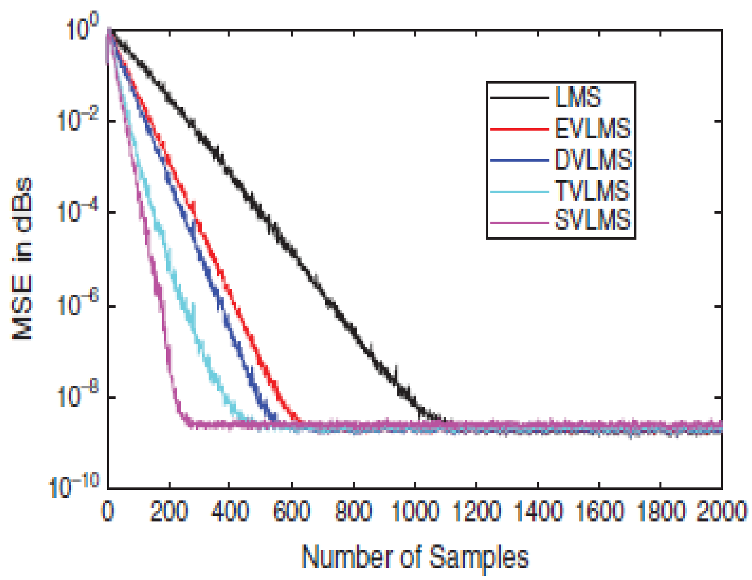

Fig. 2: Convergence characteristics of LMS and variable step size algorithms

In this paper several speech enhancement units are developed using LMS, DVLMS, EVLMS, TVLMS, and SVLMS algorithms. For all these adaptive filters the window size is taken as five. In the simulation experiments the noise elimination process is performed initially by applying additive Gaussian noise after that real noise are applied to various speech signals. From the data base five sample speech signals are taken for the experiments. The performance of the developed techniques is evaluated by taking synthetic as well as real noises and non-stationary tracking performance of adaptive algorithms. Table 1 represents the types of noises taken for our experiments. The ability of the developed SEUs is measured from the simulations. SNRI performance is measured and is mentioned in Table 2. Five speech signal samples are Wave-1, Wave-2, Wave-3, Wave-4 and Wave –5. Wave-I with 53569 samples it is practically recorded signal using anc.wav. Wave-2 & Wave-3 are male speech signals with 95232 samples and 100864 samples respectively taken from data base, wave-IV& Wave-V are female speech signals with 103936 samples and 114176 samples respectively taken from data base. Performance analysis of proposed techniques are evaluated and they are shown in table 2 and figure 3. Among all proposed techniques SVLMS based SEUs are better for any type of noise filtering.

Table 1: Noise types used in simulation

S. No	Noise type
1	Helicopter Noise
2	Crane Noise
3	High Voltage Murmuring Noise
4	Battle Field Noise
5	Random Noise

In figure 3, simulation results of removed helicopter noise is shown and it is obtained by using speech signal of wave 1. In terms of signal to noise ratio improvement, performance improvement is shown of all contaminated noise sample signals.

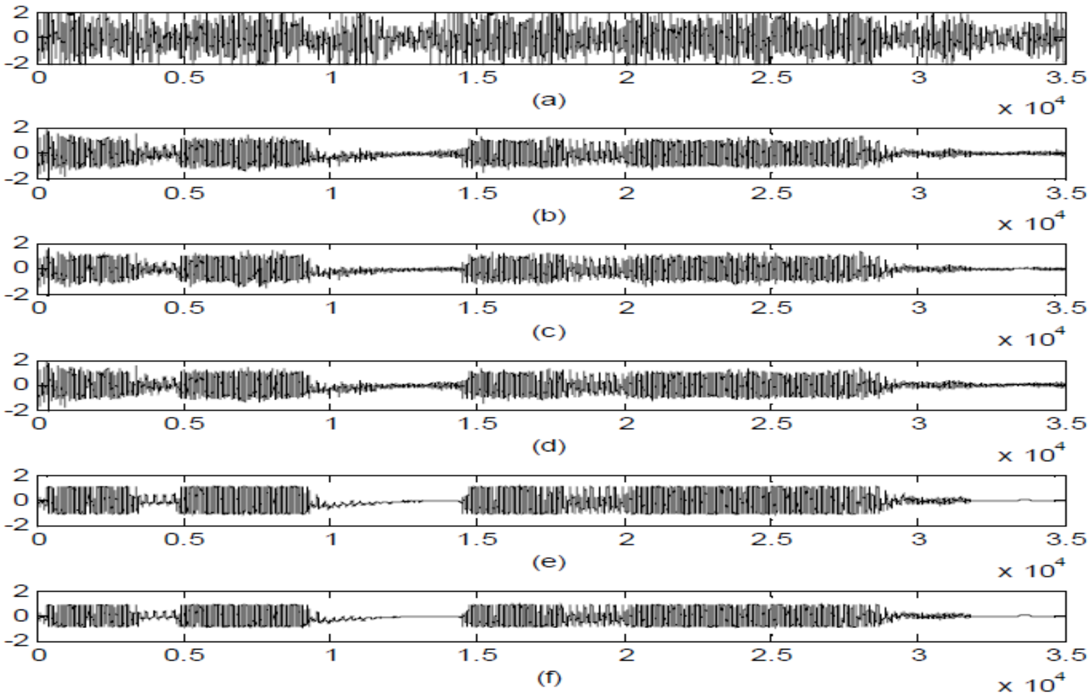

Fig.3: Helicopter Noise Removal Filtering Results for Sample – I (a) Contaminated Speech Signal, (b) Using LMS Algorithm recovered signal, (c) Using DVLMS Algorithm (d) Using EVLMS Algorithm (e) Using TVLMS (f) Using SVLMS Algorithms.

8. CONCLUSION

In this paper we developed some efficient speech enhancement methods. Several variable step size strategies are used to achieve convergence speed and filtering capability. In that contest data variable, error variable, time variable and step variable adaptive filtering techniques are implemented with the conventional Least Mean Square algorithm. As a result, various SEUs are developed using DVLMS, EVLMS, TVLMS, SVLMS algorithms. The performance of the proposed techniques is evaluated by eliminating noises like

Helicopter Noise, High Voltage Murmuring Noise, Battle Field Noise, Crane Noise and Random Noise from desired speech signals. The performance is measured in terms of SNRI, EMSE, MSAD. From the experimentation results it is clear that SVLMS has better filtering capability than the other algorithms. Hence, for speech enhancement process SVLMS based SEUs are preferable, the proposed schemes are well suited for clinical scenarios in speech therapy applications.

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