Performance Evaluation of Selected Adaptive Filters for Acoustic Echo Cancelation over Voice over Internet Protocol

[1]Ibrahim O. Oyetunji, [1]Kamoli A. Amusa, [1]Isiah A. Adejumobi, and [2]Amidu O. Mustapha
[1]Department of Electrical and Electronics Engineering, Federal University of Agriculture, Abeokuta, Nigeria
[2]Department of Physics, Federal University of Agriculture, Abeokuta, Nigeria
oyeibrahimoye@gmail.com|amusaka@funaab.edu.ng|adejumobiia@funaab.edu.ng| amidumustapha@gmail.com

Received: 27-JUL-2022; Reviewed: 04-SEP-2022; Accepted: 14-SEP-2022
https://doi.org/10.46792/fuoyejet.v7i3.897

ORIGINAL RESEARCH

Abstract- Advancement of technology has increased the value of the telecommunications industry. One of the services with the rapid growth is Voice over Internet Protocol (VoIP). However, echo is a common disturbing effect in VoIP calls. Instead of suppressing the presence of echo in the VoIP communication channel, echo cancellation works better in full-duplex mode. This paper compares performances of some selected adaptive filters for cancelation of acoustic echo in VoIP channel. The framework for adaptive echo cancellation is built around finite impulse response and fourth-order infinite impulse response Chebyshev type II filters for the modelling of echo and acoustic environment, respectively. Selected adaptive algorithms for analysis are least mean square, recursive least square and frequency domain adaptive filter. The analysis is carried out in MATLAB 2018a environment. Echo return loss enhancement, error estimate and convergence rate are the performance indices employed for performance comparison of selected adaptive algorithms. It was found that the FDAF algorithm performed best based on computed error return loss enhancement and error estimate figures. In addition, FDAF converges faster than LMS and RLS with average time of 0.026431 s over 2048 filter lengths. Thus, FDAF shows a better promise over the two variants of time domain adaptive algorithm (LMS and RLS) analysed in this paper.

Keywords- Acoustic Echo Cancellation (AEC), Frequency Domain, Time Domain, VoIP

1 Introduction

The telecommunication industry has evolved appreciably in recent years, with the introduction of new services almost on daily basis. VoIP (Voice over Internet Protocol) is an emerging communication technique that has become so popular to the extent of transforming how people communicate. There is huge save in cost generally by using VoIP for voice communication (Alsahlany, 2014). However, a major issue with VoIP network is inherent echo which degrades the voice quality (Elamin, 2016). The subscribers' voice quality is a measure of grade of service in voice communication networks. Thus, there is the need for implementation of techniques to suppress echo to the barest minimum if total elimination is impossible.

There is an increasing demand for high-quality voice communication services at a reasonable price. This is evidenced by foray of social media platforms like Telegram, WhatsApp etc. in existence today, which are rendering voice communication services through VoIP technique. Globally, the current situation has increased demand for VoIP services even more than previously, as a result of the COVID-19 pandemic. Consequently, echoes and other VoIP-related issues need to be addressed. In signal processing an unwanted signal is usually do away with via filtering operation. The effect of an echo, being an unwanted signal in the context of VoIP channel, can be mitigated through filtering.

*Corresponding Author

Section B- ELECTRICAL/ COMPUTER ENGINEERING & RELATED SCIENCES
Can be cited as:
Oyetunji I.O., Amusa K.A., Adejumobi I.A., and Mustapha A.O. (2022): Performance Evaluation of Selected Adaptive Filters for Acoustic Echo Cancelation over Voice over Internet Protocol, *FUOYE Journal of Engineering and Technology* (FUOYEJET), 7(3), 328-333. http://doi.org/10.46792/fuoyejet.v7i3.897

In this paper, analysis of selected adaptive filters is carried out, to isolate which one perform best in mitigating the effect of echo over VoIP networks.

2 Related Work

In recent years, a number of researches have been commissioned to address the problem of echo cancellation over VoIP communication networks. Of note are Mahfoud and Abderrahmane (2019), Islam et al., (2020), Srikanth and Asutosh (2020), Feiran and Jun, (2019), Yiyu et al. (2020), Swaroopa (2013) and Minho et al., (2022) to name a few. Mahfoud and Abderrahmane (2019) while evaluating the conventional Adaptive Echo Cancellers (AEC) found that AEC having Normalized Least Mean Square (NLMS) algorithm implemented performed better than those that use traditional structure of AEC. Other variants of NLMS introduced include Fast NLMS (FNLMS), Set Membership FNLSM (SM-FNLMS), Improved Set Membership FNLSM (ISM-FNLMS) and Set Membership Robust Error Bound NLSM (SMREB-NLMS). These variants of NLMS are proposed in order to improve the performance. Using convergence rate, mean square error at steady state, tracking capability of tracking as well as reduced complexity of computation as indices, ISM-NLMS is adjudged the best for AEC application (Islam et al., 2020).

Srikanth and Asutosh (2020) proposed a nonlinear acoustic cancellation adaptive algorithm termed Improved Optimized-NLMS. The proposed algorithm was found to have better Echo Return Loss Enhancement (ERLE) figure and converge faster than three variants of Link Adaptive Filter (LAF) namely Split Functional LAF (SFLAF), Proportionate FLAF (PFLAF), and PSFLAF), when used for echo cancellation.

Feiran and Jun (2019) while addressing convergence issue associated with the use of Normalized Frequency-domain

Block LMS (NFBLMS) algorithm for cancellation of echo proposed Modified FBLMS (MFBLMS). The faster convergence is realized in MFBLMS by normalizing the filter step-size by its power in each frequency bin of the algorithm. Sparsity-aware sign sub-band adaptive filtering algorithm with individual weighting factors (S-IWAF-SSAF) was introduced by Yu et al., (2020) as an improvement to IWF-SSF algorithm for acoustic echo cancellation. The improvement is premised on the use of a joint optimization method for assignment of the step size and sparsity penalty parameter for the filtering algorithm.

Swaroopa and Sravya (2013) compared performances of LMS, NLMS, Affine Projection Algorithm (APA), and Recursive Least Square (RLS) algorithms when each was employed for echo cancellation. These algorithms were tested in a simulation of an echo-producing environment in which the room dimensions, microphone positions, and source positions remained constant. It was found that RLS performed better than the other two algorithms. The traditional adaptive algorithm, LMS and its variant NLMS suffer performance deterioration when the input is highly correlated. While APA performed satisfactorily in highly correlated input, it was however found to be affected by impulsive noise. The study by Minho *et al.*, (2022) proposed the use of variable step-size saturation to overcome the problem of impulsive noise in APA when used for echo cancellation application.

Judging from above reviews, it is clear that convergence speed, echo return loss and complexity of algorithm implementation are crucial to selection of adaptive filtering algorithm for echo cancellation application. This work is concerned with performance analysis of three adaptive algorithms: NLMS, RLS and Frequency Domain Adaptive Filter (FDAF), for echo cancelation over VoIP network.

3 Methodology

In this paper, a finite impulse response is used in the generation of echo signal while infinite impulse response 4th-order Chebyshev type II filter is adopted in the modelling of VoIP environment effect. Three adaptive algorithms employed in the analysis are NLMS, RLS and Frequency Domain Adaptive Filter (FDAF).

3.1 Modelling of Echo

Echo was generated by a delay unit attached to a Finite Impulse Response (FIR) filter as proposed by Pushpalatha and Mohan (2014). The input signal, $x(n)$, to the FIR filter as shown in Figure 1 is a predetermined 1.6 kHz signal that represents a two-person phone call. The properties required to describe the delay signal known as an echo are provided by the FIR filter. In order to create the echo as the output signal for $y(n)$, $x(n)$ in Figure 1 is the saved conversations as .wav file inside MATLAB-Simulink environment. The voice signal is sampled using 16-bit signed pulse code modulation at 352 kbps.

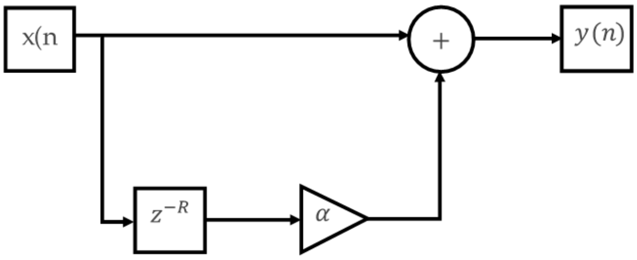


Fig. 1: Echo Filter Modeling (Pushpalatha and Mohan, 2014)

The FIR filter transfer function is expressed as:

$$\mathrm{H_z} = 1 + \alpha z^{-R}, |\alpha| < 1 \tag{1}$$

where R is the amount of time it takes for the sound wave to reach the listener after returning from the reflecting wall, α (with $|\alpha| < 1$) is the signal loss resulting from propagation and reflection.

3.2 Modelling of the VoIP Channel

As stated earlier an IIR Chebyshev type II filter is used to model the room environment that represents the VoIP channel. The Chebyshev II filter model is given by:

$$G_n(\omega, \omega_0) = \frac{1}{\sqrt{1 + \frac{1}{\varepsilon^2 T_n^2(\omega_0/\omega)}}} \tag{2}$$

where,

$$T_n(x) = \sum_{k=0}^{\lfloor \frac{n}{2} \rfloor} \binom{n}{2k} (x^2 - 1)^k x^{n-2k} \tag{3}$$

and

$$\varepsilon = \frac{1}{\sqrt{10^{\gamma/10} - 1}} \tag{4}$$

whist G_n represents the filter's frequency response, ε is the ripple factor, γ is the stopband attenuation, T_n is the Chebyshev polynomial of nth order, (ω, ω_0) represent the operating and cut-off frequency, respectively.

Table 1. Parameters for VoIP environment modelling

Parameters	Value
Stop-band Edge Frequency	$0.1 \leq W_s \leq 0.7$
Frame Size	2^{11}
Range	0.5
Filter Order (n)	4
Time Scale (s)	35

Several experiments were carried out to arrive at values of parameters shown in Table 1, with due consideration for filter quality as well as computational time. The parameter W_s in Table 1 represents the edge frequency whose effect is explained in section 4.

3.3 Adaptive Algorithm Implementation

The adaptive transversal filter proposed by Simon (2014) was adopted in this work. Figure 2 represents the general framework adopted for the implementation of different adaptive algorithms.

http://doi.org/10.46792/fuoyejet.v7i3.897 http://journal.engineering.fuoye.edu.ng/

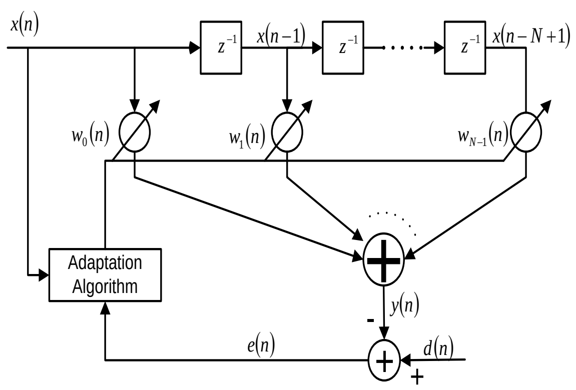


Fig. 2: Model for adaptive algorithm (Simon, 2014)

3.3.1 LMS Algorithm

Two fundamental processes characterize LMS algorithm. They are evaluation of the filter output response and estimation of error signal (Lizhe and Jiang, 2019). LMS algorithm is defined by

$$y(n) = w^T(n-1)u(n) \tag{5}$$

$$e(n) = d(n) - y(n) \tag{6}$$

$$w(n) = \alpha w(n-1) + f(u(n), e(n), \mu) \tag{7}$$

where n is the current time index, $u(n)$ denotes the input samples in the buffer, $w(n)$ is the filter weight estimates at current time index, μ is the adaptive step size which controls the weights and α is the leakage factor and has its values specified such that $0 < \alpha \leq 1$.

3.3.2 RLS Algorithm

Iterative computation of the FIR filter weights characterizes the RLS algorithm (Nascimento and Magno, 2014). The RLS filter algorithm is expressed in the following steps:

Initialize weight vector to zero, that is, $w(n) = 0$
Take inverse of correlation matrix

$$p(0) = \partial^{-1} \tag{8}$$

Each iteration calculates

$$k(n) = \frac{\lambda^{-1}P(n-1)u(n)}{1+\lambda^{-1}u^H(n)P(n-1)u(n)} \tag{9}$$

$$y(n) = w^T(n-1)u(n) \tag{10}$$

$$e(n) = d(n) - w^T(n-1)u(n) \tag{11}$$

$$w(n) = w(n-1) + k^*(n)e(n) \tag{12}$$

$$P(n) = \lambda^{-1}P(n-1) - \lambda^{-1}k(n)u^H(n)P(n-1) \tag{13}$$

where $k(n)$ and $e(n)$ are the gain vector and estimation error, respectively, λ^{-1} is the inverse of the exponential weighting factor, $w(n)$ is the filter weight update, while the forgetting factor having value in the range 0 to 1 is represented by λ.

3.3.3 FDAF Algorithm

FDAF filter operates in frequency domain unlike NLMS and RLS algorithms. A mathematical implementation of a block FIR filter proposed by Soo and Pang (1990) for FDAF algorithm implementation is adopted in this paper. It is described as follows:

Suppose L and M represent a block length and length of tapped weight vector, respectively, then the data matrix of the block of FIR filter is given as

$$A(k) = \begin{bmatrix} u(kL)\ldots & u(kL-1)\ldots & u(kL-M+1) \\ u(kL+1) & u(kL) & u(kL-M+2) \\ \ldots & \ldots & \ldots \\ u(kL+L+1) & u(kL+L-2) & u(kL+L-M) \end{bmatrix} \tag{14}$$

while the weight vector is expressed as

$$W(k) = \begin{bmatrix} G(kM) \\ G(kM+1) \\ \ldots \\ G(kM+L-1 \end{bmatrix} \tag{15}$$

provided $A(k)$ is a $L \times M$ matrix while M is the length of vector $G^T(kM)$.

Suppose the weight vector is recast as,

$$\widehat{W}(k+1) = [w_0(k) \quad w_1(k) \quad \ldots\ldots\ldots \quad w_{L-1}(k)]^T \tag{16}$$

Then, using (14) and (16), the filter output vector is obtained as

$$[y(kL)\ldots \quad y(kL+1)\ldots \quad y(kL+L-1]^T = A(k).\widehat{W}(k) \tag{17}$$

For individual element, one obtains

$$y(kL) = G(kM).\widehat{W}(k)$$

$$y(kL+1) = G(kM+1).\widehat{W}(k)$$

$$\vdots$$

$$y(kL+i) = G(kM+i).\widehat{W}(k)$$

$$= \sum_{j=0}^{M-1} w_0(k).u(kL+i-j) \tag{18}$$

provided $y(kL+i)$ is the ith output vector.

Suppose $d(kL+i)$ is the response desired for $(kL+i)$th element. The associated error signal is given by

$$e(kL+i) = d(kL+i) - y(kL+i) \tag{19}$$

Multiplication of the error vector $e(k)$ with the matrix A^T yields the cross-correlation vector, which is written as

$$\boldsymbol{\varphi}(k) = A^T(k)e(k) \tag{20}$$

The weight vector update equation is given by

$$\widehat{W}(k+1) = \widehat{W}(k) + \mu\boldsymbol{\varphi}(k) \tag{21}$$

All vector coefficients for each $(k+i)$th term is updated through continuation and repeat of these steps.

3.3.4 Algorithms Parameter Setup

Provided in this section are the parameters used to simulate algorithms for the filtering processes.

Table 2. Setup parameters for the algorithms

Algorithm	Filter length	Step size	Projection order	Averaging factor
LMS	2048	0.025		
RLS	11	0.025		
FDAF	2048	0.025	0.01	0.98

The value of time samples defined in this work during the filtering of $y(k)$ in (6), (11), and (19) is 2048, which defines the filter length. The value works for LMS and FDAF algorithms but not for RLS due to divergence and instability of results. Arising from several experiments, a value of 11 is found to guarantee stability and convergence of RLS algorithm, hence its use in this work. For all the three algorithms, the same step size with a value of 0.025 is adopted while other local parameters for FDAF, employed in the simulation, are as specified in Table 2.

http://doi.org/10.46792/fuoyejet.v7i3.897 http://journal.engineering.fuoye.edu.ng/

3.3.5 Performance Indices for Evaluation

Convergence rate (CR): this is a measure of the number of iterations before steady state is reached.

$$\sigma = \lim_{n\to\infty} \frac{|x_{n+1} - r|}{|x_n - r|^{\alpha}} \quad (22)$$

where α is defined as the rate of convergence, x_n is the input signal at an instant n while r is the threshold.

Estimated error: this measures the average mean square error occurring in the filtering process. It is expressed as

$$\xi = \sum |e(i)|^2 \quad (23)$$

where $e(i)$ is the ith expected value of the error.

ERLE: It is defined in decibel as

$$ERLE = 10 \log \frac{E[d^2\,(n)]}{E[e^{\,2}(n)]} \quad (24)$$

where ($E[d^2\,(n)]$, $E[e^{\,2}(n)]$) are the power of the echo signal and residual error signal, respectively, at an instant.

4 Results and Discussion

4.1 Acoustic VoIP Environment

Figure 3 depicts the modelled acoustic VoIP environment using a fourth-order Chebyshev type II IIR filter. The sampling frequency fs is set to 8000 while the edge frequency Wn is the range $0.1 < Wn < 0.7$ as presented in Table 1. It can be deduced from Figure 3 that the range of the passband is $0.15\pi \longrightarrow 0.59\pi$ while that of stopband is $0 \longrightarrow 0.1\pi$ and $0.7\pi \longrightarrow \pi$.

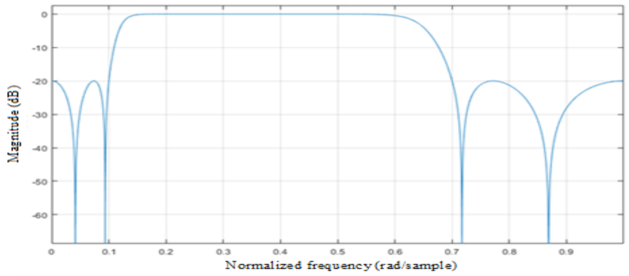


Fig. 3: Modelled VoIP environment

Based on filter rule, if a band-pass filter has unequal transition bandwidths, the smaller one is used. The transition bandwidth used in this paper is 0.05π ($0.15\pi - 0.1\pi$), which is the transition band before the pass-band (Figure 3) since it is smaller than 0.11π ($0.7\pi - 0.59\pi$), the transition band after the pass-band. As a result, the frequency of the voice signal that can pass through the designed filter that represents the VoIP channel is within the pass-band range of $0.15\pi \longrightarrow 0.59\pi$.

4.2 Speech Signal Simulation

Acoustic echo cancellation was modelled using known signals from recorded phone calls. The far end signal was fed into the modelled VoIP environment before reaching the speaker in the near end. Amplification of the far-end speech signal by direct speech (near-end signal) generates the microphone signal.

For algorithms implementation, parameters such as step size and forgetting factor are set in order to prevent occurrence of mis-adjustment of filter response based on entries in Table 2. In addition, filter length is specified in advance to ensure that the time duration of 35 s is maintained, irrespective of the adaptive filter used.

Figures 4, 5, and 6 portray the simulated far-end speech, near-end, and microphone signals, respectively. Figures 7, 8 and 9 illustrate obtained outputs when LMS, RLS and FDAF algorithms are implemented in echo cancellation framework, respectively.

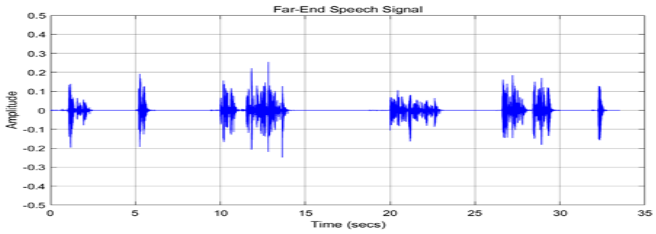


Fig. 4: Simulated far-end speech signal

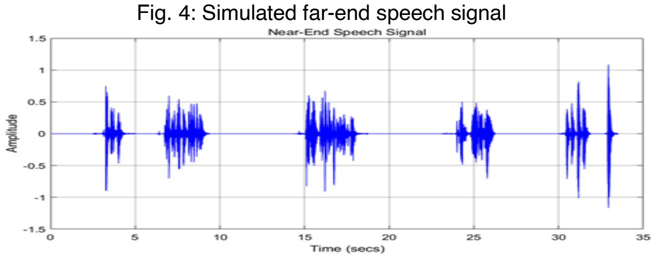


Fig. 5: Simulated near-end speech signal

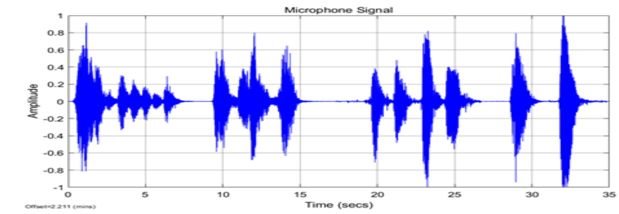


Fig. 6: Simulated microphone signal

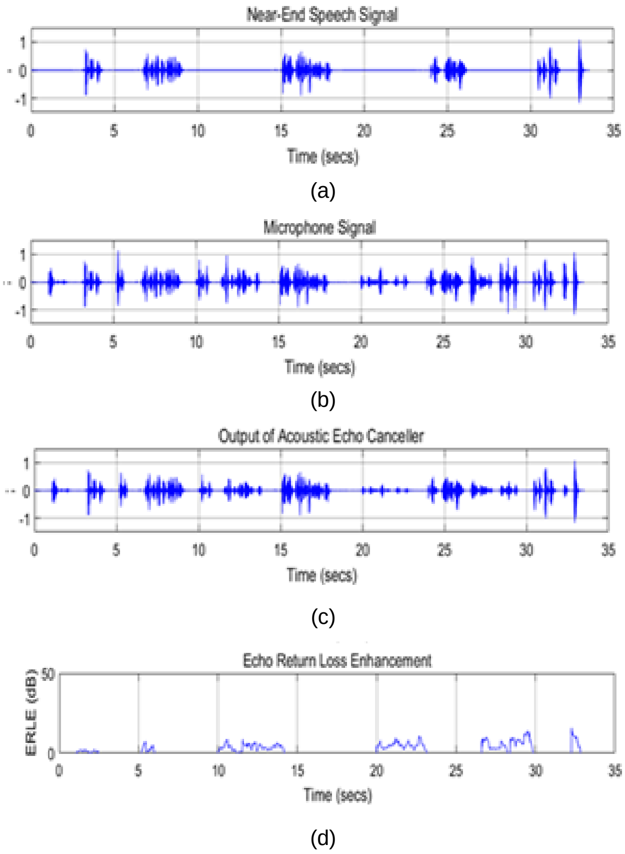
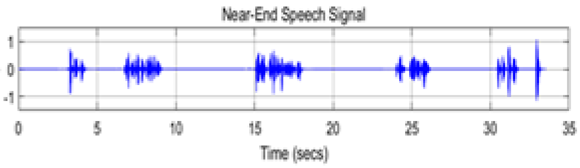
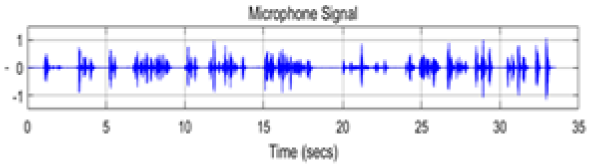


Fig. 7: Filter response for LMS algorithm (a) near-end signal (b) microphone signal (c) output of echo canceller (d) associated ERLE

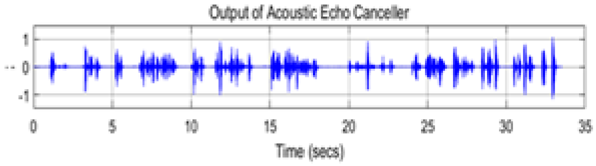
http://doi.org/10.46792/fuoyejet.v7i3.897 http://journal.engineering.fuoye.edu.ng/



(a)



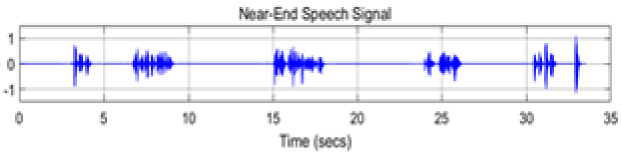
(b)



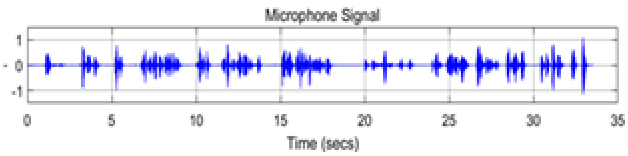
(c)

(d)

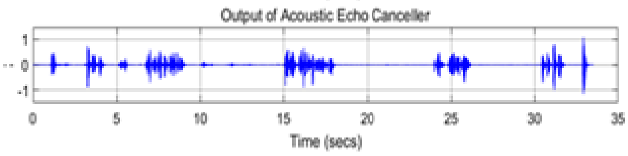
Fig. 8: Filter response for RLS algorithm (a) near-end signal (b) microphone signal (c) output of echo canceller (d) associated ERLE



(a)



(b)



(c)

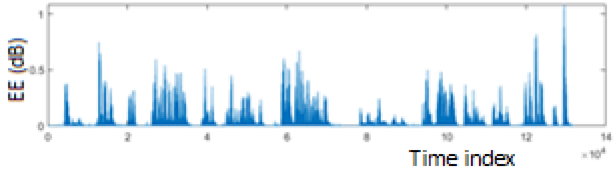
(d)

Fig. 9: Filter response for FDAF algorithm (a) near-end signal (b) microphone signal (c) output of echo canceller (d) associated ERLE

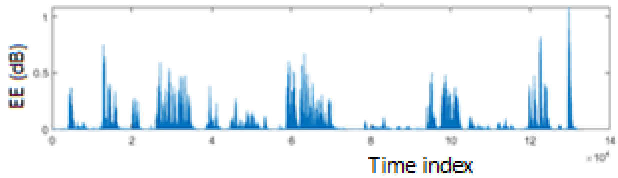
Output from AEC implementation when each of LMS, RLS and FDAF algorithms is implemented are shown in Figures 7(c), 8(c) and 9(c), respectively. The responses indicate the amplitude level of how the algorithms attenuated the echo in the microphone signal. A cursory look at the intervals between 0 -3 seconds; 5 – 7 seconds; 10 – 15 seconds; 20 – 23 seconds; 26 – 30 seconds; and 32 – 33 seconds, enable isolation of the strength and weaknesses of different algorithms in attenuating the echo. Associated ERLE are shown in Figures 7(d), 8(d) and 9(d), respectively, for LMS, RLS and FDAF algorithms implementation. It obvious from Figures 7 – 9 that the AEC output utilizing FDAF algorithm has closer semblance of the near-end speech signal than what obtains from LMS and RLS algorithms. This observation is corroborated by the associated ERLE. This indicates that FDAF algorithm performs best out of the three algorithms analysed for echo cancellation application.

4.3 Further Evaluation of Performances

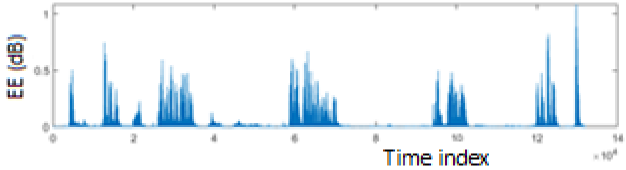
In furtherance of the analysis of LMS, RLS and FDAF algorithms for echo cancellation application, what is embarked upon here is comparison of Error Estimate (EE) in dB and convergence rate in addition to ERLE. Figure 10 present results of error estimate when LMS, RLS and FDAF algorithms are implemented in echo cancellers over a VoIP channel while Figure 11 depicts those of convergence rate.



(a)



(b)



(c)

Fig. 10: Error estimate from implementation of different algorithms in AEC (a) LMS (b) RLS (c) FDAF

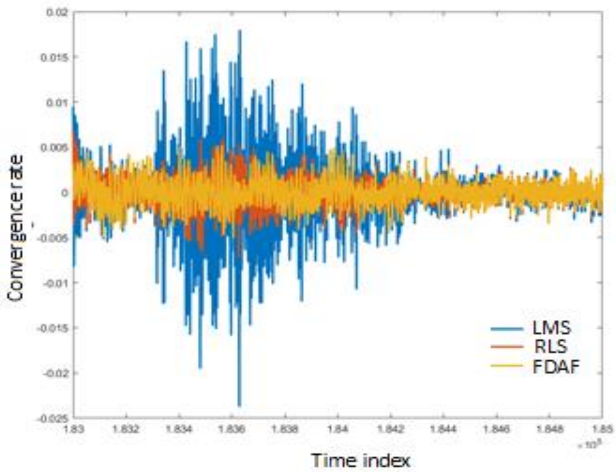


Fig. 11: Profiles of convergence rate of different adaptive algorithms analysed for AEC implementation

http://doi.org/10.46792/fuoyejet.v7i3.897 http://journal.engineering.fuoye.edu.ng/

Table 3 presents data (maximum value) extracted from plots of echo return loss enhancement, error estimates and convergence rate for the three adaptive algorithms under analysis.

Table 3. Numerical data for comparison of LMS, RLS, and FDAF algorithms

Algorithms	ERLE (dB)	Error Estimate dB)	Convergence Rate (ms)
RLS	6.2785	5500	0.0414
LMS	19.637	4400	0.0332
FDAF	38.349	3500	0.0266

As figure of merits, high value of ERLE, low value of error estimates as well as convergence rate translate to better performance of the implemented algorithm. It is obvious from entries of table 3 that FDAF algorithm is the best performed algorithms out of the three. These results agreed with findings of Srinivasaprasath (2003) where it was stated that the ERLE output for an adaptive algorithm for AEC application must lies within the range of 30 – 40 dB.

5 Conclusion

This paper presents performances evaluation of three adaptive algorithms (LMS, RLS and FDAF) for echo cancellation application. It was found that FDAF algorithm perform best out of the three. This is evident in terms of its ERLE, error estimates and convergence time figures when compare with those of LMS and RLS algorithms. This is a clear pointer that echo cancellation application implemented in frequency domain hold more promise than implementation realized in time domain.

References

Alsahlany, A.M. (2014). Performance Analysis of VoIP Traffic over Integrating Wireless LAN and WAN Using Different Codecs. *International Journal of Wireless & Mobile Networks*, 6(3), 79-89

Elamin, S.O. (2016). Performance Analysis of VoIP Quality of Service in IPv4 and IPv6 Environment. *M.S. Thesis, Dept. of Computer Engineering*, Sudan University of Science & Technology, Khartoum, Sudan.

Feiran, Y., & Jun, Y. (2019). Mean-square performance of the modified frequency-domain block LMS algorithm, *Signal Processing* (2019), Doi: https://doi.org/10.1016/j.sigpro.2019.04.030

Islam, H., Arezki, M., & Ahmed, B. (2020). A Novel Set Membership Fast NLMS algorithm for Acoustic Echo Cancellation. *Applied Acoustics, 163(), 107210* doi: 10.1016/j.apacoust.2020.107210

Lizhe, T., & Jiang, J. (2019). Digital Signal Processing || DSP Systems, *Basic Filtering Types, and Digital Filter Realizations.* (pp.173–228). doi:10.1016/B978-0-12-815071-9.00006-3

Mahfoud, H., & Abderrahmane, A. (2019). Improving Acoustic Echo Cancellation in Hands-free Communication Systems. *IEEE 6th International Conference on Image and Signal Processing and their Applications (ISPA)* (pp. 1-5). doi:10.1109/ISPA48434.2019.8966823

Minho, L., Junwoong, H., Taesu, P., & PooGyeon, P. (2022). Variable step-size saturation affine projection algorithm against impulsive noise. *Journal of the Franklin Institute,* 359(13), 7025-7050 https://doi.org/10.1016/j.jfranklin.2022.07.012

Nascimento, V.H., & Magno, T. M. (2014). Adaptive Filter. *Academic Press Library in Signal Processing, 1st Edition. Department of Electronic Systems Engineering, University of São Paulo,* São Paulo, SP, Brazil, pp. 619-760.

Pushpalatha, G.S., & Mohan, K.N. (2014). Echo Cancellation Algorithms using Adaptive Filters: A Comparative Study, *Int. J. on Recent Trends in Engineering and Technology,* Vol. 10, No. 2.

Simon, H. (2014), Adaptive Filter Theory, *5th Edition, Pearson Education Limited Edinburgh, Gate Harlow Essex CM20 2JE, England.*

Soo, J.S., & Pang, K.K. (1990). "Multidelay Block Frequency Domain Adaptive Filter," *IEEE Trans. Acoust. Speech, Signal Processing,* vol. ASSP- 38, 373-376.

Srikanth, B., & Asutosh, K. (2020). Performance analysis of an improved split functional link adaptive filtering algorithm for nonlinear AEC. *Applied Acoustics* 176 (2021) 107863. https://doi.org/10.1016/j.apacoust.2020.107863

Srinivasaprasath, R. (2003). Implementation of an acoustic echo canceller using MATLAB. *M. S Thesis, Department of Electrical Engineering,* University of South Florida.

Swaroopa, A.N., & Sravya, B. (2013). Performance Analysis of different Adaptive Algorithms based on Acoustic Echo Cancellation. *M.S. Thesis, Dept. of Electrical Engineering with Emphasis on Signal Processing,* Blekinge Institute of Technology, 37179 Karlskrona, Sweden.

Yu, Y., Yang, T., Chen, H., Lamer, R.-D., & Li, Y. (2020). Sparsity-aware SSAF algorithm with individual weighting factors: performance analysis and improvements in acoustic echo cancellation. Signal Processing, 178. Doi: 10.1016/1.sigpro.2020.107806