RESEARCH ARTICLE OPEN ACCESS

Performance Analysis of Acoustic Echo Cancellation Techniques

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ABSTRACT
Mainly, the adaptive filters are implemented in time domain which works efficiently in most of the applications. But in many applications the impulse response becomes too large, which increases the complexity of the adaptive filter beyond a level where it can no longer be implemented efficiently in time domain. An example of where this can happen would be acoustic echo cancellation (AEC) applications. So, there exists an alternative solution i.e. to implement the filters in frequency domain. AEC has so many applications in wide variety of problems in industrial operations, manufacturing and consumer products. Here in this paper, a comparative analysis of different acoustic echo cancellation techniques i.e. Frequency domain adaptive filter (FDAF), Least mean square (LMS), Normalized least mean square (NLMS) &Sign error (SE) is presented. The results are compared with different values of step sizes and the performance of these techniques is measured in terms of Error rate loss enhancement (ERLE), Mean square error (MSE)& Peak signal to noise ratio (PSNR).
Keywords–Acoustic echo cancellation, Error rate loss enhancement, Frequency domain adaptive filtering, Least mean square, Mean square error, Normalized least mean square, Peak signal to noise ratio, Sign error.

I. INTRODUCTION

The term echo cancellation is basically used in a telephony system for describing the process of removing echo from a voice communication system. The history of echo cancellation started from 10th July 1962[1]. Echo cancellation is basically required to improve the call quality, to provide enhanced network performance, for excellent tone rejection, to maintain customer reliability & to provide excellent ERLE performance [1]. There are some challenges which should be kept in mind at the time of designing AEC techniques i.e. circuit complexity, selection of filter length, selection of suitable step size, in finding echo path, different types of noises (acoustic, thermal, DSP related noise) present in circuit, convergence time/speed, computational cost, number of required iterations, computational complexity, residual error and sampling rate [1].

In a telecommunication system, echo can degrades the quality of service. Echo is the repetition of a waveform due to reflection from points where the characteristics of the medium through which the wave propagates changes. In a communication system, echo is generally undesirable but unavoidable [4]. So echo cancellation is an important part of communication system. In an AEC system, as shown in fig.1, a measured microphone signal (d(n)) contains two signals: - the far-end echoed speech signal (x(n)) and the near-end speech signal (v(n)). The aim is to remove the far-end echoed speech signal from the microphone signal using different adaptive filter algorithms, sothat only the near-end speech signal is transmitted. An adaptive filter is a digital filter which adjusts its coefficients to provide the best match to a given desired signal [8].

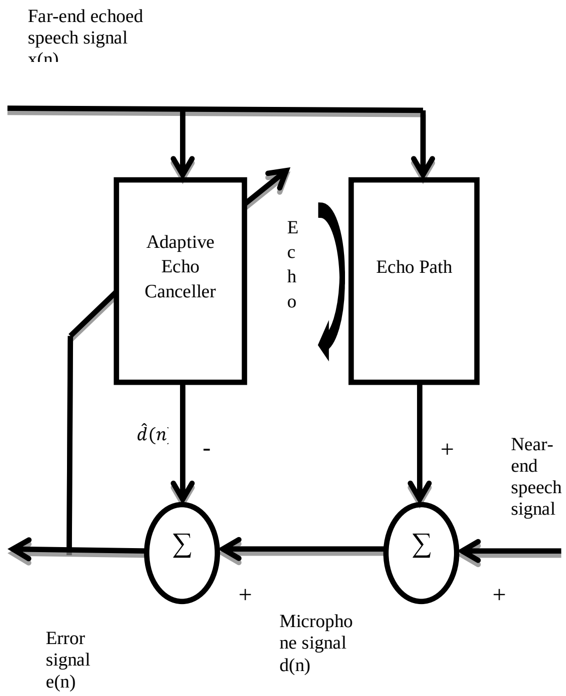

Fig.1. General Configuration of An Adaptive Echo Cancellor

The remainder of the paper is described as follow: Section 1 briefly describes the basic introduction about echo cancellation. Section 2 describes different types of algorithms/ techniques which are used for acoustic echo cancellation. In section 3, the various performance analysis parameters are presented. In Section 4, the results of different echo cancellation techniques are presented & in section 5, the conclusion and future scope is discussed.

II. AEC TECHNIQUES

In this section, some of the techniques are described which are used for the echo cancellation and these are as follow:

i. FIR frequency domain adaptive filter

The frequency domain adaptive filter used in AEC is very beneficial when the impulse response of the system to be identified is long[2]. In order to compute the output signal and filter updates, this filter uses a fast convolution technique. The main advantage of this kind of filter is that they have improved convergence performance through frequency-bin step size normalization and quickly executes in MATLAB[3].

Generally, the adaptive filters are implemented in time domain which works efficiently for most of the applications[4]. But in many of the applications the impulse response of the filter becomes too large, which increases the complexity of the filter beyond a certain level where it can be no longer implemented effectively in time domain i.e. in AECapplications [5].That is why the filter is implemented in frequency domain. Mainly the Fast Fourier Transform (FFT) and Discrete Fourier Transform (DFT) used for the conversion of signals from time domain to frequency domain[6].

The frequency domain weight vector is defined as[3],

W(k) = $[W_0(k), \dots\dots, W_{M-1}(k)]^T$ (1)

And the input signal matrix is given as[3],

X(k) = diag{X_0(k),……,$X_{M-1}(k)$}(2)

Where diag{.} is an operator which generates a diagonal matrix. The number of elements, M, depends on FDAF configuration (usually M = N or M = 2N). The frequency-domain output vector can be given as the following matrix/vector product[3]:

Y(k) = X(k)W(k) (3)

and the weight update equation is given as[3],

W(k+1) = W(k) + 2Gμ(k)$X^H(k)E(k)$(4)

where superscript H denotes complex conjugate transpose,μ(k) represents the time varying diagonal matrix which contains step sizes,matrix G shows a constraint on gradient$X^H(k)E(k)$&E(k) is the fourier transform of error matrix e(n), which is computed as,

e(n) = d(n) - $\hat{d}$(n)

This technique has very low computational complexity, faster convergence and consumes less processing power at the same time.

ii. FIR frequency domain adaptive filter with LMS algorithmq

The LMS method is initially proposed by widrow Hoff in 1959[7]. This algorithm adapts to a solution of minimizing mean-square error. This method is based on steepest-descent method. In this, the gradient of mean-squared error is find out with respect to h. If w(n) is the weight vector and x(n) is the input signal of adaptive filter then, output y(n) of the adaptive filter is given by[14]

y(n) = $w(n)^T$x(n) (5)

and the error signal e(n) is given by[14],

e(n) = d(n)-y(n) (6)

and the weight update equation is given by[14],

w(n+1) = w(n) + μe(n)x(n) (7)

where μ is the step size which controls the convergence rate. If the value of μ is small, then the convergence time is more. So the selection of suitable value of step size is very important[3],[8].

This algorithm is very simple and only requires few numbers of additions and multiplications per iteration for an N-tap filter. It has low computational complexity and the problem of double-talk is removed. But this method takes a fixed value of step size for every iteration [9].

iii. FIR frequency domain adaptive filter with NLMS algorithm

Basically, this algorithm is an extension of LMS. This method achieves faster convergence in time-domain as compared to frequency domain. Also, it has less complexity than LMS algorithm[10],[11]. It uses the weight updation equation as[14],

$w_{(n+1)} = w_n + \mu \frac{x(n)}{\|x(n)\|^2}$e(n) (8)

where μ is step size. Here, with the normalization of step size by$\|x(n)\|^2$, the noise amplification problem is diminished but problem occurs when $\|x(n)\|$ becomes too small. Therefore, the NLMS algorithm is modified as[14],

$$w_{(n+1)} = w_n + \mu \frac{x(n)}{\epsilon+\|x(n)\|^2}e(n) \quad (9)$$

where$\boldsymbol{\epsilon}$ is a small positive number.

This converges faster than LMS algorithm because it uses time varying step size calculation, but its computational complexity is high.

iv. FIR frequency domain adaptive filter with Sign-Error algorithm

Here, the sign-error algorithm is used with frequency domain adaptive filter. It is same as the LMS approach with the difference of different convergence time & computational complexity[12],[13]. Also this method provides better results for high value of filter length & for small value of step sizes.

III. PERFORMANCE ANALYSIS PARAMETERS

The various performance parameters which are used here for the performance evaluation of different AEC methods are as follow:

i. ERLE (Error rate loss enhancement): It is a smoothed measure of the amount (in dB) that the echo has been attenuated. The formula which is used for ERLE is given by[9],

$$\text{ERLE} = 10\log_{10}\frac{E[d^2(n)]}{E[e^2(n)]} \quad (10)$$

where d(n) is the far-end echoed signal and e(n) is the residual echo after cancellation.

ii. Mean square error: It contains the sequence of mean-square errors. This column vector contains predictions of the mean-square error of adaptive filter at each time instant.The MSE is calculated as[5],

$$\text{MSE} = \frac{1}{N}\sum_{k=1}^{N} e(k)^2 (11)$$

where N is the filter length and e(k) is the error signal achieved at the output of filter.

iii. Peak signal to noise ratio (PSNR): PSNR computes the peak signal-to-noise ratio, between two signals. This ratio is often used as a quality measurement between the original and the output signal. The higher the PSNR, the better the quality of output signals.The PSNR is calculated as,

PSNR = 10*log10((R*R)/MSE) (12)

whereMSE is the value of mean square error and R is the maximum fluctuation in the input signal.

IV. RESULT & DISCUSSIONS

Firstly, the acoustics of the loudspeaker-to-microphone signal path are described where the speakerphone is located. As shown in fig.2(a), a long finite impulse response filter is used to describe these characteristics which generates a random impulse response at a sampling rate of fs = 8000 Hz.

The teleconferencing system's user is mainly located near the system's microphone which is called as near end speech signal as shown in fig. 2(b). A voice travels out the loudspeaker, bounces around in the room, and this voice is picked up by the system's microphone; this voice signal is called as far end speech signalas shown in fig.2(c). Also in fig.2(d), the microphone signal contains both the near end speech and the far end speech that has been echoed throughout the room is shown.

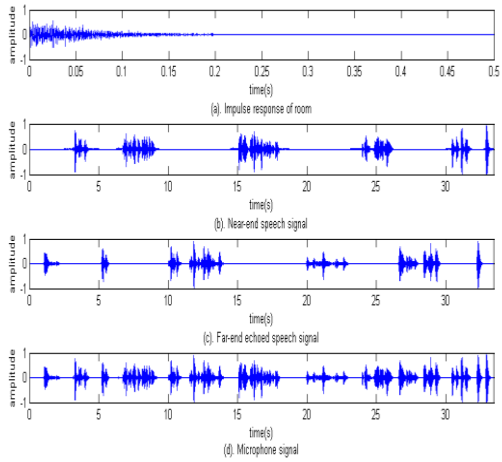

Fig.2: (a).Impulse response of room, (b).Near-end speech signal, (c).Far-end echoed speech signal, (d).Microphone signal

Output of acoustic echo canceller is observed by using frequency domain adaptive filtering method as shown in fig.3 to fig.6.Here, the value of filter length (N) is varied and the value of step size (μ) is taken as constant i.e. 0.025.

The goal of adaptive echo canceller is to remove the far end echoed speech signal, so that only near end speech signal is transmitted back to the far-end listener. Since, we have access to both near end and far end speech signals, so echo return loss enhancement is also calculated, which is the amount (in dB) that how much echo has been attenuated. From fig.6 it has been seen that approx. 30 dB ERLE is achieved at the end of convergence period using FDAF algorithm.

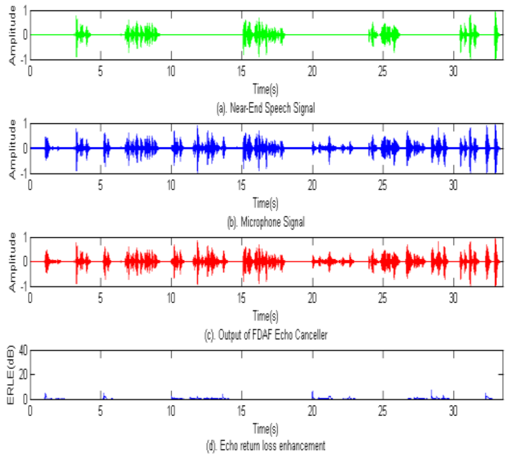

Fig.3: (a).Near-end speech signal, (b).Microphone signal, (c).Output of FDAF algorithm when filter length, N = 32 & μ = 0.025, (d).Echo return loss enhancement

In all the figures from fig.3 to fig.18, (a)&(b) part shows the near-end speech signal and the microphone speech signalrespectively. In fig. 3(c), the output of FDAF algorithm is shown when the filter length is 32 & step size is 0.025. In fig.3(d), the Amount of ERLE achieved is shown i.e approx. 1 dB.

Also in fig. 4(c), the output of FDAF algorithm is shown when the filter length is 128& step size is 0.025. In fig.4(d), the Amount of ERLE achieved is shown i.e approx. 8 dB.

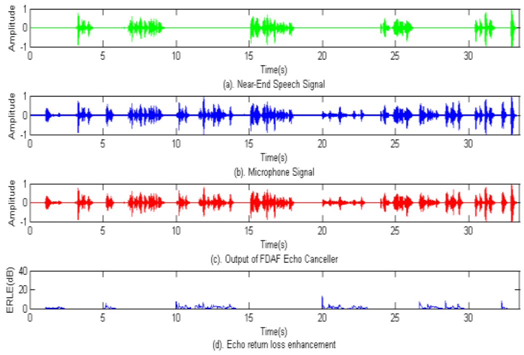

Fig.4: (a).Near-end speech signal, (b).Microphone signal, (c).Output of FDAF algorithm when filter length, N = 128& μ = 0.025, (d).Echo return loss enhancement

In fig. 5(c), the output of FDAF algorithm is shown when the filter length is 512& step size is 0.025. In fig.5(d), the Amount of ERLE achieved is shown i.e approx. 20 dB.

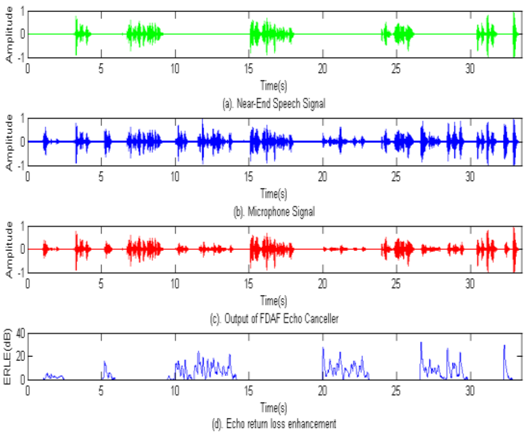

Fig.5: (a).Near-end speech signal, (b).Microphone signal, (c).Output of FDAF algorithm when filter length, N = 512& μ = 0.025, (d).Echo return loss enhancement

In fig. 6(c), the output of FDAF algorithm is shown when the filter length is 2048& step size is 0.025. In fig.6(d), the Amount of ERLE achieved is shown i.e approx. 30 dB.

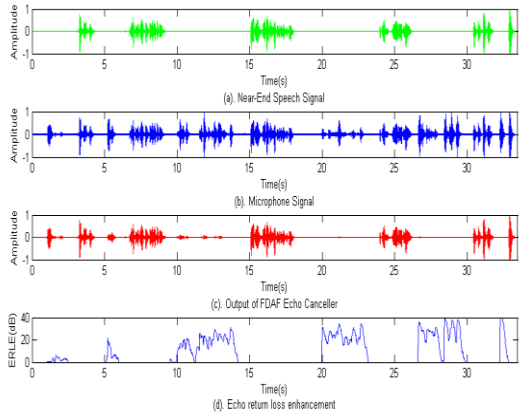

Fig.6: (a).Near-end speech signal, (b).Microphone signal, (c).Output of FDAF algorithm when filter length, N = 2048& μ = 0.025, (d).Echo return loss enhancement

Table 1shows the ERLE achieved for different values of step sizes and filter lengths for the FDAF algorithm. It is clear from the results of table that if the value of filter length is constant & the value of step size is increases, then the amount of ERLE achieved at the end of convergence period is decreases. So, FDAF algorithm works better for the filter length of 2048 and step size of 0.025.

Now, the output of acoustic echo canceller is observed by using frequency domain adaptive filter which uses LMS algorithm as shown in fig.7 to fig.10. Here, the value of filter length (N) is varied and the value of step size (μ) is taken as constant i.e. 0.07 for achieving best results.

In fig. 7(c), the output of LMS algorithm is shown when the filter length is 32 & step size is 0.07. In fig.7(d), the Amount of ERLE achieved is shown i.e approx. 4 dB.

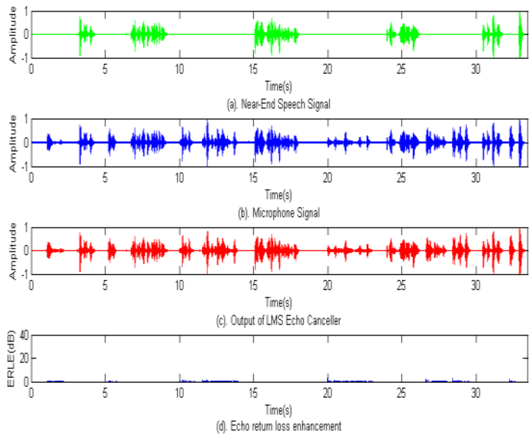

Fig.7: (a).Near-end speech signal, (b).Microphone signal, (c).Output of LMS algorithm when filter length, N = 32 & μ = 0.07, (d).Echo return loss enhancement

Also in fig. 8(c), the output of LMS algorithm is shown when the filter length is 128& step size is

0.07. In fig.8(d), the Amount of ERLE achieved is shown i.e approx.5 dB.

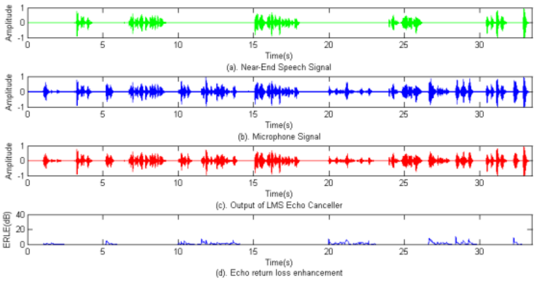

Fig.8: (a).Near-end speech signal, (b).Microphone signal, (c).Output of LMS algorithm when filter length, N = 128 & μ = 0.07, (d).Echo return loss enhancement

In fig. 9(c), the output of LMS algorithm is shown when the filter length is 512& step size is 0.07. In fig.9(d), the Amount of ERLE achieved is shown i.e approx. 15 dB.

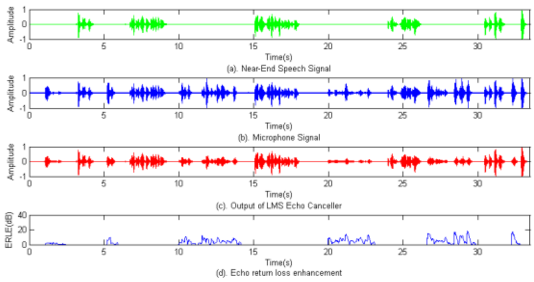

Fig.9: (a).Near-end speech signal, (b).Microphone signal, (c).Output of LMS algorithm when filter length, N = 512 & μ = 0.07, (d).Echo return loss enhancement

In fig. 10(c), the output of LMS algorithm is shown when the filter length is 2048& step size is 0.07. In fig.9(d), the Amount of ERLE achieved is shown i.e approx. 20 dB.

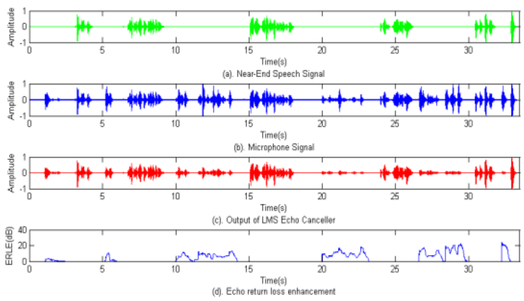

Fig.10: (a).Near-end speech signal, (b).Microphone signal, (c).Output of LMS algorithm when filter length, N = 2048& μ = 0.07, (d).Echo return loss enhancement

Table 2 shows the ERLE achieved for different values of step sizes and filter lengths for the LMS algorithm. It is clear from the results of table that if the value of filter length is constant & the value of step size is increases, then the amount of ERLE achieved at the end of convergence period is firstly increases, then decreases. So, LMS algorithm works better for the filter length of 2048 and step size of 0.07.

Now, the output of acoustic echo canceller is observed by using frequency domain adaptive filter which uses NLMS algorithm as shown in fig.11 to fig.14. Here, the value of filter length (N) is varied and the value of step size (μ) is taken as constant i.e. 0.1 for achieving best results.

In fig. 11(c), the output of NLMS algorithm is shown when the filter length is 32 & step size is 0.1. In fig.11(d), the Amount of ERLE achieved is shown i.e approx. 0.2 dB.

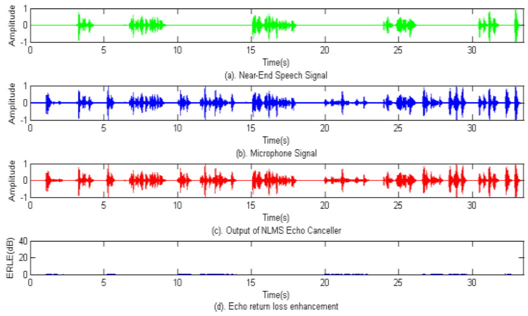

Fig.11:(a).Near-end speech signal, (b).Microphone signal, (c).Output of NLMS algorithm when filter length, N = 32 & μ = 0.1, (d).Echo return loss enhancement

Also in fig. 12(c), the output of NLMS algorithm is shown when the filter length is 128& step size is 0.1. In fig.12(d), the Amount of ERLE achieved is shown i.e approx.1 dB.

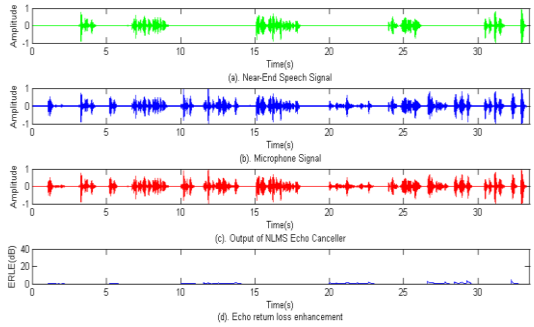

Fig.12: (a).Near-end speech signal, (b).Microphone signal, (c).Output of NLMS algorithm when filter length, N = 128& μ = 0.1, (d).Echo return loss enhancement

In fig. 13(c), the output of NLMS algorithm is shown when the filter length is 512& step size is 0.1. In fig.13(d), the Amount of ERLE achieved is shown i.e approx.2 dB.

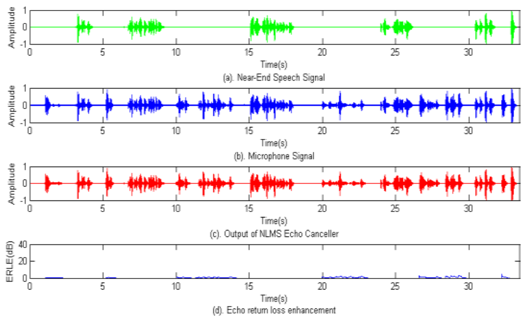

Fig.13: (a).Near-end speech signal, (b).Microphone signal, (c).Output of NLMS algorithm when filter length, N = 512& μ = 0.1, (d).Echo return loss enhancement

In fig. 14(c), the output of NLMS algorithm is shown when the filter length is 2048& step size is 0.1. In fig.14(d), the Amount of ERLE achieved is shown i.e approx.2 dB.

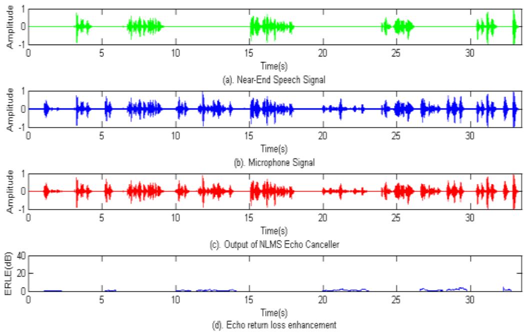

Fig.14: (a).Near-end speech signal, (b).Microphone signal, (c).Output of NLMS algorithm when filter length, N = 2048& μ = 0.1, (d).Echo return loss enhancement

Table 3 shows the ERLE achieved for different values of step sizes and filter lengths for the NLMS algorithm. It is clear from the results of table that if the value of filter length is constant & the value of step size is increases, then the amount of ERLE achieved at the end of convergence period is increases. So, the results shows that NLMS algorithm does not provides better results for the assuming range of filter length and step size.

Now, the output of acoustic echo canceller is observed by using frequency domain adaptive filter which uses SE algorithm as shown in fig.15 to fig.18. Here, the value of filter length (N) is varied and the value of step size (μ) is taken as constant i.e. 0.025 for achieving best results.

In fig. 15(c), the output of SE algorithm is shown when the filter length is 32 & step size is 0.025. In fig.15(d), the Amount of ERLE achieved is shown i.e approx.2 dB.

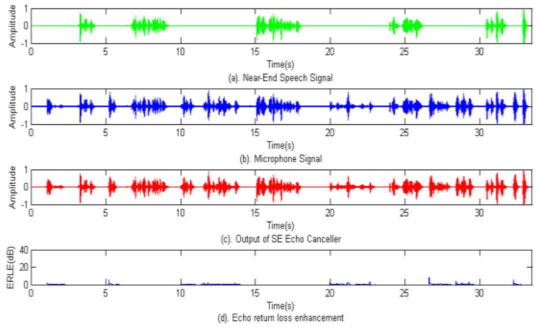

Fig.15: (a).Near-end speech signal, (b).Microphone signal, (c).Output of SE algorithm when filter length, N = 32& μ = 0.025, (d).Echo return loss enhancement

In fig. 16(c), the output of SE algorithm is shown when the filter length is 128& step size is 0.025. In fig.16(d), the Amount of ERLE achieved is shown i.e approx.8 dB.

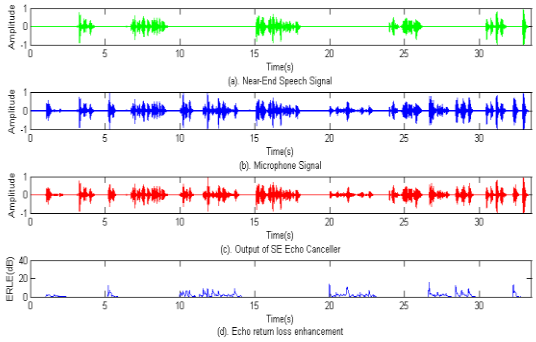

Fig.16: (a).Near-end speech signal, (b).Microphone signal, (c).Output of SE algorithm when filter length, N = 128& μ = 0.025, (d).Echo return loss enhancement

In fig. 17(c), the output of SE algorithm is shown when the filter length is 512& step size is 0.025. In fig.17(d), the Amount of ERLE achieved is shown i.e approx.14 dB.

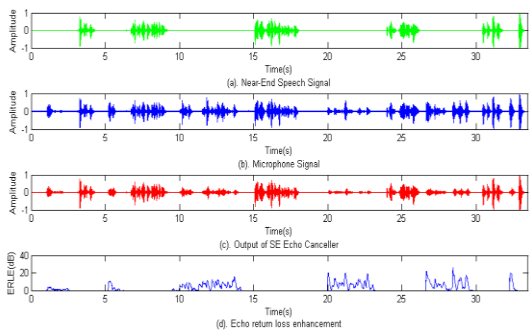

Fig.17: (a).Near-end speech signal, (b).Microphone signal, (c).Output of SE algorithm when filter length, N = 512& μ = 0.025, (d).Echo return loss enhancement

Parameters	FDAF ALGORITHM											
Filter length	N = 32			N = 128			N = 512			N = 2048		
Step size (μ)	0.025	0.07	0.1	0.025	0.07	0.1	0.025	0.07	0.1	**0.025**	0.07	0.1
ERLE (dB)	1	1	1	8	5	5	20	12	12	**30**	20	18

Table no.1.ERLE for different filter length & step sizes for FDAF algorithm

Parameters	LMS ALGORITHM											
Filter length	N = 32			N = 128			N = 512			N = 2048		
Step size (μ)	0.025	0.07	0.1	0.025	0.07	0.1	0.025	0.07	0.1	0.025	**0.07**	0.1
ERLE (dB)	3	4	2	6	5	4	8	15	10	10	**20**	15

Table no.2.ERLE for different filter length & step sizes for LMS algorithm

Parameters	NLMS ALGORITHM											
Filter length	N = 32			N = 128			N = 512			N = 2048		
Step size (μ)	0.025	0.07	0.1	0.025	0.07	0.1	0.025	0.07	**0.1**	0.025	0.07	0.1
ERLE (dB)	0.1	0.1	0.2	0.2	0.5	1	0.5	0.5	**2**	1	2	2

Table no.3.ERLE for different filter length & step sizes for NLMS algorithm

Parameters	SE ALGORITHM											
Filter length	N = 32			N = 128			N = 512			N = 2048		
Step size (μ)	0.025	0.07	0.1	0.025	0.07	0.1	0.025	0.07	0.1	**0.025**	0.07	0.1
ERLE (dB)	2	2	2	8	5	8	14	10	8	**15**	12	5

Table no.4.ERLE for different filter length & step sizes for SE algorithm

Algorithms→ Paramaters ↓	LMS			NLMS			SE		
Step size(μ)	0.025	0.7	0.1	0.025	0.7	0.1	0.025	0.7	0.1

ERLE(dB)	3	4	2	0.1	0.1	0.2	2	2	2
MSE	0.0070	0.0070	0.0067	0.0077	0.0078	0.0070	0.0074	0.0071	0.0064
PSNR(dB)	21.5653	21.5323	21.7142	21.1190	21.0599	21.5718	21.3193	21.4668	21.9349

Table no.5 (when filter length N = 32)

Algorithms→ Paramaters ↓	LMS			NLMS			SE		
Step size(μ)	0.025	0.7	0.1	0.025	0.7	0.1	0.025	0.7	0.1
ERLE(dB)	6	5	4	0.2	0.5	1	8	5	8
MSE	0.0062	0.0061	0.0064	0.0064	0.0061	0.0062	0.0061	0.0061	0.0058
PSNR(dB)	22.0921	22.1718	21.9136	21.9495	22.1387	22.0921	22.1718	22.1235	22.3347

Table no.6 (when filter length N = 128)

In fig. 18(c), the output of SE algorithm is shown when the filter length is 2048 & step size is 0.025. In fig.18(d), the Amount of ERLE achieved is shown i.e approx. 15 dB.

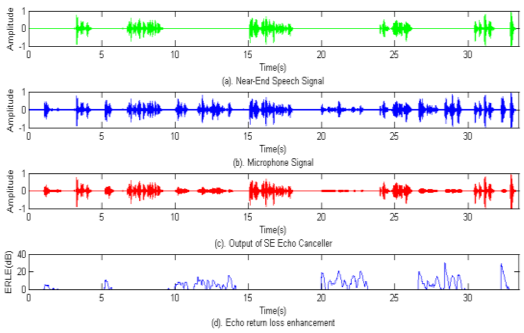

Fig.18: (a).Near-end speech signal, (b).Microphone signal, (c).Output of SE algorithm when filter length, N = 2048 & μ = 0.025, (d).Echo return loss enhancement

Table 4 shows the ERLE achieved for different values of step sizes and filter lengths for the SE algorithm. It is clear from the results of table that if the value of filter length is constant & the value of step size is increases, then the amount of ERLE achieved at the end of convergence period is mostly decreases. So, SE algorithm provides better results for the filter length of 2048 and step size of 0.025.

Also the performance analysis of these algorithms is done by calculating ERLE, MSE & PSNR by using different values of step sizes and filter length, which is shown in table no.5 & 6.

It is also clear from table no.5 that the LMS algorithm provides better results i.e. ERLE = 4 dB, MSE = 0.070 & PSNR = 21.5323 for the filter length of 32 and step size of 0.7. Also if the value of step size is increases, the value of MSE decreases and the value of PSNR increases.

It is also clear from table no.6 that the SE algorithm provides better results i.e. ERLE = 8 dB, MSE = 0.058 & PSNR = 22.3347 for the filter length of 128 and step size of 0.1. Also if the value of step size is increases, the value of MSE decreases and the value of PSNR increases.

V. CONCLUSION AND FUTURE SCOPE

From the above tables & results it is clear that for the step size of 0.025 & filter length of 2048, the FDAF algorithm provides better results i.e. the ERLE of 30 dB. Similarly, the LMS algorithm works better for the step size of 0.07 and filter length of 2048. But if the value of step size is increases up to 0.3, then approx. 35 dB ERLE is achieved. The NLMS algorithm does not provide better results for the given range of step size &filter length. Similarly, the SE algorithm provides good results for the step size of 0.025 & filter length of 2048.

Also, by studying all these algorithms regarding echo cancellation, the use of better performance algorithm and different filter structure for the elimination of echo signal would be the future research. Each algorithm has some operational limitations, but a reliable system can be developed using suitable algorithm for echo removal.

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