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ADAPTIVE SPEECH ENHANCEMENT TECHNIQUES FOR COMPUTER BASED SPEAKER RECOGNITION

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ABSTRACT

Extraction of high resolution speech signals is important task in all practical applications. During the transmission of desired signals many noises are contaminated. The Least Mean Square (LMS) algorithm is a basic adaptive algorithm has been widely used in many applications as a significance of its simplicity and robustness. In practical application of the LMS algorithm, an important parameter is the step size. It is well known that if the convergence rate of the LMS algorithm will be rapid for the step size is fast, but the drawback is steady-state mean square error (MSE) will raise. On the other side, for the small step size, 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. Make the step size variable rather than fixed to enhance the performance of the LMS algorithm, 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 Normalized LMS (NLMS) algorithms. In this technique the step size is not constant and varies according to the error signal at that instant. In order to improve the quality of the speech signal, decrease the mean square error and increasing signal to noise ratio of the filtered signal, Weight Normalized LMS(WNLMS), Error Normalized LMS(ENLMS), Unbiased LMS (UBLMS) algorithms are being introduced as quality factor. These Adaptive noise cancellers are compared with respect to Signal to Noise Ratio Improvement (SNRI).

Keywords: *Adaptive filtering, Noise cancellation, SNRI, Speech enhancement, Unbiased.*

1. INTRODUCTION

Speech enhancement improves the quality and intelligibility of voice communication for a wide range of applications [1-3] including mobile phones, hands-free phones, in-car communication, teleconference systems, hearing aids, voice coders, automatic speech recognition, and forensics. In real time environment the speech signals are corrupted by several forms of noises. In all such situations extraction of high resolution signals is the important task. The main goal of speech enhancement is to improve the quality of speech signals by using various adaptive noise cancellation (ANC) techniques. The intention is to improve the intelligibility and overall perceptual quality of the degraded speech signal by using signal processing tools. The most common approach in speech enhancement is noise removal and retaining the clean speech signal only. For eliminating noise we use filtering process. Basically filtering techniques are broadly classified as non-adaptive and adaptive filtering [4] techniques. In conventional filtering techniques by estimation of noise characteristics we cancel noise components. So using non adaptive filtering techniques requires prior information about the noise characteristics. In practical cases the statistical nature of information signal is non-stationary; as a result non-adaptive filtering may not perform better in different forms of noise. Filtering techniques like Finite Impulse Response (FIR) filtering, Infinite Impulse Response (IIR) filtering, Notch filter [5] etc., are the examples of non-adaptive filtering techniques. In all these filters the filter tap coefficients are constant irrespective of the noise characteristics. This leads to inaccurate filtering, causes lost of information content. In order to avoid these problems adaptive signal processing [6] presents several filtering techniques. In these techniques the key point is the filter tap coefficients are not constant, rather, they varies from one iteration to another, in accordance with the noise contamination residual in the output signal. There are varieties of such filtering algorithms are available to update the coefficients [7]-[9]. Among all algorithms the Least Mean Square (LMS) algorithm is the fundamental algorithm. Several papers have been presented in

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the area of adaptive signal processing [10]-[12] where an adaptive solution based on the LMS algorithm is suggested. In a recent study, however, a steady state convergence [13]-[15] 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. The step size according to which the filter weight coefficients are updating is constant due to which it is called as biased.

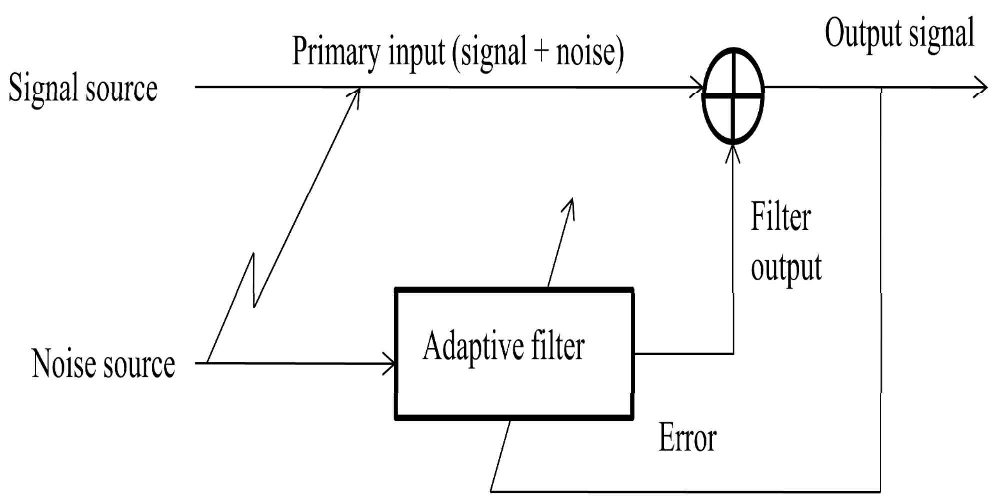

Figure 1: Block Diagram Of An Adaptive Noise Cancellation System.

To handle this drawback another strategy was considered for estimating the coefficients of the filter is given by Normalized Least Mean Square (NLMS) algorithm [16]-[18]. In this technique the step size is not constant and varies according to the input signal at that instant. In order to decrease the mean square error and improve the quality of the speech signal by removing noise and increasing signal to noise ratio of the filtered signal, Weight Normalized LMS(WNLMS) [19], Error Normalized LMS(ENLMS), Unbiased LMS (UBLMS) [20], [21] algorithms are being introduced. For practical implementation we have taken original speech signal and five different noises from the data base. In Section 2, the adaptive algorithms used for speech enhancement are presented and discussed. Section 3 presents the simulation results and discussions on results. Section 4 concludes the research work presented in this paper.

2. ADAPTIVE ALGORITHMS FOR NOISE CANCELLATION

Fig. 2 shows the block diagram for the adaptive filter method used in this paper. Here we indicate the FIR filter coefficients as tap weight vector, i(n) represents vector samples, z^{-1} indicates the delay of one sample periods, o(n) is adaptive filter output, g(n) represents the desired echoed signal and c(n) is the estimation error at time instance n. The goal of an adaptive filter is to measure the difference between the desired signal and the output of adaptive filter, c(n). This error signal is fed back to the adaptive filter and its coefficients are updated algorithmically in order to minimize difference parameter, known as the cost parameter. In the case of noise cancellation, the optimal adaptive filter output is equal in value to the unwanted signal. When the output of adaptive filter is equal to the desired signal the error signal is zero. In this situation the contaminated signal would be completely cancelled and at the other end user would not hear any of their original speech returned to them.

This section organizes with adaptive filters with various algorithms. The Mean Square Error (MSE) adaptive filters are aimed to minimize a cost function equal to the expectation of the square of the difference between the desired signal g(n), and the actual output of the adaptive filter o(n).

$$z(n)=E[c^2(n)]=E[(g(n)-o(n))^2] \quad (1)$$

2.1 The Least Mean Square (LMS) algorithm

The derivation of the LMS algorithm builds upon the theory of the wiener solution for the optimal filter tap weights, u_0. It also depends on the steepest descent algorithm [4], this is a formula which updates the filter coefficients using the current tap weight vector and the current gradient of the cost function with respect to the filter tap weight coefficient vector, ∇z(n).

$$u(n+1)=u(n)-S\nabla z(n) \quad (2)$$
$$z(n)=E[c^2(n)]$$

As the negative gradient vector points in the direction of steepest descent for the N dimensional quadratic cost function, each recursion shifts the value of the filter coefficients closer toward their optimum value, which corresponds to the minimum achievable value of the cost function, z(n). The LMS algorithm is a random process [6] implementation of the steepest descent algorithm.

Here the expectation for the error signal is not known so the instantaneous value is used as an estimate. The steepest descent algorithm then becomes,

$$u(n+1)=u(n)-S\nabla z(n) \quad (3)$$

where $z(n)=c^2(n)$

Finally, the recursion for the LMS [5-8] adaptive algorithm can be written as,

$$\mathbf{u}(n+1) = \mathbf{u}(n) + 2Sc(n)\mathbf{i}(n) \quad (4)$$

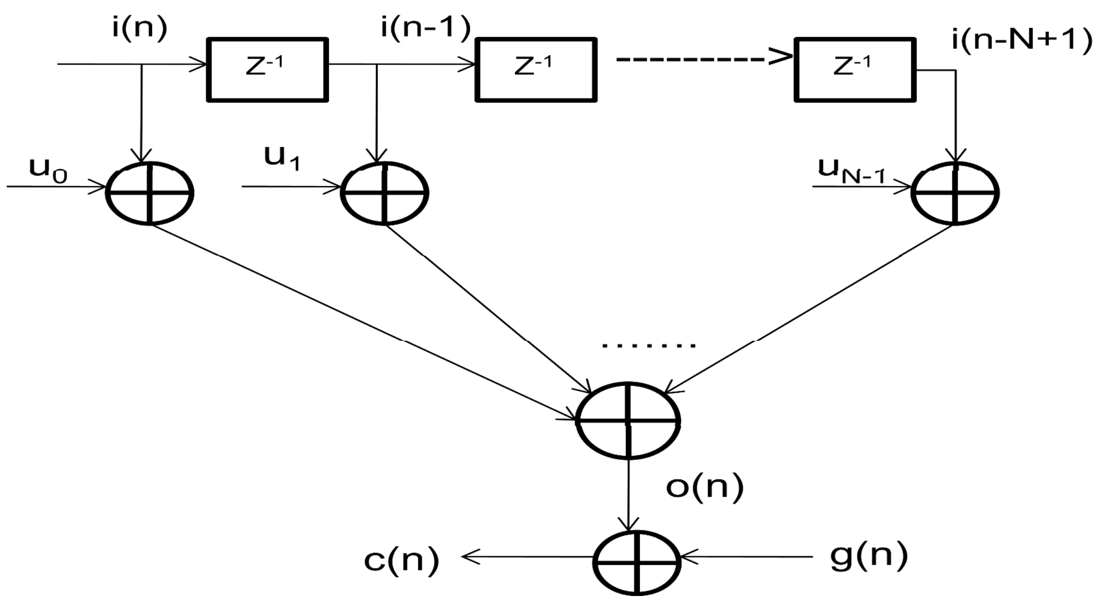

Figure 2: Block Diagram Of An Adaptive Filter.

2.2 The Normalized LMS (NLMS) Algorithm

NLMS algorithm is another class of adaptive algorithm used to train the coefficients of the adaptive filter. One of the problems in design and implementation of the LMS adaptive filter is the selection of the step size. For the stationary process the LMS algorithm converges in the mean if $0 < S < \frac{2}{\delta_{max}}$ and converges in the mean square if $0 < S < \frac{2}{tr(R_x)}$, however, since the R_x is generally unknown then either, δ_{max} or R_x, must be estimated in order to use these bounds.

The bound on the step size for mean-square convergence:

$$0 < S < \frac{2}{i^T(n)i(n)}$$

more over the upper bound is given as

$$S(n) = \frac{S}{i^T(n)i(n)} = \frac{S}{||i(n)||^2} \quad (5)$$

In overcoming the gradient noise amplification problem associated with the conventional LMS filter, the normalized LMS filter introduces a problem of its own, namely the tap input vector **i**(n) is small, numerical difficulties may arise because then we have to divide by a small value for the squared norm. To overcome this problem, we modify the above recursion by adding a small positive constant α. The parameter α is set to avoid denominator being too small and step size parameter is too big.

Now the step size parameter is written as,

$$S(n) = \frac{S}{\alpha + ||i(n)||^2} \quad (6)$$

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where $S(n)$ is a normalized step size with $0 < S < 2$. Replacing S in the LMS weight vector update equation with S (n) leads to the NLMS, which is given as

$$u(n+1) = u(n) + \frac{S}{||i(n)||^2} c(n)i(n) \qquad (7)$$

In the LMS algorithm, the correction that is applied **u**(n) is proportional to the input vector **i**(n) is large, the LMS algorithm experiences a problem with gradient noise amplification. With the normalization of the LMS step size by $||\boldsymbol{i}(n)||^2$ in the NLMS algorithm, however, this noise amplification problem is diminished. Although the NLMS algorithm bypasses the problem of noise amplification, we are now faced with a similar problem that occur when $||i(n)||$ becomes too small. An alternative is to use the following modification to the NLMS algorithm:

$$\boldsymbol{u}(n+1) = \boldsymbol{u}(n) + \frac{S}{\alpha + ||\boldsymbol{i}(n)||2} c(n)\boldsymbol{i}(n) \qquad (8)$$

the update equation of NLMS is a scaled version of that of LMS algorithm. The size of the change to weight vector **u**(n) is therefore be in inversely proportional to the norm of data vector **i**(n). The data vector **i**(n) with a large norm will generally lead to a small change to **u**(n) than a vector with a smaller norm. This normalization results smaller step size values than conventional LMS. The normalized algorithm usually converges faster than the LMS algorithm, since it utilizes a variable convergence factor aiming at the minimization of the instantaneous output error.

2.3 Error Normalized LMS (ENLMS)Algorithm

In NLMS algorithm we choose variable step size parameter rather than constant step size as in LMS algorithm. It is given by

$$S(n) = 1/k+(i^T(n)i(n)) \qquad (9)$$

For normalizing the step size parameter here input data vector is taken. Instead of input data vector error vector can be taken. So in ENLMS the varying step size parameter is inversely proportional to squared norm of the estimated error vector whose length is equal to the number of iterations.

The advantage of using ENLMS algorithm lies in decreasing excess mean square error which will reduce the signal distortion. In LMS based algorithms, the noise cancelled signal contains large value of excess mean square error. The filter coefficient update equation is given by

$$u(n+1)=u(n)+(1/k+(c^T(n)c(n)))i(n)c(n) \qquad (10)$$

The step size parameter can be given as,

$$S(n) = 1/k+(c^T(n)c(n)) \qquad (11)$$

2.4 Weight Normalized LMS (WNLMS) algorithm

In NLMS algorithm we choose variable step size parameter rather than constant step size which improves the convergence speed. It is given by,

$$S(n) = 1/k+(c^T(n)c(n)) \qquad (12)$$

In this weight normalized LMS algorithm, for normalizing the step size parameter, maximum value of the tap weight vector is taken. So in WNLMS the varying step size parameter is inversely proportional to squared norm of the maximum value of the tap weight vector.

The advantage of using WNLMS algorithm lies in improving the (SNR) Signal to Noise Ratio of the original signal by removing the noise from the primary input. The filter coefficient update equation is given by

$$u(n+1)=u(n)+ (1/k+(\max(u)\max(u))))i(n)c(n) \qquad (13)$$

The step size parameter can be given as,

$$S(n) = 1/k+(\max(u)*\max(u)) \qquad (14)$$

u(n) = $[u_0(n)\ u_1(n-1)u_2(n-2)..u_{N-1}(n-N+1)]^T$, it is the adaptive FIR filter coefficient vector.

2.4 The Unbiased LMS (UBLMS) algorithm

Set the coefficients to uniformly distributed random values with zero mean and unit variance. Normalize the coefficients to have unit sum. At time instant n, activate the UBLMS model [26] with noise reference r(n) and estimated values of the coefficients $\hat{u}_k(n)$

$$f(n) = \sum_{m=1}^{M} \hat{u}_m(n) j(n-m+1)$$

For the UBLMS [26] updated the coefficients for the next time instant $n + 1$ is given as

$$u_k(n+1) = u_k(n) + 2\gamma j(n-k+1) \sum_{m=1}^{M} u_m(n)[i(n) - j(n-m+1)] \qquad (15)$$

$$\hat{u}_k(n+1) = \frac{u_k(n+1)}{\sum_{k=1}^{M} u_k(n+1)}$$

Where , j(n): present noise reference input sample
$j(n - m + 1)$: preceding $m - 1$, $(1 < m \leq M)$, noise reference input samples

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i(n): present noise-contaminated primary input sample
γ: learning-rate parameter, a positive constant
$u_k(n)$: instantaneous value of the k th coefficient during the adaptation process
$\hat{u}_k(n + 1)$: estimated value of the k th normalized coefficient for time instant n + 1. Based on these algorithms a typical speech enhancement unit is designed. The typical block diagram is shown in Fig. 3.The recorded speech signal is tested for type of noise using power spectral density (PSD) estimation. Based on the area under the PSD curve, the type of noise is identified and the corresponding reference signal is supplied to the speech enhancement unit.

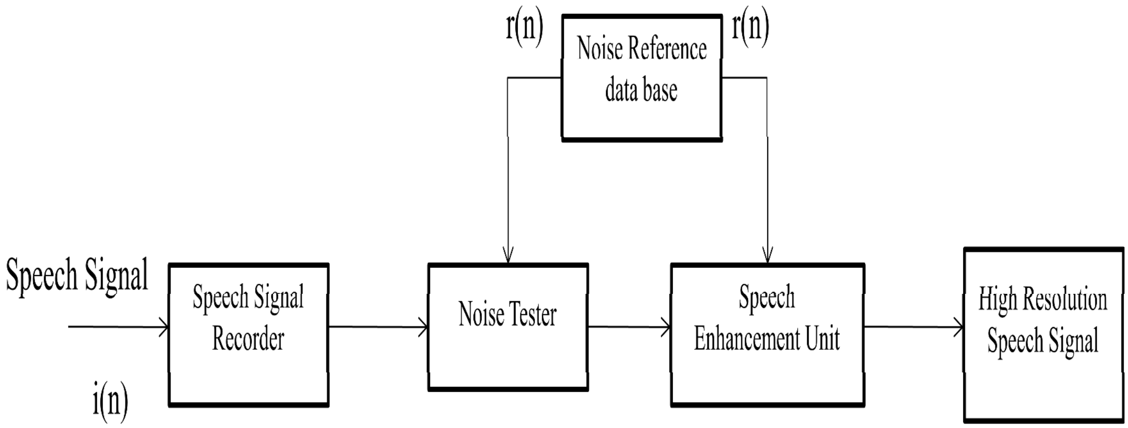

Figure 3: A typical block diagram of Experimental Setup used for Speech enhancement

3. RESULTS & DISCUSSION

Fig.5. shows the convergence curves for various algorithms. The convergence rate determines the rate at which the filter converges to its resultant state. Usually a faster convergence rate is a desired characteristic of an adaptive system. Convergence rate is not, however, independent of all of the other performance characteristics. There will be a tradeoff, in other performance criteria, for an improved convergence rate and there will be a decreased convergence performance for an increase in other performance. For example, if the convergence rate is increased, the stability characteristics will decrease, making the system more likely to diverge instead of converge to the proper solution**.** Likewise, a decrease in convergence rate can cause the system to become more stable from the figure it is clear that SRUBLMS algorithms converge fast than the conventional algorithms.

In this paper various adaptive noise cancellers are implemented using LMS, NLMS, WNLMS, ENLMS, and UBLMS algorithms. In all the filters the filter length is chosen as five. In this experiment initially the concept of noise cancellation is proved by applying additive Gaussian noise and then several speech signals with real noise are applied. To prove the ability of the proposed adaptive algorithms speech signals are chosen for filtering. For that purpose five sample speech signals are taken from the data base. Both synthetic and real noises are taken to prove the performance analysis of the proposed adaptive algorithms and the non-stationary tracking performance of the algorithms. These noises are mentioned in the Table 1. The methodology of speech enhancement unit is shown in Fig. 4. Using the algorithms discussed in section 2, various speech enhancement units are developed and tested for the ability of noise cancellation. The performance measure is computed in terms of SNRI and are recorded in Table 2.

The wave-I is anc.wav which is practically recorded signal with 53569 samples. wave-II is male signal obtained from database and it has 95232 samples. Wave-III is a male voice recorded one with 100864 samples, wave-IV has 103936 samples and wave-V are female speech signals from data base records with 114176 samples respectively.

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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

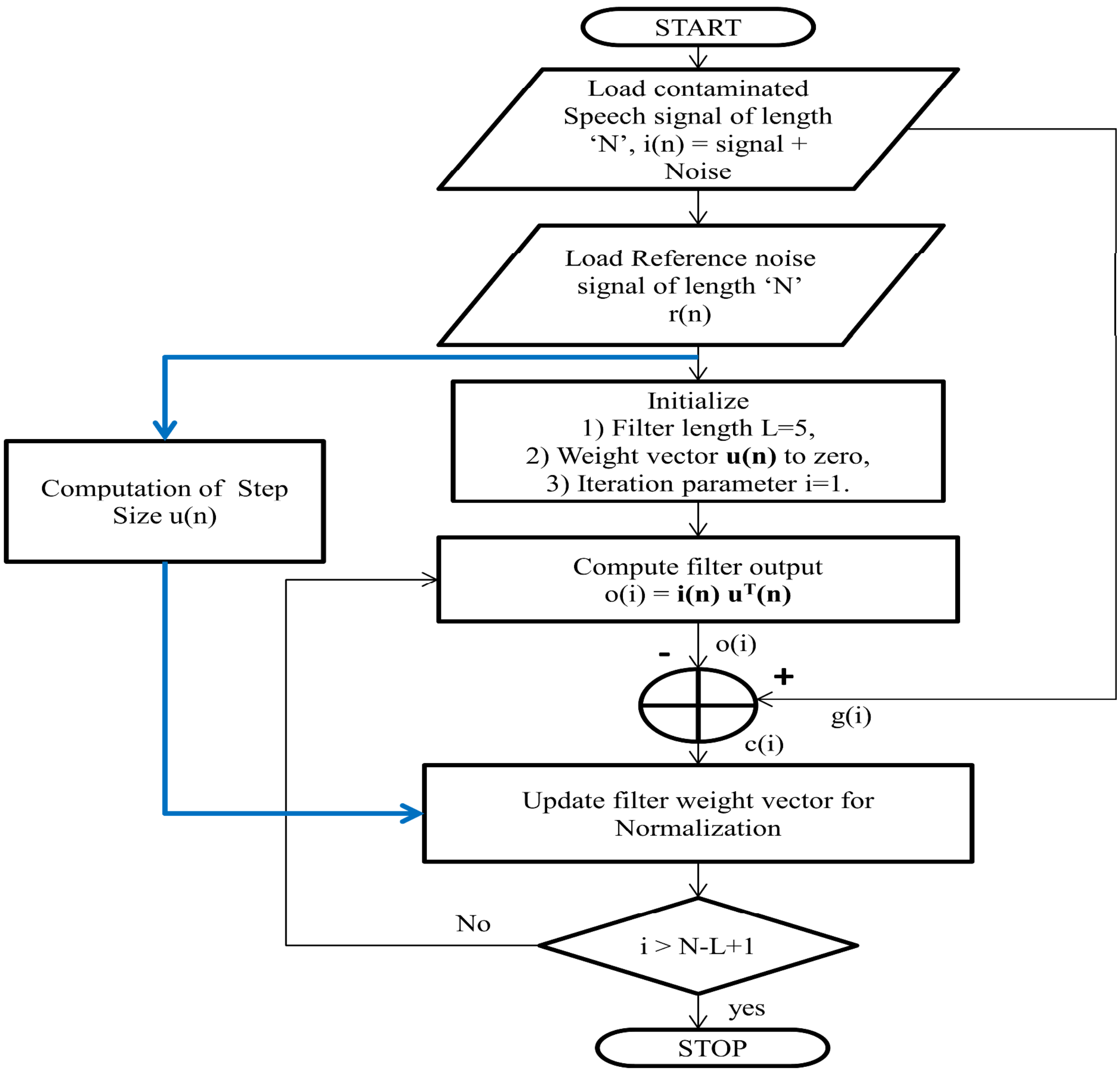

Figure 4:Methodology Of Speech Enhancement Using The Experimental Setup Shown In Figure.3.

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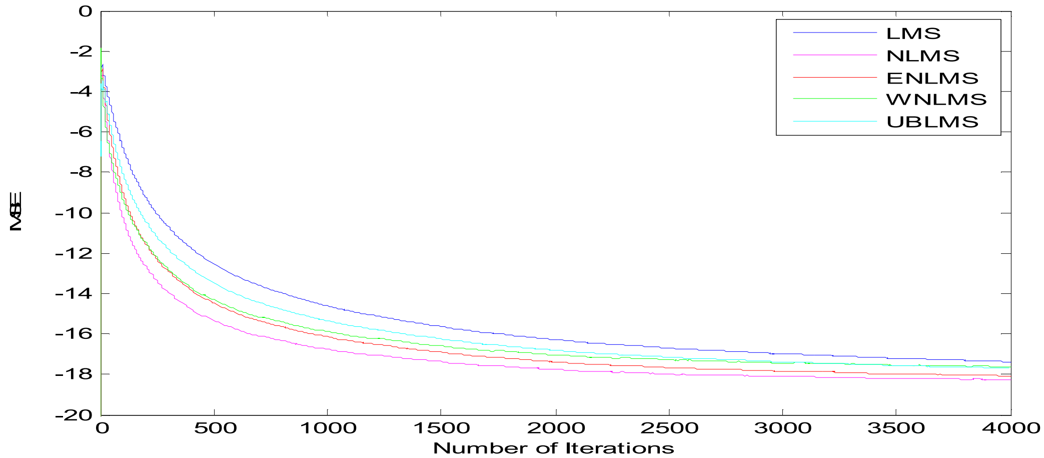

Figure 5: Convergence Curves For Various Adaptive Algorithms During Speech Enhancement

The simulation results for removal of helicopter noise is shown in the Fig.6. these results are the simulation outputs for wave-1 speech sample. The performance of all types of samples contaminated with various noises are measured in terms of signal to noise ratio improvement (SNRI). These parameter values are represented in Table 2.

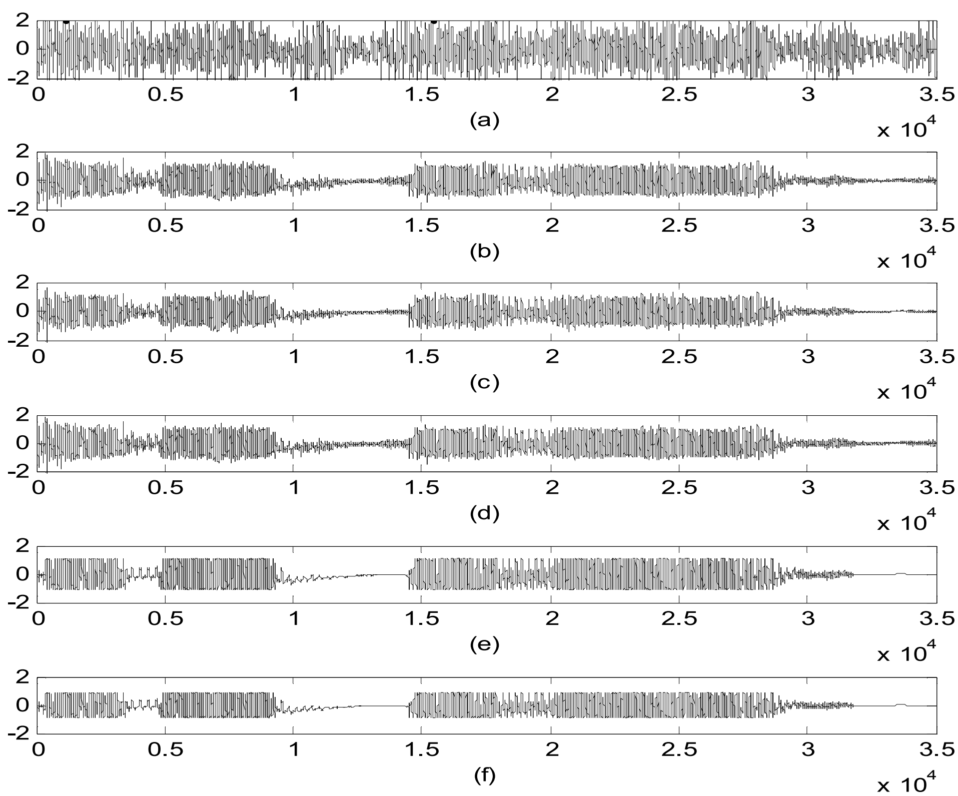

Figure 6: Typical Filtering Results Of Sample –I For Helicopter Noise Removal (A) Contaminated Speech Signal, (B) Recovered Signal Using LMS Algorithm, (C) Recovered Signal Using NLMS Algorithm (D) Recovered Signal Using ENLMS Algorithm (E) Recovered Signal Using WNLMS (F) Recovered Signal Using UBLMS Algorithm.

Table 2: SNRI Improvement Of Proposed Algorithms (All Values Are In Dbs)

Sl.no	Noise type	Sample	LMS	NLMS	ENLMS	WNLMS	UBLMS
1.	Helicopter Noise	Wave-1	8.5795	14.7864	16.3567	18.7538	20.5312
		Wave -2	8.1673	14.2705	16.0435	18.3471	20.4527
		Wave -3	8.8705	14.9074	16.9804	18.8859	20.7696
		Wave -4	8.3691	14.3296	16.1247	18.3905	20.5115
		Wave -5	8.7753	14.8527	16.7995	18.8048	20.6903
2.	Crane Noise	Wave-1	6.1468	12.0687	14.2657	16.2157	18.1474
		Wave -2	6.3617	12.5568	14.4337	16.3389	18.3651
		Wave -3	6.5784	12.6287	14.5538	16.6744	18.6639
		Wave -4	6.8665	12.7584	14.7479	16.8963	18.9736
		Wave -5	6.0346	12.0195	14.0836	16.1783	18.2338
3.	High Voltage Murmuring Noise	Wave-1	5.6385	11.7548	13.5783	15.7107	17.6955
		Wave -2	5.1893	11.2645	13.4320	15.2268	17.3413
		Wave -3	5.3866	11.3673	13.5763	15.3864	17.4858
		Wave -4	5.9582	11.8973	13.8897	15.9057	17.9126
		Wave -5	5.7418	11.8052	13.8163	15.8673	17.8241
4.	Battle Field Noise	Wave-1	7.9127	13.8032	15.9058	17.8705	19.8428
		Wave -2	7.0836	13.1225	15.2521	17.3537	19.2523
		Wave -3	7.3353	13.4543	15.3954	17.3372	19.3084
		Wave -4	7.7538	13.8083	15.8275	17.8892	19.7936
		Wave -5	7.5253	13.7439	15.6632	17.6583	19.7032
5.	Random Noise	Wave-1	9.0314	15.1734	17.2698	19.1835	21.0763
		Wave -2	9.9735	15.8905	17.8853	19.9768	21.8898
		Wave -3	9.2946	15.3754	17.3562	19.2835	21.3759
		Wave -4	9.5904	15.6723	17.5846	19.5903	21.5529
		Wave -5	9.7733	15.8084	17.7335	19.7439	21.6053

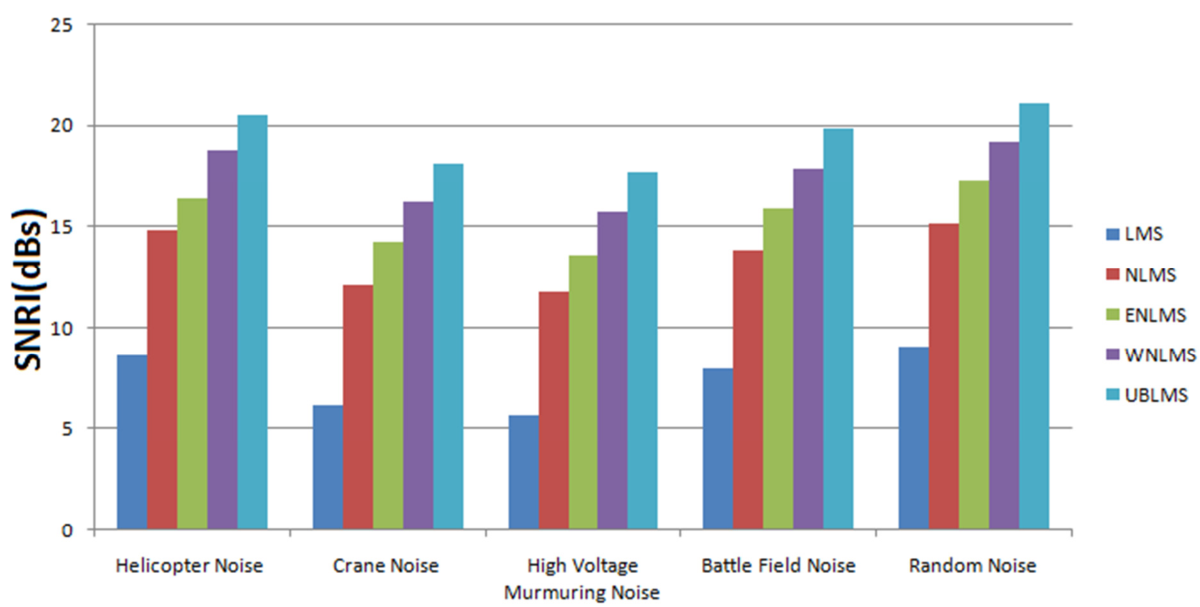

Figure 7:Data Analysis Of SNRI Obtained During The Process Of Speech Enhancement

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From Table 2 and Fig. 7 the data analysis can be completed. Among the various algorithms UBLMS algorithm based speech enhancement is found to be better in terms of filtering in any type of noise environment. The next place goes to WNLMS based enhancement. Based on this analysis it is clear that UBLMS based speech enhancement unit is found to be better in computerized noise cancellation in speech signals.

4. CONCLUSION

This paper deals with adaptive noise cancellation of speech samples for eliminating various types of noise. With the fixed step size the conventional LMS algorithm results gradient noise. To solve this problem variable step size techniques are suitable. In this the step size is updated with reference to the statistical nature of the input signal. In our work the methodology to change the step size is data normalization. With respect to input data sequence the step size is divided instantaneously. We have extended our work by implementing a combination of unbiased (UB) technique with LMS it results UBLMS and weight normalized LMS (WNLMS) instead of data normalization and also introduced Error Normalization LMS (ENLMS). The considered UBLMS model does not contain a bias unit and the coefficients are adaptively updated. The corresponding adaptation is designed to minimize the instantaneous error between the estimated signal power and the desired noise free signal power. The convergence performance of the UBLMS algorithm, ENLMS algorithm, WNLMS algorithm is compared with conventional LMS and NLMS algorithms. A convergence characteristic proves that the UBLMS algorithm, ENLMS algorithm, WNLMS algorithm are superior to the LMS and NLMS algorithms. Finally various adaptive filter structures are implemented using LMS, NLMS, ENLMS algorithm, WNLMS algorithm and UBLMS algorithms. Signal to noise ratio improvement (SNRI) is measured to test the performance of proposed filters. Simulation results shows that ENLMS, WNLMS algorithm, UBLMS algorithm are superior than the LMS algorithm.

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