Modified Least Mean Square Adaptive Noise Reduction algorithm for Tamil Speech Signal under Noisy Environments

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Abstract—Over the past several decades, the problem of noise reduction for speech enhancement has attracted a considerable amount of research attention. In this research work, the modified Least Mean Square Adaptive Noise Reduction (LMS-ANR) algorithm is proposed for enhancing the noisy Tamil speech signal under various non-stationary noise environments. This algorithm, adapts its coefficients automatically to changes with respect to input signals. Objective and subjective measures for the various noises with different input SNR levels of IIT database sentences are made and compared between the existing and proposed adaptive noise reduction algorithms. From the simulated results, it is observed that the proposed LMS-ANR algorithm for performance metrics improvement upto 60.22% and reduction upto 59.52% when compared to the existing algorithms under different noisy environments of various speech sentences.

Index Terms - Noise Reduction, Speech Enhancement, Adaptive Filter, LMS, Tamil Speech Sentences.

I. INTRODUCTION

Some of the speech processing applications existing in mobile phones, hands-free phones, in-car communication, teleconferencing systems, hearing aids, voice coders, automatic speech recognition, and forensics, the clean speech signals are corrupted by the background noise which degrades the speech signal quality. Speech enhancement algorithms are widely used for these applications in order to remove the noise from the degraded speech in the noisy environment. Some of the existing noise reduction methods are Spectral Subtraction, Wiener Filter, Adaptive Filter, and Minimum Mean Square Error-Short Time Spectral Amplitude (MMSE-STSA) estimation methods (Haykin 2007).

Over the past decades, the problem of noise reduction has attracted a considerable amount of research attention. Wiener filter is an optimal and most fundamental approach, it has been delineated in different forms and adopted in diversified applications. Wiener filter is a linear time-invariant filter which is used to produce an estimate of a desired or target random process from observed noisy process. Assume that, the signal and noise are stationary process with known spectra and additive in nature. This filter minimizes the mean square error between the estimated random process and the desired process. But, it achieves noise reduction with some integrity loss of the speech signal (Almajai & Milner 2011, El-Fattah 2014).

Comelis et al (2011) developed the noise reduction approach using wiener filter, in which the noise signal is removed by applying the signal through this filter. It requires the estimate of the power spectrum of the clean speech and noise signals. In addition, its performance depends on the estimated clean speech and noise spectrum. This method results in speech signal suppression but phase spectrum remains unaltered.

In order to overcome the shortcomings in the wiener filter, the adaptive filter is developed for noise reduction. It is used to estimate the gradient vector from the available noisy data. The Least Mean Square (LMS) adaptive algorithm is an iterative procedure that makes corrections to the weight vector in the direction of the negative gradient vector which eventually leads to the minimum mean square error. It does not require the statistics of the clean speech and noise signals (Haykin & Widrow, 2003, Kuo 1996, Shubhra 2017).

Chi et al (2003) presented the Filtered-x LMS (FxLMS) adaptive noise reduction algorithm which is used to reduce the effect due to the secondary path in adaptive noise control applications. When compared to the wideband approach, this provides good cancellation efficiency, convergence behavior, and better output sound quality for speech signals. But, it produces the tolerant mean square error (Hellgren 2002, Huang 2013, Douglas 1999).

Rahman et al (2009) suggested the Block LMS (BLMS) algorithm for adaptive noise reduction, in which the filter coefficients are updated only once for each block of data. Hence, it reduces the computational requirements. This is the solution of the steepest descent strategy for minimizing the mean square error in a complete signal occurrence. It is to be steady-state unbiased and with a lower variance than the LMS algorithm. But, it introduces the mean square error.

Huang et al (2012) described the Normalized LMS
(NLMS) based adaptive noise reduction algorithm in order to solve the dilemma of fast convergence rate or low excess mean-square error in the past two decades. In this, the step-size update is controlled by the mean-square error and the estimated system noise power. It is easy to implement and it potentially has fast convergence rate, good tracking, and low misadjustment. But, it produces more residual noise (Mohammed & Shafi 2012, Benesty 2006, Benshad 1986, Arif 2017).

In order to overcome the shortcomings in the existing algorithms, the LMS-ANR algorithm is proposed in this research paper. This research method enhances the speech signal by reducing the background noise at a significant level when compared to that of existing algorithms under various Tamil speech signal conditions.

This paper is organized as follows: Section II provides the overview of Least Mean Square Adaptive Algorithm. The proposed LMS-ANR algorithm is described in Section III. Section IV illustrates the performance evaluation of the existing and proposed algorithms and Section V concludes this paper.

II. LEAST MEAN SQUARE ADAPTIVE ALGORITHM

Basic form of Wiener theory assumes that the signals are stationary but generally that is not the case in all the environments. Under these conditions, an Adaptive filter has been developed for noise reduction which adapts its coefficients automatically to the changes with respect to input signals. Hence, this Adaptive filters has the capability of adaptively tracking the signal under non-stationary conditions. In this, the desired result is achieved, such as identifying an unknown system or cancelling the noise in the input signal automatically (Haykin & Widrow 2003, Mohanty 2013).

Adaptive filters used for noise reduction process is shown in Figure 1. This requires the noise component of the corrupted signal as the reference for filter input. This filter is a time varying one because the signal and noise are always non-stationary process. So, designing of this type of filter is much more difficult than Wiener filter. In order to minimize the mean square error, the filter coefficients are updated at each time ‘n’ as follows,

$$w_{n+1} = w_n + \Delta w_n$$

where, $\Delta w_n$ is the correction term added to $w_n$ at time ‘n’ to get a new set of filter coefficients $w_{n+1}$ at time ‘n+1’.

Here, signal and noise statistic are unknown, hence it is estimated from the observed signals.

In order to minimize the MSE, the iterative procedure like steepest decent algorithm was developed. The weight is updated based on ensemble averages and it is described as,

$$w_{n+1} = w_n + \mu E[w(n)d(n)]$$

where, $\mu$ is the step size which controls the convergence speed of this algorithm. In most of the applications, the ensemble averages $E[w(n)d(n)]$ are unknown and it is estimated from the signal.

In the conventional LMS algorithm, the estimate of expectation is replaced by the sample mean in such a way that it reduces the MSE. The weight update equation for this LMS algorithm is described by,

$$w_{n+1} = w_n + \mu e(n)d(n)$$

where, $d(n)$ is the reference input noise signal, $y(n)$ is the adaptive filter output and it is defined as,

$$y(n) = w_n^T d(n)$$

and $\mu$ is the step size or convergence parameter. The error signal $e(n)$ can be generated by the output of the digital filter $y(n)$ subtracted from the noisy signal $x(n)$ is given by,

$$e(n) = x(n) - y(n) = z(n)$$

where, $z(n)$ is the enhanced clean speech signal. When the LMS performance criterion for $e(n)$ has achieved to its minimum value through the iterations of the adapting algorithm, then the adaptive filtering process is completed and its coefficients have converged to a solution. Now, the output from the adaptive filter matches closely to the reference noise signal $d(n)$. When the input data characteristics changed, the filter adapts to the new environment by generating a new set of coefficients for the new data. Notice that, when $e(n)$ goes to zero and remains there which indicates that the perfect adaptation is achieved and this is the ideal condition but not likely to exist in the real world (Aboulnasr et al 1997, Serizel et al 2012).

Figure 1. Block Diagram of Adaptive Noise Reduction
The LMS algorithm is the most popular adaptive algorithm and its performance is dependent on the filter order, signal condition and convergence parameter ($\mu$). To satisfy the robustness of the adaptive algorithm, the value of step size ‘$\mu$’ needs to be small. The convergence performance of the LMS algorithm for Finite Impulse Response (FIR) filter structure is controlled by the input signal statistics. The condition which is important for the convergence criterion and the convergence factor of LMS algorithm must be chosen in the range given by,

$$0 < \mu < \frac{2}{\varphi_{\max}}$$

where, $\varphi_{\max}$ is the largest eigen value of the correlation matrix $R_x$ of the input signal (Haykin 2007).

**III. PROPOSED LEAST MEAN SQUARE ADAPTIVE NOISE REDUCTION (LMS-ANR) ALGORITHM**

In NLMS algorithm, the estimation of norm value is the tedious process under non-stationary noise conditions and this estimation alters the magnitude of the enhanced signal. This increases the mean square error. To reduce this error, the step size $\mu$ for this proposed method is represented as,

$$\mu(n) = \frac{2\alpha}{N(\beta + \alpha N)\sigma^2(n)}$$ for

$$0 < \alpha < 1 \text{ and } 0 < \beta < 2$$

where, $N$ - order of the filter; $\sigma^2(n)$ - reference input noise signal; $\alpha$ - smoothing factor; $\beta$ - normalized step size respectively. Suitable selection of these parameters leads to fast convergence. Then, the output of the proposed LMS adaptive filter $x(n)$ and its error signal $e(n)$ are computed using the equations described in Equation (4) and Equation (5) respectively.

In this research work, step size $\mu$ depends on the signal information, order, smoothing factor and normalized step size. Optimal values of these parameters are found easily and they are fixed as constant values depending on the signal environments.

Then, the filter coefficients $W_{n+1}$ are updated from the filter coefficients $W_n$ in time domain as

$$W_{n+1} = W_n + \frac{2\alpha N \sigma^2(n)}{N(\beta + \alpha N)\sigma^2(n)} e(n)$$

The steps involved to enhance the noisy speech signal using proposed LMS-ANR algorithm is demonstrated in Algorithm 1 as follows:

### Algorithm 1 Proposed Least Mean Square Adaptive Noise Reduction (LMS-ANR) Algorithm

1: for all time index ‘$n$’
2: With reference to noise signal $d(n)$ as input, $w_n$ is the proposed LMS adaptive filter coefficients then the output $y(n)$ of the filter is calculated using Equation (4).
3: Using Equation (5), compute the error signal $e(n)$ with $x(n)$ is the noisy signal of various noise environments.
4: For a given time index, obtain the time varying step size $\mu(n)$ which is described in Equation (7). Here, $N$ - order of the filter; $\alpha$ - smoothing factor; $\beta$ - Normalized step size. In this research work, $N = 5$, $\alpha = 0.95$ and $\beta = 0.001$ are found as optimal values from the simulation and it is used in this evaluation.
5: Then, the filter coefficients $W_{n+1}$ are updated from the filter coefficients $W_n$ in time domain as expressed in Equation (8).
6: end for

**V. RESULTS AND DISCUSSIONS**

For the evaluation, different input speech signals using different speakers are obtained from the database of IIIT consisting of various Tamil speech sentences. Further, the input speech signal from the NOIZEUS database with various environments such as, airport, car, babble, exhibition, restaurant, street, station and train noises with different input SNR (0dB, 5dB, 10dB and 15dB) levels are used for evaluation of existing and proposed adaptive noise reduction algorithms.

This algorithm is simulated with different speech sentences from the two databases under various noise environments as mentioned earlier. Objective and subjective performance measures are evaluated and compared between the proposed and existing algorithms. In this research work, the following performance measures viz., Peak Signal-to-Noise Ratio (PSNR), Segmental SNR improvement (\(\Delta\)SNRseg), Mean Opinion Score (MOS), Log Spectral Distance (LSD) and Mean Square Error (MSE) are used for evaluation. In the proposed LMS-ANR algorithm, the step size or convergence parameter $\mu$ is obtained from the observation of signal and does not require the norm (statistical) value of the speech signal. Figure 2 shows the average value of convergence parameter ‘$\mu$’ for each frame using NLMS-ANR and proposed LMS-ANR algorithms.
From these graphical results, it is observed that there is an improvement of \( \mu \) value in each frame when compared to that of the existing algorithms. This improvement provides faster convergence with less mean square error. Figure 3 illustrates the performance evaluation of PSNR in dB for tam_0010 sentence of IIIT database under various noise environments with different input SNR levels.

Here, there is an improvement in PSNR value while the variations of the input speech SNR levels from 0dB to 15dB due to reduction in noise signal levels. From the numerical investigations, it is found that PSNR improvement of 0.6 to 2.9 dB in sp01 sentence and 0.5 to 3.3 dB in tam_0010 sentence for the proposed LMS-ANR algorithm when compared to the existing algorithms. Frequently used method for subjective quality evaluation is the Mean Opinion Score (MOS). The listeners can describe their impression of the speech quality only in five discrete steps according to the defined scale. This experiment is carried out for 40 listeners from different educational background. The experiment is randomly tested with clean, noisy and enhanced speech signals 10 times. Then, the rating is allotted from the above listeners and MOS is evaluated by averaging the rating of all the listeners.

The percentage of improvement of the proposed LMS-ANR algorithm when compared to the existing algorithms is tabulated in Table 1. This improvement

![Figure 2 Average value of Convergence Parameter (\( \mu \)) for each frame using NLMS-ANR and Proposed LMS-ANR Algorithms](image)

![Figure 3 Peak Signal to Noise Ratio (PSNR) in dB for the Proposed LMS-ANR and Existing LMS Algorithms for tam_0010 speech sentences under various noise environments with different input SNR levels (0-15dB)](image)

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<th>Performance Measures</th>
<th>BLMS</th>
<th>FxLMS</th>
<th>NLMS</th>
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<tr>
<td>PSNR (dB)</td>
<td>8.05</td>
<td>5.50</td>
<td>4.27</td>
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<tr>
<td>( \Delta \text{SNR}_{\text{seg}} ) (dB)</td>
<td>60.22</td>
<td>56.59</td>
<td>49.31</td>
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<td>MOS</td>
<td>47.44</td>
<td>38.68</td>
<td>26.72</td>
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<td>LSD</td>
<td>40.86</td>
<td>35.49</td>
<td>22.19</td>
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<td>MSE</td>
<td>59.52</td>
<td>57.89</td>
<td>48.48</td>
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indicates that the proposed LMS adaptive algorithm improves the speech signal quality under various noise environments. It also reduces the speech signal distortion and residual noises at a significant level.

V. CONCLUSION

In this research work, the proposed LMS-ANR algorithm for Tamil speech signal is proposed to enhance the speech signal under various noisy environments. The experiments are conducted to evaluate the objective and subjective measures in order to validate the performance of the existing and proposed adaptive noise reduction algorithm. While comparing the proposed LMS-ANR with existing algorithms, the improvement of PSNR value from 4.27% to 8.05%, $\Delta$SNR$\text{seg}$ value from 49.31% to 60.22% and MOS value from 26.72% to 47.44% are achieved. In addition, this proposed LMS-ANR algorithm reduces the LSD value from 22.19% to 40.86% and MSE value from 48.48% to 59.52% when compared to the existing LMS algorithms. From the above results, it is concluded that the performance of the proposed LMS-ANR algorithm is significantly better than the other LMS adaptive noise reduction algorithms under non stationary noisy environments.

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REFERENCES
