Adaptive Noise Reduction Algorithm for Speech Enhancement

M. Kalamani, S. Valarmathy, M. Krishnamoorthi

Abstract—In this paper, Least Mean Square (LMS) adaptive noise reduction algorithm is proposed to enhance the speech signal from the noisy speech. In this, the speech signal is enhanced by varying the step size as the function of the input signal. Objective and subjective measures are made under various noises for the proposed and existing algorithms. From the experimental results, it is seen that the proposed LMS adaptive noise reduction algorithm reduces Mean square Error (MSE) and Log Spectral Distance (LSD) as compared to that of the earlier methods under various noise conditions with different input SNR levels. In addition, the proposed algorithm increases the Peak Signal to Noise Ratio (PSNR) and Segmental SNR improvement (ΔSNRseg) values; improves the Mean Opinion Score (MOS) as compared to that of the various existing LMS adaptive noise reduction algorithms. From these experimental results, it is observed that the proposed LMS adaptive noise reduction algorithm reduces the speech distortion and residual noise as compared to that of the existing methods.

Keywords—LMS, speech enhancement, speech quality, residual noise.

I. INTRODUCTION

THE hearing impaired people experience great difficulties to communicate in the noisy environment. Under this condition, the hearing aid technology is used to increase the speech signal quality and reduce the hearing loss in such way that these hearing impaired people hearing the same level of the speech signal which is hear by the normal hearing people. In this technology, speech enhancement methods are widely used to reduce the noise and to enhance speech signal quality with the acceptable hearing loss. Conventional speech enhancement methods such as a Spectral subtraction method, Subspace algorithm, Wiener filtering and Adaptive Filtering etc., are based on variants of Short-Time Spectral Amplitude (STSA) estimates of speech [20], [5].

In the spectral subtraction method, the speech signal is enhanced by subtracting the estimated noise spectrum from the noisy speech spectrum. It has low complexity, but it produces more residual noise [7], [17], [21]. Subspace algorithm is a non parametric linear estimate of the unknown clean speech signal. This method maintains better balance between speech distortion and residual noise. But it has high

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complexity and needs pre-whitening before actual noise reduction [3]. In Wiener filtering (WF) method, the noise signal is removed by applying the signal through wiener filter. It requires the estimate of the speech and the noise signal power spectrum. In addition, its performance depends on the estimated speech and noise spectrum. This results in the speech signal suppression in the frequency domain. In addition, the phase spectrum of noisy signal is not processed [2], [9], [11].

In order to overcome the shortcomings in the wiener filter, the adaptive filter is proposed. It is used to estimate the gradient vector from the available noisy data. The LMS adaptive algorithm is an iterative procedure that makes corrections to the weight vector in the direction of the negative of the gradient vector which eventually leads to the minimum mean square error. It does not require the statistics of the clean speech and noise signals [12], [13].

In Block LMS (BLMS) algorithm, the filter coefficients are updated only once for each block of data which reduce the computational requirements. But, it introduces the mean square error [19]. Filtered-X LMS (FxLMS) is used to reduce the effect due to the secondary path in the adaptive noise control applications. Convergence of this algorithm is much faster than other algorithms, but it produces the tolerant mean square error [8], [10], [14], [15]. Normalized LMS (NLMS) algorithm is potentially fast converging one as compared to other LMS algorithms, but it produces more residual noise [1], [4], [6], [16], [18].

In order to reduce the mean square error and provide better convergence, the modified LMS adaptive noise reduction algorithm for speech enhancement is proposed in this paper. In this method, the trade-off between the convergence and MSE can be achieved by selecting the step size 'μ' as the function of time varying one.

This paper is organized as follows: Section II describes about the LMS adaptive noise algorithm and Section III provides the existing LMS algorithms. The proposed LMS adaptive noise reduction algorithm is described in Section IV. Section V illustrates the experimental results of subjective and objective measures of the existing and proposed algorithms and Section VI gives the conclusion of this paper.

II. LMS ADAPTIVE ALGORITHM

In Adaptive filters, the filter coefficients adjust themselves to achieve the desired result, such as identifying an unknown system or cancelling noise in the input signal and it is shown in Fig. 1.

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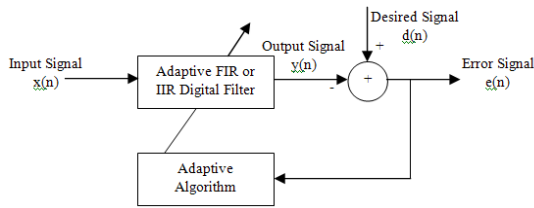International Journal of Electronics and Communication Engineering
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Fig. 1 Block diagram of Adaptive Noise Cancellation

In the conventional LMS algorithm, the estimate of expectation is replaced by the sample mean. The weight update equation for this LMS algorithm is described by,

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

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

$$y(n) = w_n^T x(n) \qquad (2)$$

and μ is the step size or convergence parameter. The error signal $e(n)$ can be generated by the output of the digital filter $y(n)$ is subtracted from the desired (reference) signal $d(n)$ and it is given by,

$$e(n) = d(n) - y(n) \qquad (3)$$

When the LMS performance criterion for $e(n)$ has achieved its minimum value through the iterations of the adapting algorithm, the adaptive filter is finished and its coefficients have converged to a solution. Now the output from the adaptive filter matches closely the desired 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 and ideal result is achieved.

The LMS algorithm is the most popular adaptive algorithm and its performance is dependent on the filter order, signal condition and convergence parameter (μ). To satisfy the robustness of the adaptive algorithm, the value of step size μ needs to be small. The convergence performance of the LMS algorithm for 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 which is given by,

$$0 < \mu < \frac{2}{\lambda_{max}} \qquad (4)$$

where, λ_{max} Is the largest eigenvalue of the correlation matrix R_x of the input signal [20].

III. EXISTING LMS ALGORITHMS FOR NOISE REDUCTION

A. Block LMS (BLMS) Algorithm

In this method, the filter coefficients are held constant over each block of the input signal. The filter output $y(n)$ and error signal $e(n)$ are calculated using filter coefficients of that block.

Then, the filter coefficients are updated at the end of each block using an average of the L gradient estimates over that block.

For k^{th} block, the output of the filter is described as,

$$y(kL + l) = w_{kL}^T . x(kL + l) \qquad (5)$$

and the error signal is given by,

$$e(kL + l) = d(kL + l) - y(kL + l) \qquad (6)$$

where, L is the block length and $d(n)$ is the desired signal. The weight update equation of the kth block is given by,

$$w_{(k+1)L} = w_{kL} + \mu \frac{1}{L} \sum_{l=0}^{L-1} e(kL + l)x(kL + l) \qquad (7)$$

where, μ is the step size which controls the convergence. In this, the computational requirements get reduced and cause more speech distortion [19].

B. Filtered-X LMS (FxLMS) Algorithm

In this, the input signal is filtered before being used by the standard LMS algorithm which compensates the secondary path effects. Then weight updating is described as,

$$w_{n+1} = w_n + \mu e(n)x'(n) \qquad (8)$$

where, μ is the step size and $e(n)$ is the error signal which is defined as,

$$e(n) = d(n) - y(n) \qquad (9)$$

where, $d(n)$ is the desired signal and $y(n)$ is the output of the adaptive filter which is given as,

$$y(n) = w_n^T . x(n) \qquad (10)$$

Then, $x'(n)$ is the filtered input signal and it is defined as,

$$x'(n) = C_n^T . x(n) \qquad (11)$$

where, $x(n)$ is the input signal and C_n is the filter coefficients of the input filter which is updated as follows,

$$C_{n+1} = C_n + \mu e'(n)y(n) \qquad (12)$$

where, $e'(n)$ the error signal due to input filtering and it is described as,

$$e'(n) = e(n) - r(n) \qquad (13)$$

where, $r(n)$ is defined as follows,

$$r(n) = C_n^T . y(n) \qquad (14)$$

For a large number of weights, this algorithm has a slow convergence rate [15].

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C. Normalized LMS (NLMS) Algorithm

In the earlier LMS algorithms, the step size μ is fixed based on the statistics of the input signal which causes slow convergence. Generally in the noisy environment, the statistics of the input signal are unknown. In this method, the step size is normalized and it is expressed as,

$$\mu(n) = \frac{\beta}{\|x(n)\|^2} \qquad (15)$$

where, β is the normalized step size with $0 < \beta < 2$. In this case, the filter coefficients are updated as,

$$w_{n+1} = w_n + \beta \frac{x(n)}{\|x(n)\|^2} e(n) \qquad (16)$$

and it is converged more rapidly than other LMS algorithms [18].

IV. PROPOSED LMS ALGORITHM FOR NOISE REDUCTION

In the NLMS algorithm, the magnitude of the enhanced signal is altered due to norm $\|.\|$ value. This increases the mean square error. To reduce this error, the step size μ for this proposed method is described as,

$$\mu(n) = \frac{2\alpha}{M(\beta + x(n)x^T(n))} \qquad (17)$$

where, M is the order of the filter and α, β is selected in the range $0 < \alpha < 1, 0 < \beta < 2$ respectively in which it is converged to its solution. The weight updating is given by,

$$w_{n+1} = w_n + \frac{2\alpha x(n)}{M(\beta + x(n)x^T(n))} e(n) \qquad (18)$$

where, x(n) is the input signal and e(n) is the error signal which is defined in (9).

V. PERFORMANCE EVALUATION

In this section, the performance of the proposed LMS adaptive noise reduction algorithm is compared with the existing BLMS, FxLMS and NLMS algorithms. For the evaluation, the input noisy signal is taken from the NOIZEUS database for various noise environments such as: airport, car, babble, exhibition, restaurant, street, station and train noises. The different input SNR (0dB, 5dB, 10dB and 15dB) levels are used throughout the evaluation for the existing and proposed algorithms. The time domain plot of the clean speech, noisy speech and enhanced speech signals by the existing and proposed LMS adaptive noise reduction algorithms for the airport and train noises with different input SNR (0dB, 5dB, 10dB & 15dB) levels are shown in Figs. 2 and 3.
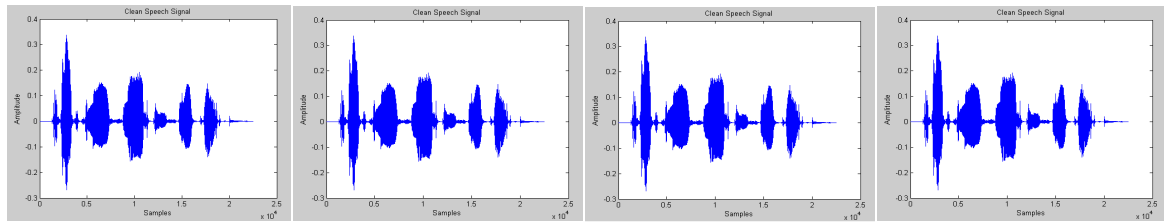
From this plot, it is seen that the proposed method produces the enhanced speech signal is closer to the original clean speech as compared to that of existing BLMS, FxLMS and NLMS algorithms. This result improves the speech signal quality and intelligibility of the enhanced speech signal.

Table I shows the performance comparison of the segmental SNR improvement (ΔSNRseg) in dB for existing and proposed LMS adaptive noise reduction algorithms. The various noises like babble, car, exhibition, restaurant, station and street with different input SNR levels are used to evaluate the existing and proposed algorithms. From these experimental results, it is observed that the proposed LMS adaptive noise reduction algorithm increases 50.2 dB to 72.6 dB, 34.7 dB to 65 dB and 13.3 dB to 57.5 dB of ΔSNRseg as compared to that of the existing BLMS, FxLMS and NLMS algorithms respectively.
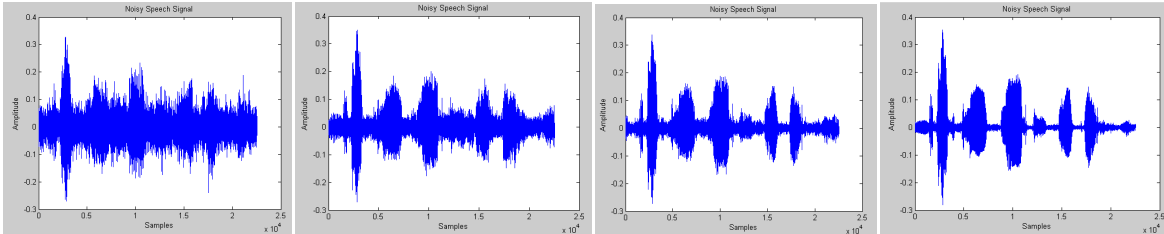
Frequently used method of subjective quality evaluation is the Mean Opinion Score (MOS). The listeners can describe their impression of the speech quality only in five discrete steps according to the defined scale. In this paper, this experiment is carried out among 40 listeners from different educational background. The experiment is randomly tested for clean, noisy and enhanced speech signals for 15 times. Then, the rating is allotted from the above listeners. MOS is evaluated for the proposed and existing spectral subtraction algorithms by averaging the rating of all listeners.

TABLE I
COMPARISON OF SEGSNR IMPROVEMENT (ΔSNRSEG) IN DB FOR VARIOUS NOISES AT DIFFERENT INPUT SNR LEVELS BY BLMS, FXLMS, NLMS AND PROPOSED LMS NOISE REDUCTION ALGORITHMS
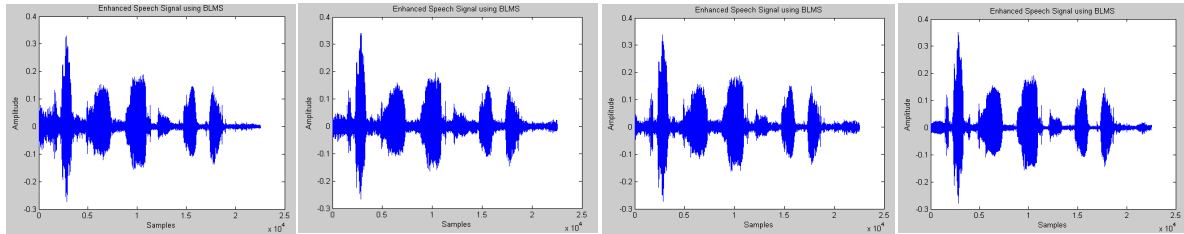
Spectral Subtraction Algorithms	Input SNR in dB	Babble	Car	Exhibition	Restaurant	Station	Street
BLMS	0	-4.22	-4.56	-4.23	-4.13	-4.16	-4.15
	5	-5.07	-5.04	-4.64	-4.54	-4.84	-4.79
	10	-5.34	-5.54	-5.78	-5.07	-5.37	-5.03
	15	-6.07	-6.85	-6.03	-5.67	-5.82	-5.41
FxLMS	0	-3.34	-3.46	-3.02	-3.07	-3.23	-3.25
	5	-3.87	-3.82	-3.47	-3.34	-3.67	-3.66
	10	-4.21	-4.16	-4.53	-4.21	-4.31	-3.83
	15	-4.86	-4.52	-4.88	-4.84	-4.93	-4.12
NLMS	0	-2.75	-2.42	-2.53	-2.45	-2.18	-2.12
	5	-2.13	-3.63	-2.87	-2.68	-2.38	-2.36
	10	-2.78	-3.82	-3.06	-3.12	-3.62	-3.52
	15	-3.45	-3.37	-3.53	-3.43	-3.90	-3.93
Proposed	0	-1.17	-1.49	-1.85	-1.13	-1.58	-1.17
	5	-1.54	-1.81	-1.97	-1.58	-1.79	-1.50
	10	-2.26	-2.04	-2.36	-2.49	-2.15	-2.28
	15	-2.99	-2.83	-2.53	-2.69	-2.37	-2.69

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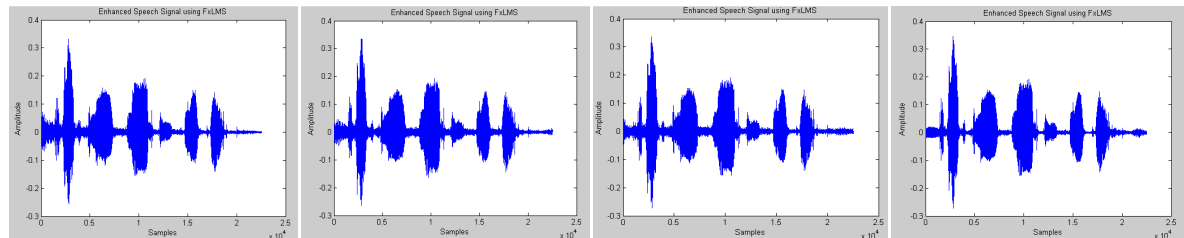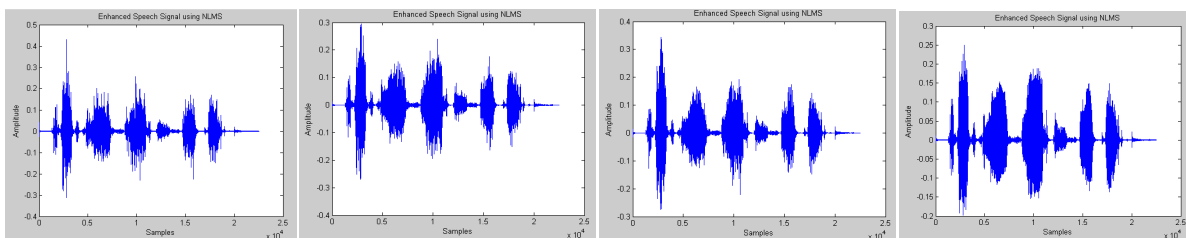Vol:8, No:6, 2014

(a) Clean Speech

(b) Noisy Speech

(c) Enhanced Speech by BLMS

(d) Enhanced Speech by FxLMS

(e) Enhanced Speech by NLMS

(f) Enhanced Speech by Proposed

| 0dB | 5dB | 10dB | 15dB |

Fig. 2 Time domain plot for the Clean, Noisy and Enhanced speech signals by BLMS, FxLMS, NLMS and Proposed LMS adaptive noise reduction algorithms for the airport noise with different input SNR levels (a) to (f)

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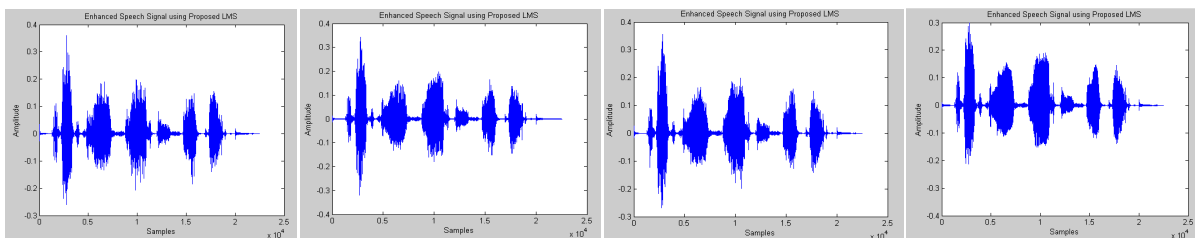(a) Clean Speech

(b) Noisy Speech

(c) Enhanced Speech by BLMS

(d) Enhanced Speech by FxLMS

(e) Enhanced Speech by NLMS
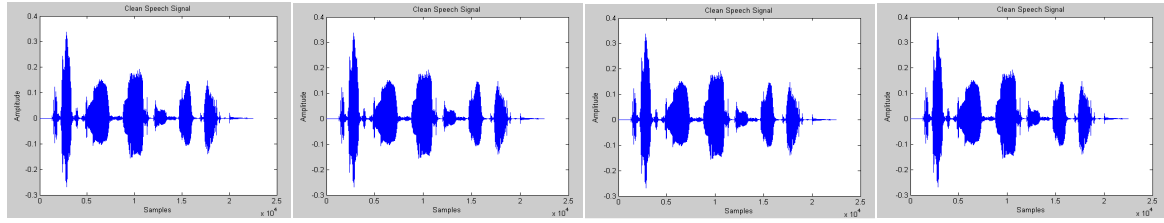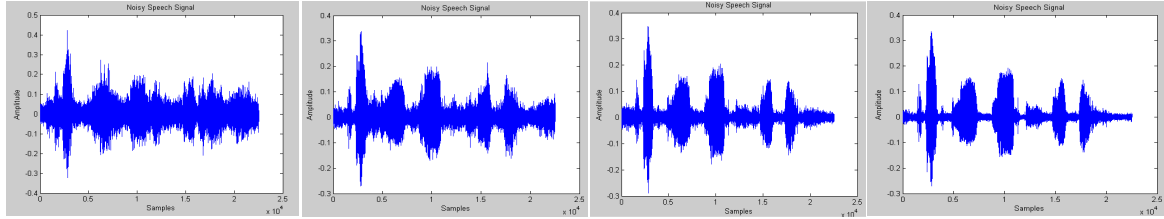
(f) Enhanced Speech by Proposed
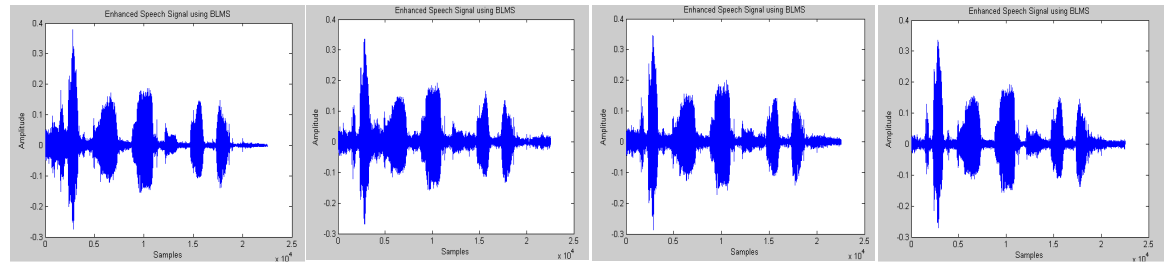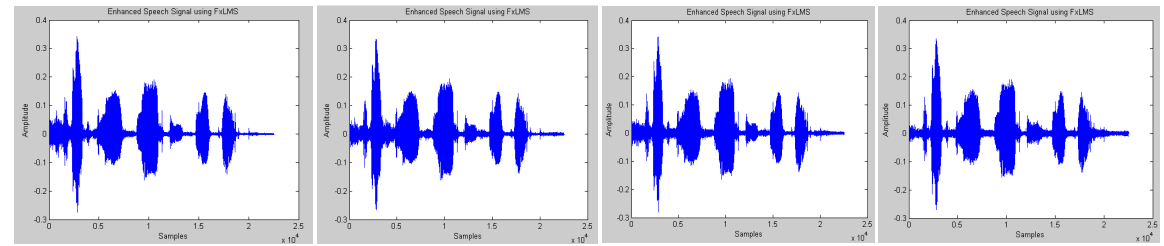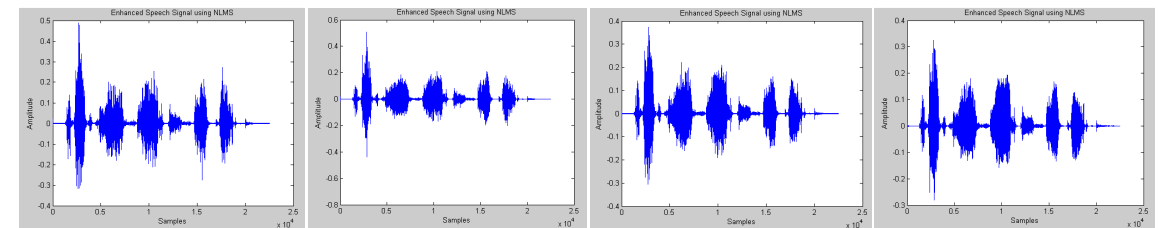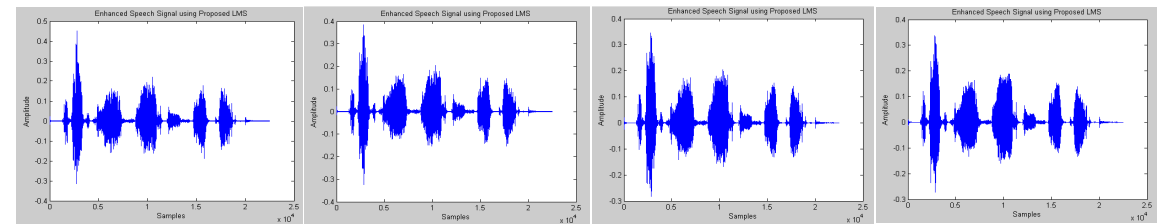
| 0dB | 5dB | 10dB | 15dB |

Fig. 3 Time domain plot for the Clean, Noisy and Enhanced speech signals by BLMS, FxLMS, NLMS and Proposed LMS adaptive noise reduction algorithms for the train noise with different input SNR levels (a) to (f)

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Table II shows the performance comparison of Mean Opinion Score (MOS) for the BLMS, FxLMS and NLMS and proposed LMS adaptive noise reduction algorithms for the various noises as mentioned above. From these experimental results, it is observed that the proposed LMS adaptive noise reduction algorithm improves the MOS as 8% to 33.7%, 5% to 42.4% and 1.4% to 15.6% as compared to that of BLMS, FxLMS and NLMS algorithms respectively.

Table III shows the performance comparison of Log Spectral Distance (LSD) for the BLMS, FxLMS and NLMS and proposed LMS adaptive noise reduction algorithms for the various noises as discussed earlier. From these experimental

results, it is observed that the proposed LMS adaptive noise reduction algorithm decreases 39.1 dB to 71.3 dB, 29.7 dB to 58.4 dB and 15 dB to 49.3 dB of LSD as compared to that of BLMS, FxLMS and NLMS algorithms respectively.

Table IV shows the performance comparison of Mean Square Error (MSE) for the BLMS, FxLMS and NLMS and proposed LMS adaptive noise reduction algorithms for the various noises. From these experimental results, it is observed that the proposed LMS adaptive noise reduction algorithm reduces the MSE as 23.4% to 68.4%, 16% to 64.7% and 12.2% to 46.2% as compared to that of BLMS, FxLMS and NLMS algorithms respectively.

TABLE II
COMPARISON OF MEAN OPINION SCORE (MOS) FOR VARIOUS NOISES AT DIFFERENT INPUT SNR LEVELS BY BLMS, FXLMS, NLMS AND PROPOSED LMS NOISE REDUCTION ALGORITHMS

Spectral Subtraction Algorithms	Input SNR in dB	Babble	Car	Exhibition	Restaurant	Station	Street
	0	1.95	2.06	2.32	2.17	2.32	2.08
BLMS	5	2.52	2.34	2.79	2.53	2.54	2.37
	10	2.95	2.73	2.99	2.84	2.79	2.74
	15	3.31	3.15	3.07	3.00	2.92	2.99
	0	1.72	2.23	2.86	2.27	2.46	2.36
FxLMS	5	2.05	2.57	2.93	2.52	2.74	2.50
	10	2.94	3.09	3.12	2.95	2.89	2.91
	15	3.12	3.37	3.37	3.18	3.07	3.11
	0	2.12	2.42	2.93	2.47	2.59	2.51
NLMS	5	2.36	2.69	3.02	2.69	2.83	2.74
	10	3.32	3.12	3.19	3.01	3.03	2.98
	15	3.53	3.41	3.46	3.22	3.16	3.27
	0	2.45	2.62	3.06	2.65	2.68	2.78
Proposed	5	2.72	2.86	3.34	2.79	2.92	2.92
	10	3.43	3.25	3.51	3.18	3.14	3.14
	15	3.58	3.62	3.68	3.62	3.56	3.64

TABLE III
COMPARISON OF LOG SPECTRAL DISTANCE (LSD) FOR VARIOUS NOISES AT DIFFERENT INPUT SNR LEVELS BY BLMS, FXLMS, NLMS AND PROPOSED LMS NOISE REDUCTION ALGORITHMS

Spectral Subtraction Algorithms	Input SNR in dB	Babble	Car	Exhibition	Restaurant	Station	Street
	0	7.13	8.17	6.76	7.27	7.56	8.15
BLMS	5	6.45	7.53	5.58	6.74	6.34	7.56
	10	5.73	6.76	4.13	5.79	5.07	6.61
	15	3.68	5.25	3.26	4.32	4.12	5.56
	0	6.17	7.47	5.55	5.53	6.87	7.18
FxLMS	5	5.35	6.31	4.47	4.52	5.54	6.20
	10	4.58	5.48	3.82	3.73	4.87	5.45
	15	2.79	4.37	2.36	2.51	3.23	4.28
	0	5.67	5.27	4.57	4.42	5.15	6.37
NLMS	5	4.61	4.87	3.62	3.18	4.46	5.82
	10	3.58	3.22	2.59	2.48	3.67	4.69
	15	2.26	2.56	1.87	2.20	2.87	3.61
	0	4.34	4.18	3.37	2.53	3.27	4.45
Proposed	5	3.61	3.37	2.96	2.00	2.92	3.67
	10	2.48	2.28	1.82	1.67	2.31	2.72
	15	1.92	1.67	1.51	1.24	1.73	1.83

Table V shows the performance comparison of Peak Signal to Noise Ratio (PSNR) for the BLMS, FxLMS and NLMS and proposed LMS adaptive noise reduction algorithms for the various noises. From these experimental results, it is observed

that the proposed LMS adaptive noise reduction algorithm improves the PSNR as 5.2% to 15.4%, 2.3% to 10.8% and 0.5% to 8.2% as compared to that of BLMS, FxLMS and NLMS algorithms respectively.

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TABLE IV
COMPARISON OF MEAN SQUARE ERROR (MSE) FOR VARIOUS NOISES AT DIFFERENT INPUT SNR LEVELS BY BLMS, FxLMS, NLMS AND PROPOSED LMS NOISE REDUCTION ALGORITHMS

Spectral Subtraction Algorithms	Input SNR in dB	Babble	Car	Exhibition	Restaurant	Station	Street
BLMS	0	0.37	0.38	0.32	0.35	0.34	0.47
	5	0.30	0.32	0.27	0.30	0.30	0.42
	10	0.25	0.26	0.23	0.27	0.28	0.38
	15	0.19	0.21	0.19	0.22	0.25	0.33
FxLMS	0	0.31	0.34	0.30	0.32	0.31	0.43
	5	0.28	0.23	0.24	0.29	0.26	0.37
	10	0.21	0.19	0.21	0.25	0.22	0.31
	15	0.18	0.15	0.17	0.20	0.20	0.26
NLMS	0	0.28	0.30	0.25	0.27	0.28	0.41
	5	0.22	0.21	0.21	0.24	0.24	0.32
	10	0.19	0.16	0.18	0.19	0.20	0.27
	15	0.14	0.13	0.15	0.17	0.17	0.24
Proposed	0	0.20	0.22	0.17	0.19	0.21	0.36
	5	0.16	0.18	0.14	0.16	0.18	0.22
	10	0.11	0.12	0.11	0.13	0.15	0.19
	15	0.09	0.07	0.06	0.11	0.10	0.13

TABLE V
COMPARISON OF PEAK SIGNAL TO NOISE RATIO (PSNR) FOR VARIOUS NOISES AT DIFFERENT INPUT SNR LEVELS BY BLMS, FxLMS, NLMS AND PROPOSED LMS NOISE REDUCTION ALGORITHMS

Spectral Subtraction Algorithms	Input SNR in dB	Babble	Car	Exhibition	Restaurant	Station	Street
BLMS	0	74.5	72.6	75.4	73.5	74.6	73.4
	5	76.3	73.7	76.2	74.0	75.5	74.5
	10	77.5	75.6	78.6	76.3	76.3	75.3
	15	79.7	76.4	80.4	77.5	78.1	78.2
FxLMS	0	76.2	73.0	76.8	75.4	75.0	75.0
	5	78.5	74.5	77.6	76.6	76.5	77.3
	10	80.3	76.6	79.0	78.8	78.7	78.4
	15	81.6	79.1	82.5	80.1	79.8	81.1
NLMS	0	77.4	75.8	79.4	77.3	77.9	79.2
	5	79.9	77.9	80.8	78.7	78.8	82.3
	10	81.5	79.4	82.1	80.6	81.	83.9
	15	82.5	80.1	85.3	81.9	85.8	85.7
Proposed	0	79.8	78.6	82.5	80.2	80.5	82.5
	5	80.3	79.0	83.1	82.8	83.3	84.1
	10	82.5	83.6	85.6	83.0	85.4	86.9
	15	84.7	86.7	87.7	84.6	87.6	88.5

VI. CONCLUSION

In this paper, the modified LMS adaptive noise reduction algorithm is proposed for enhancing the speech signal. The simulation is carried out under various noises with different input SNR (0dB, 5dB, 10dB and 15dB) levels, namely airport, babble, station, exhibition, restaurant, car, street and train noises for the proposed and existing algorithms. From the experimental results, it is observed that the proposed LMS adaptive noise reduction algorithm increases 0.5 dB to 15.4 dB of PSNR value, 13.3 dB to 72.6 dB of ΔSNRseg, reduces 15 dB to 71.3 dB of LSD, 12.2% to 68.4% of MSE and also it improves 1.4% to 33.7% of MOS as compared to that of the various existing algorithms under various noises with different input SNR levels. From the above evaluated results, it is observed that the proposed LMS adaptive noise reduction algorithm improves the speech signal quality and intelligibility as compared to that of the existing methods. In addition, it reduces speech distortion and residual noise in the enhanced speech signal.

REFERENCES

[1] T. Aboulnasr and K. Mayyas, "A robust variable step-size LMS-type algorithm: analysis and simulations", *IEEE Transactions on Signal Processing*, vol. 45 no.3, pp.631 – 639, 1997.
[2] I.Almajai and B.Milner, "Visually Derived Wiener Filters for Speech Enhancement", *IEEE Transactions on Audio, Speech and Language Processing*, vol. 19 no.6, pp.1642 – 1651, 2011.
[3] F.Asano, S.Hayamizu, T.Yamada and S.Nakamura, "Speech Enhancement Based on the Subspace Method", *IEEE transactions on Speech and Audio Processing*, vol. 8 no.5, pp.97-507, 2000.
[4] J.Benesty, H.Rey, L.R.Vega and S.Tressens, "A Nonparametric VSS NLMS Algorithm", *IEEE Signal Processing Letters*, vol. 13, no.10, pp. 581-584, 2006.

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[5] J.Benesty and Y.Huang, *Adaptive Signal Processing: Applications to Real-world Problems*. Berlin, Springer, 2003.
[6] N.J.Bershad, "Analysis of the Normalized LMS Algorithm with Gaussian Inputs", *IEEE Transactions on Acoustics, Speech and Signal Processing*, vol. ASSP-34, no.4, pp.93-806, 1986.
[7] S.Boll, "Suppression of acoustic noise in speech using spectral subtraction", *IEEE Transactions on Acoustics, Speech and Signal Processing,* vol. ASSP-27, no.2, pp.113–120,1979.
[8] H.F.Chi, S.X.Gao, S.D.Soli and A.Alwan, "Band-limited feedback cancellation with a modified Filtered-X LMS algorithm for hearing aids", *Speech Communication*, vol. 39, pp.147–161, 2003.
[9] B.Cornelis, M.Moonen and J.Wouters, "Performance Analysis of Multichannel Wiener Filter-Based Noise Reduction in Hearing Aids under Second Order Statistics Estimation Errors", *IEEE Transactions on Audio, Speech and Language Processing*, vol. 19, no.5, pp.1368-1381, 2011.
[10] S.C.Douglas, "Fast Implementations of the Filtered-X LMS and LMS Algorithms for Multichannel Active Noise Control", *IEEE Transactions on Speech and Audio Processing*, vol. 7, no.4, pp.454-465, 1999.
[11] M.A.A.El-Fattah, M.I.Dessouky, et al., "Speech enhancement with an adaptive Wiener filter", *International Journal on Speech Technology*, vol. 17, pp.53–64, 2014.
[12] S.Haykin, *Adaptive Filter Theory*. Prentice-Hall, 2001.
[13] S.Haykin, *Least-Mean-Square Adaptive Filters*. Wiley, 2003.
[14] J.Hellgren, "Analysis of Feedback Cancellation in Hearing Aids with Filtered-X LMS and the Direct Method of Closed Loop Identification", *IEEE Transactions on Speech and Audio Processing*, vol. 10, no.2, pp.119-131, 2002.
[15] B.Huang, Y.Xiao, J.Sun and G.Wei, "A Variable Step-Size Fx-LMS Algorithm for Narrowband Active Noise Control", *IEEE Transactions on Audio, Speech, and Language Processing*, vol. 21, no.2, pp.301-312, 2013.
[16] H.C.Huang and J.Lee, "A New Variable Step-Size NLMS Algorithm and Its Performance Analysis", *IEEE Transactions on Signal Processing*, vol. 60, no.4, pp.2055-2060, 2012.
[17] Y.Lu and P.C.Loizou, "A geometric approach to Spectral subtraction", *Speech Communication*, vol. 50, pp.453-466, 2008.
[18] J.R.Mohammed, M.S.Shafi, S.Imtiaz, R.I.Ansari and M.Khan, "An Efficient Adaptive Noise Cancellation Scheme Using ALE and NLMS Filters", *International Journal of Electrical and Computer Engineering*, vol. 2, no.3, pp. 325-332, 2012.
[19] B.K.Mohanty and P.K.Meher, "A High Performance Energy-Efficient Architecture for FIR Adaptive Filter Based on New Distributed Arithmetic Formulation of Block LMS Algorithm", *IEEE Transactions on Signal Processing*, vol. 61, no.4, pp.921-932, 2013.
[20] R.Serizel, M.Moonen, J.Wouters and S.H.Jensen, "A Zone-of-Quiet Based Approach to Integrated Active Noise Control and Noise Reduction for Speech Enhancement in Hearing Aids", *IEEE Transactions on Audio, Speech and Language Processing*, vol. 20, no.6, pp.1685-1697, 2012.
[21] B.L.Sim, Y.C.Tong, J.Chang and C.T.Tan, "A parametric formulation of the generalized spectral subtraction method", *IEEE Transactions on Speech and Audio Processing*, vol. 6, no.4, pp.328–337, 1998.

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