International Journal of Electrical and Electronics Engineering Studies

Vol.6, No.1, pp. 27-42, 2020

Published by ECRTD-UK

ISSN 2056-581X (Print), ISSN 2056-5828(Online)

LMS-BASED ADAPTIVE FILTERING TECHNIQUE FOR REMOVING NOISE FROM VOICE SIGNALS AND ITS COMPARISON WITH RLS-BASED TYPE

Mbachu C. B[1]., Akaneme S. A.[2]

[1, 2]Department of Electrical and Electronic Engineering, Chukwuemeka Odumegwu Ojukwu University, Uli, Anambra State, Nigeria.

ABSTRACT: *Every adaptive filter requires an appropriate adaptive algorithm to effectively remove noise components from noise-contaminated desired signals. In line with the requirement finite impulse response filters can be driven by an appropriate adaptive algorithm to remove noise from voice signals. Without the removal, the noise components will degrade the quality of the signal, and the result will be a distortion and substantial loss of message content. In this paper a finite impulse response digital filter driven by least mean square adaptive algorithm for coefficient update is designed to remove overlapping noise component from a voice signal. A real voice statement "Creative Research is Very Essential for the Sustainable Development of Any Nation" is converted to electrical voice signal using microphone and stored in a file in a computer system. With "audioread" command the stored voice signal is loaded into a matlab edit window. The loaded signal is contaminated with a 10.5dB additive white Gaussian noise component generated with matlab. When the contaminated signal is applied to the designed filter the result shows that the noise is effectively removed. The result is evaluated with six properties; listening, signal morphologies, frequency domain analysis, noise attenuation, mean square error, and signal to noise ratio. A comparison of the LMS algorithm and recursive least square algorithm with respect to noise removal from voice signals is performed. The matlab codes for the simulation of this work are provided in this paper.*

KEYWORDS: Voice signals, LMS, additive white Gaussian noise, adaptive algorithm.

INTRODUCTION

When voice signals are carried over transmission lines they can suffer interferences by different noise components before they get to their destinations. If these noise components are not removed they can degrade the voice signals such that partial or total loss of the information contents of the signals at their receiving ends may result. Many researchers have used different adaptive filtering algorithms to deal with the removal of these unwanted components. In [1] the authors demonstrated the performance of recursive least square (RLS) algorithm with variable forgetting factor in the minimization of noise in speech signals. They obtained a clean speech signal from Hindi speech database and three noise components; machine gun, F16 and speech noises from NOISE-92 database. Both the clean signal and the noise components have sampling frequency of 16 KHz and 16 bit resolution. Each of the three noises was added to a clean speech signal in turn at a signal to noise ratio (SNR) of -5dB, 0dB, 5dB and 10dB levels to obtain twelve different noisy speech signals. Each of the noisy signals was fed into six different designed filters for simulation. Two of the filters, one of order 5 and the other, of order 10 are driven by the non variable forgetting factor RLS (NVFFRLS) or simply RLS algorithm, whereas the other four filters, two being of order 5 and two being of order 10 are driven by variable forgetting factor RLS (VFFRLS) algorithm. The value of the forgetting factor in the case of RLS is λ=0.99 whereas in the case of the VFFRLS, the value is λ_{min}=0.95.

Vol.6, No.1, pp. 27-42, 2020
Published by ECRTD-UK
ISSN 2056-581X (Print), ISSN 2056-5828(Online)

Results show that VFFRLS algorithm is superior to RLS algorithm for noise minimization. This is because the VFFRLS algorithm is able to track the variations in noisy signal more closely than RLS algorithm. The results agree with the findings of the researchers in [2]-[6] that RLS algorithm with variable forgetting factor has shown improvements in performance for non stationary process. In [7] a new adaptive filtering algorithm known as modified adaptive filtering with averaging (MAFA) algorithm was developed by the researchers and used to cancel white Gaussian noise in speech signals. They modified an existing algorithm known as adaptive filtering with averaging (AFA) [8] developed to improve on the high computational and stability issues inherent in RLS algorithm. The result of the experiment shows that the new algorithm (MAFA) improved the said issues inherent in RLS algorithm, as stated in [8] and provided higher signal to noise ratio than AFA algorithm when denoising speech signals of white Gaussian noise. In [9] the researchers used LMS adaptive algorithm with step size of 0.006 on finite impulse response (FIR) filter to cancel out from a voice signal, a combination of additive white Gaussian noise and another random noise of 0.25 amplitude. The result shows that the LMS algorithm effectively cancelled out the composite random noise. In [10] a comparison of three different adaptive filters designed with least mean square (LMS), normalised least mean square (NLMS) and recursive least square (RLS) algorithms to denoise an audio signal of pink noise, is carried out. The result shows that each algorithm cancels the pink noise in the contaminated audio signal but the output from the NLMS algorithm has the highest signal to noise ratio. Enhancing speech signal with RLS based adaptive filtering method was demonstrated by [11]. Here a noisy data is prepared by adding Babble and pink noise to a clean speech samples. The noisy speech which is sampled at a frequency of 8 kHz was filtered with RLS based adaptive filter, and result shows a significant reduction in the noise content of the speech signal. In [12] an adaptive filter based on LMS algorithm was used to reduce additive white Gaussian noise in audio signal. The authors used a sampling frequency of 8000Hz, filter order of 29, step size parameter of 0.006. The result shows that the algorithm performed effectively. The authors in [13] compared the performance of least mean square and recursive least square algorithms in adaptive systems for noise reduction in radio (mobile) communication network. Number of samples equal to 50,000 samples was used for each algorithm. Results show that both algorithms reduced the noise. The researcher in [14] used LMS adaptive filter to remove additive white Gaussian noise, traffic noise and airplane noise from voice signals. The phenomenon of fading was also demonstrated with the adaptive filter by [14]. The order of the filter and the algorithm step size depend on the noise to be removed. What appears to be a shortcoming in [14] is the order of the filter which seems to be unnecessarily high for such application. In [15] the authors used RLS based adaptive filtering technique to filter out additive white Gaussian noise from transmitted audio signal in a graphic user interface (GUI) or filter builder platform of matlab and compared the performance and that of non-adaptive linear filters. The result shows that for the same noisy audio signal the RLS based filter output has a better filtered signal waveform almost devoid of the noise component. Fast block least mean square (FBLMS) algorithm is also very effective in cancelling white Gaussian noise in speech [16]. The original noise free signal is a recorded audio signal, and a white Gaussian noise generated with matlab is added to the original speech signal to form a noisy audio/speech signal. When the designed adaptive filter is used to filter the noisy signal result shows that the algorithm can remove the different levels of noise more efficiently and effectively and may exhibit faster response. In addition it has a low computational complexity property than LMS algorithm.

No researcher has demonstrated the use of LMS algorithm on voice signal of windows media audio (.wma) format which is a double column vector. The researcher in [14] did a similar work but used a different wave format and a filter order too high for the intended purpose. In this paper, removing additive white Gaussian

International Journal of Electrical and Electronics Engineering Studies
Vol.6, No.1, pp. 27-42, 2020
Published by ECRTD-UK
ISSN 2056-581X (Print), ISSN 2056-5828(Online)

noise in voice signal of windows media audio (.wma) format with LMS based finite impulse response adaptive filter is proposed. Six properties which include listening, signal morphology, frequency domain analysis, attenuation, mean square error (MSE) and signal to noise ratio (SNR) are used in evaluating the performance of the filter. A comparison of the performance of the algorithm with that of RLS algorithm is carried. The matlab codes for the simulation are provided in this paper.

DESIGN OF LMS BASED ADAPTIVE FILTER

With a filter order of 32, sampling frequency of 44.10 kHz and step size of 0.0002, the object of the filter is created with matlab as in (1). Based on the object the instantaneous responses of the filter including impulse response, magnitude response, phase response and z domain response are generated as shown fig.1, fig. 2, fig. 3 and fig. 4 respectively.

ha=adaptfilt.lms(L+1,mu); (1)

where L is the order of the filter and mu, the step size parameter.

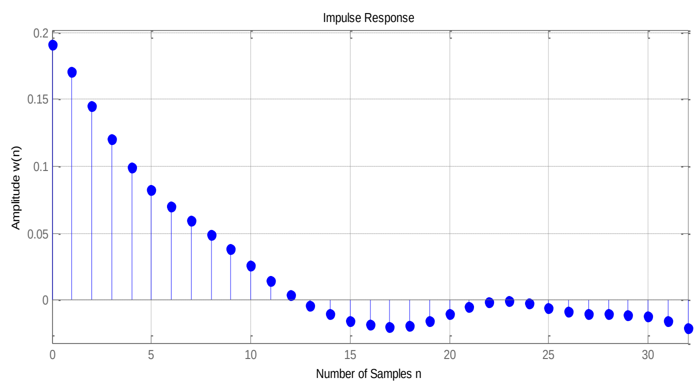


Fig. 1: Impulse Response of the Filter

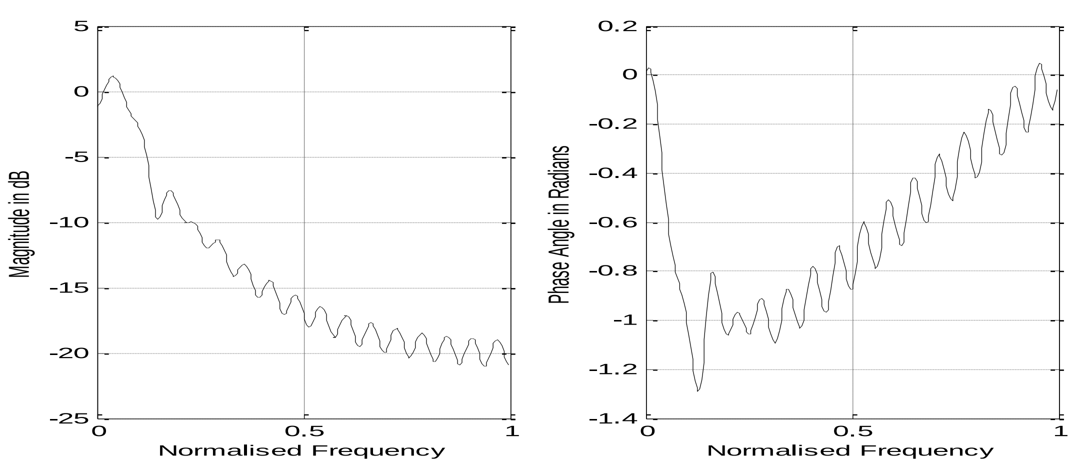


Fig. 2: Magnitude Response of the Filter Fig. 3: Phase Response of the Filter

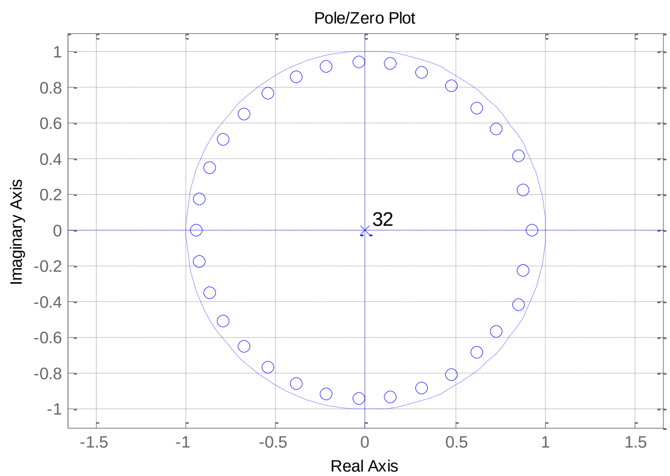


Fig. 4: z domain Response of the Filter

The impulse response shows that the designed filter is stable because there is a gradual collapse of the response from the origin and completely collapsed to near zero at the last sample value. The magnitude response also shows that system is stable because the size of the side lobes continues to dwindle from the main lobe and there are no sustained oscillations. The phase response shows clear linearity within the required frequency bandwidth. In fig.4 the poles and zeros are confined within a unit circle and the zeros are in alignment, implying that the filter is stable. These properties imply that the filter is good enough to be tried in denoising voice signal of .wma format of additive white Gaussian noise.

RESULT

Results are generated by converting a real voice statement “Creative Research is Very Essential for the Sustainable Development of Any Nation” to electrical voice signal using microphone and stored in a file in a computer system. With “audioread” command the stored voice signal which has 231349 samples is loaded into a matlab edit window as original voice signal. A 10.5dB additive white Gaussian noise component is generated with matlab and added to the signal to constitute a contaminated voice signal. Fig. 5 depicts the original voice signal whereas the contaminated voice signal is depicted as fig. 6. The contaminated voice signal is thereafter used as input to the designed adaptive filter and outputs recorded. Fig. 7 indicates the filtered voice signal and fig. 8, the noise estimate in the contaminated voice signal. Also generated for purposes of result evaluation are the frequency domain versions of the signals obtained, by taking the fast Fourier transform (FFT) of the original, contaminated and filtered voice signals, represented as fig. 9, fig. 10 and fig. 11 respectively, as well as the power spectral densities of the original, contaminated and filtered voice signals as depicted in fig. 12, fig. 13 and fig. 14 respectively.

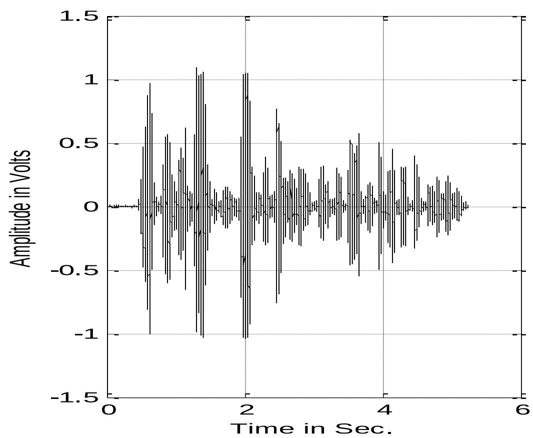


Fig. 5: Original Voice Signal

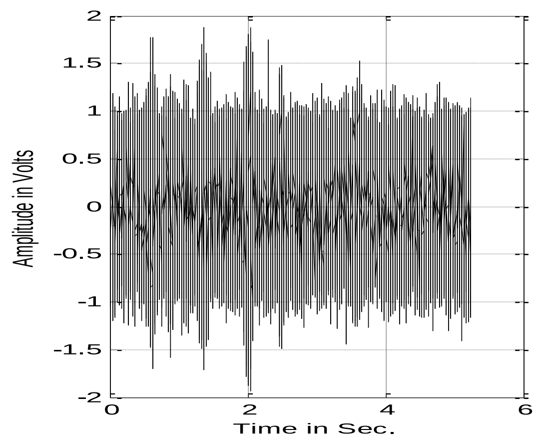


Fig. 6: Contaminated Voice Signal

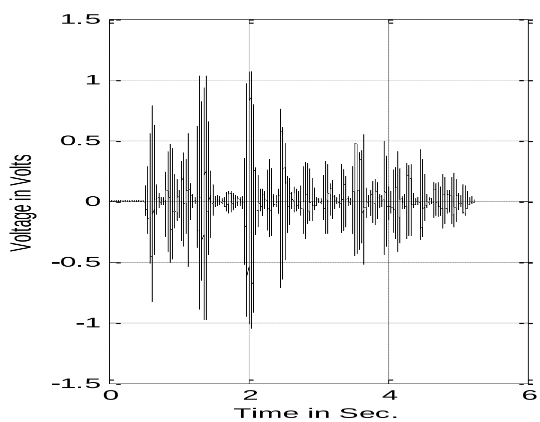


Fig. 7: Filtered Voice Signal

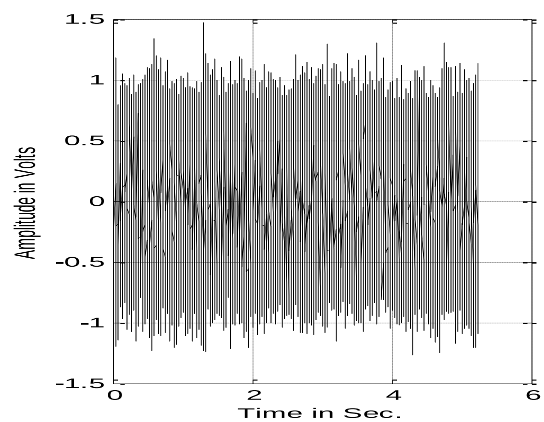


Fig.8: Noise Estimate in the Noisy Voice

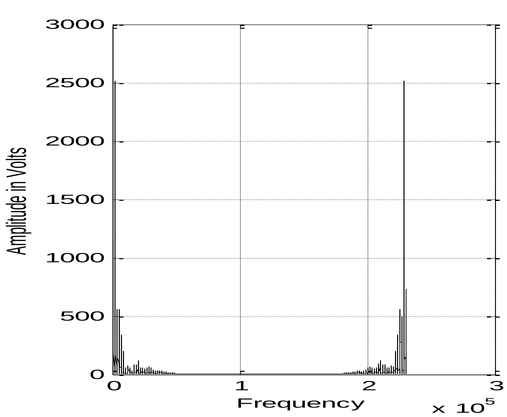


Fig. 9: Original Voice in Frequency Domain

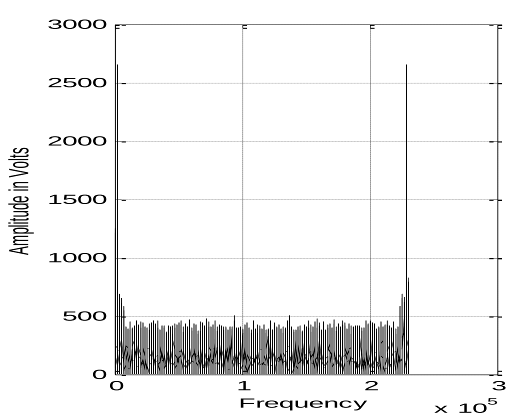


Fig. 10: Noisy Voice in Frequency Domain

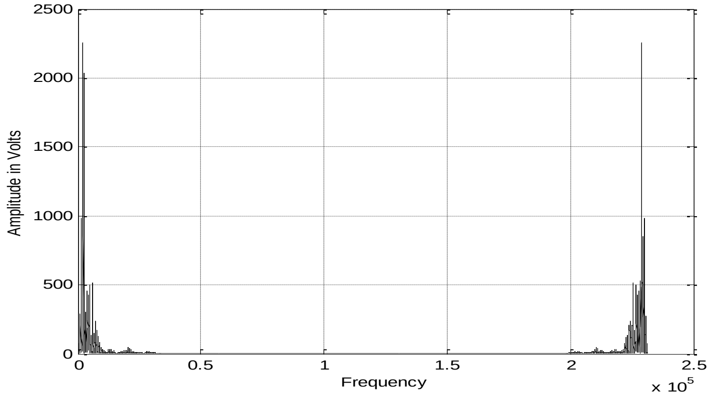
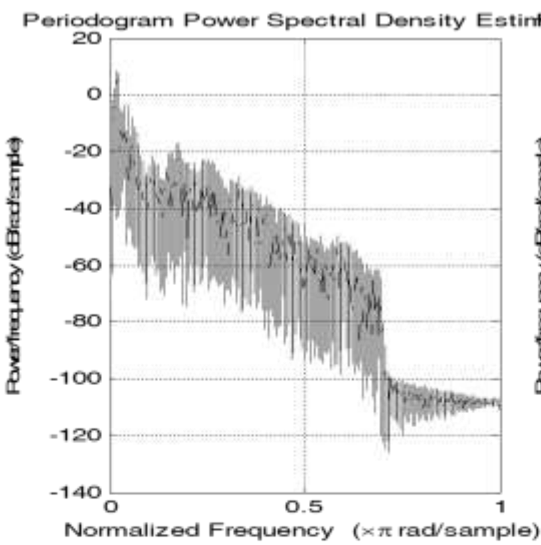


Fig. 11: Filtered Voice Signal in Frequency Domain



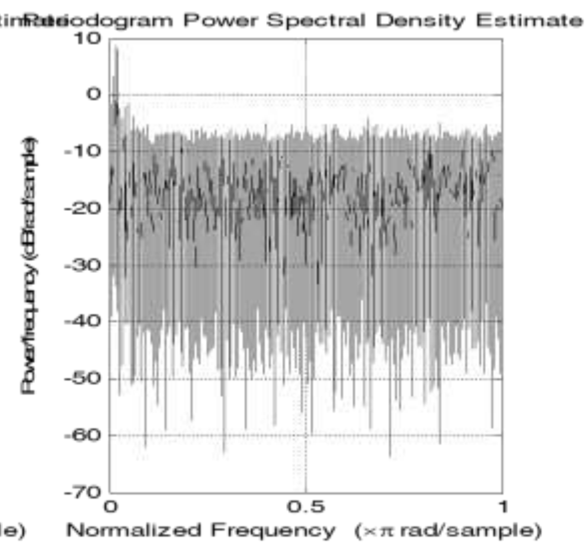


Fig.12: Power Spectral Density of Original Voice Fig. 13: Power Spectral Density of Noisy Voice

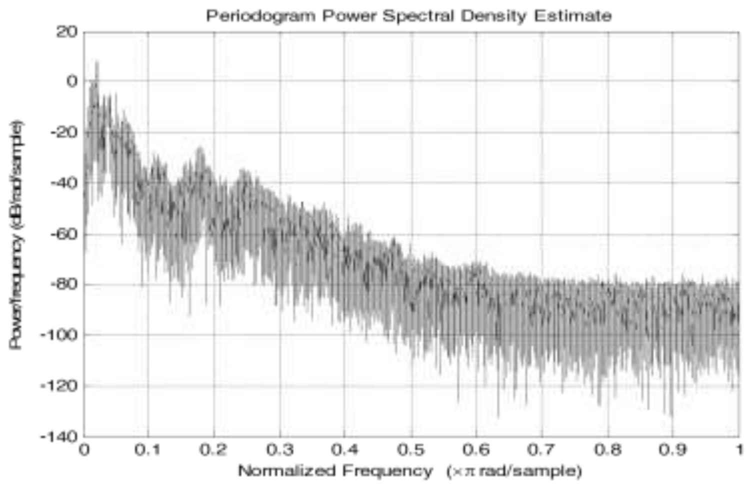


Fig. 14: Power Spectral Density of Filtered Voice Signal

EVALUATION OF RESULTS

Six properties are considered in evaluating the results of this work; (a) listening to the signals (b) observing the signal morphologies (c) frequency domain analysis of the signals (d) signal attenuation (e) mean square error and (f) signal to noise ratio. In (a) by listening to the original voice signal, the contaminated voice signal and the filtered voice signal shows that the filtered voice signal is as clear as the original voice signal and gives out the same message whereas the contaminated voice signal is very noisy, meaning that the adaptive filter drastically reduced the noise component in the contaminated voice signal. In (b), by examining the appearances of the original and filtered voice signals it can be seen that they are the same, meaning that the filter did not distort the signal.
In (c) the original, contaminated and filtered voice signals are generated in frequency domain by performing descrete Fourier transforms on them using the formula (2) [17]- [19].

$$X(K) = \sum_{n=0}^{N-1} x(n)\, e^{-j2\pi nk/N} \qquad (2)$$

Where N is the number of samples, and n and k are integer values that vary from a reference point to equivalent number of samples in N. That is, n and k can vary from 0 to N-1, 1 to N, 2 to N+1, etc.

The matlab code for the transform is as in (3) [20]

$$Y = fft(X, N); \qquad (3)$$

where X is the function and N, the number of samples desired. From figures 9, 10 and 11 above it can be seen that the original and filtered signals have the same frequency distributions devoid of noise components whereas the frequency distribution of the contaminated voice signal displays much noise content.

Vol.6, No.1, pp. 27-42, 2020
Published by ECRTD-UK
ISSN 2056-581X (Print), ISSN 2056-5828(Online)

In (d) the degree of attenuation of the noise in the contaminated signal by the filter can be determined from the power spectral densities of the original, contaminated and filtered voice signals, considered at nine different frequencies. Table 1 shows the signal power magnitudes at the nine different normalised frequencies of 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8 and 0.9, as can be obtained from power spectral densities of fig. 12, fig. 13 and fig. 14. The noise power present in the filtered voice signal is calculated from (4) [13], [23], [24].

$$N_0 = S - S_F \qquad (4)$$

where S is the power of the original voice signal and S_F, the power of the filtered voice signal.

By comparing the power magnitudes for the original, contaminated and filtered voice signals at the nine frequency positions in table 1, it clearly shows that the adaptive filter drastically reduced the noise at each of the frequencies. The noise power present in the filtered signal is shown in the table which in each case is very small enough to translate to high signal to noise ratio for the filtered signal. Notice that once the filtered signal power is equal or more than the original signal power the noise present in the filtered signal is equal to zero. This is because the filter attenuated the whole noise and as such no noise is expected to remain in the filtered signal under such circumstance. Notice also that the contaminated signal power at each of the nine frequency positions is very low; meaning that noise present in them is high. Active speech did not get up to frequency of 0.8 and above and that accounted for the noise power present in the filtered signal, which in anyway does not disturb the active speech content and quality.

Table 1: Signal Powers at Different Frequencies for LMS Algorithm

Normalised Frequency	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
Original Signal Power in dB (S)	-27.70	-23.52	-32.82	-37.35	-52.21	-51.61	-64.48	-102.90	-105.20
Contaminated Signal Power in dB	-6.52	-6.54	-6.80	-6.98	-5.02	-6.94	-6.85	-7.32	-7.40
Filtered Signal power in dB (S_F)	-34.32	-34.98	-46.88	-57.80	-68.90	-70.07	-75.28	-76.45	-77.33
Noise Power Present in the Filtered Signal in dB (N_0)= $S-S_F$	0.0	0.0	0.0	0.0	0.0	0.0	0.0	-26.45	-27.87

International Journal of Electrical and Electronics Engineering Studies
Vol.6, No.1, pp. 27-42, 2020
Published by ECRTD-UK
ISSN 2056-581X (Print), ISSN 2056-5828(Online)

In (e) the mean square error (MSE) is a measure of the deviation between the filtered signal and the original signal in terms of amplitude. A small MSE implies an effective and efficient filter and algorithm. The formula for computing the MSE is given by (5) [10], [11], [23]

$$MSE = \frac{\sum_{k=1}^{N} \left(A(k) - A_f(k)\right)^2}{N} \tag{5}$$

Where ' $A(k)$ ' is the amplitude of the original voice signal and ' $A_f(k)$ ', the amplitude of the filtered voice signal as 'k' varies from 1 to the number of samples N. The original and filtered amplitudes must be measured at the same or equivalent points in the system and within the same system bandwidth. In this work the whole length of the signal, N=231349 is used in the computation. Therefore by invoking (5) the mean square error of the filtered voice signal is

MSE=0.0027

The value is very small and as such it can be declared that LMS adaptive algorithm is very effective in denoising voice signals of additive white Gaussian noise.
In (f) the signal to noise ratio (SNR) is a figure of merit that measures the proportion of noise present in the filtered signal. A high figure means that small noise is present in the filtered signal and the quality of the filtered signal is high. The formula for computing signal to noise ratio is given as (6) [11], [18], [21]-[23]

$$SNR = 10 \log \frac{\sum_{k=1}^{N} A^2(k)}{\sum_{k=1}^{N} N_a^2(k)} \tag{6}$$

Where ' $A(k)$ ' is the amplitude or power of the original voice signal and ' $Na(k)$ ', the amplitude or power of the noise present in the filtered voice signal as 'k' varies from 1 to the number of samples N. The original and filtered signal power or amplitudes must be measured at the same or equivalent points in the system and within the same system bandwidth. The noise amplitude is obtained from (7)

$$Na(k) = A(k) - A_f(k) \tag{7}$$

In this work the whole length of the signal, N=231349 is used in the computation. Therefore by invoking (6) the signal to noise ratio (SNR) of the filtered voice signal is

SNR=10.30dB

The value is quite high, implying that the proportion of noise in the filtered signal is very small. It can therefore be declared that the least mean square adaptive algorithm is very effective in denoising voice signals of additive white Gaussian noise.

International Journal of Electrical and Electronics Engineering Studies
Vol.6, No.1, pp. 27-42, 2020
Published by ECRTD-UK
ISSN 2056-581X (Print), ISSN 2056-5828(Online)

COMPARISON OF LMS AND RLS BASED ADAPTIVE FILTERING

The comparison is based on six properties; (a) stability (b) linearity (c) mean square error (d) signal to noise ratio (e) signal morphology and (f) listening to the two filtered signals. The first approach in this comparison is to design an RLS based filter and use it to filter the same contaminated voice signal used in LMS based filtering.
With a filter order of 32, sampling frequency of 44.10 kHz, forgetting factor of 1.0 and initializing constant of 0.5 for inverse covariance matrix P0, the object of the RLS based filter is created with matlab as in (8). Based on the object the instantaneous responses of the filter; impulse response, magnitude response, phase response and z domain response are generated as shown in fig.15, fig. 16, fig. 17 and fig. 18 respectively.

ha=adaptfilt.rls(L+1,lam, P0); (8)

where L is the order of the filter, lam, forgetting factor and P0, inverse covariance matrix of the input signal. The filtered voice signal based on RLS algorithm is depicted in fig. 19 while fig. 20 is the corresponding power spectral density of the filtered voice signal.

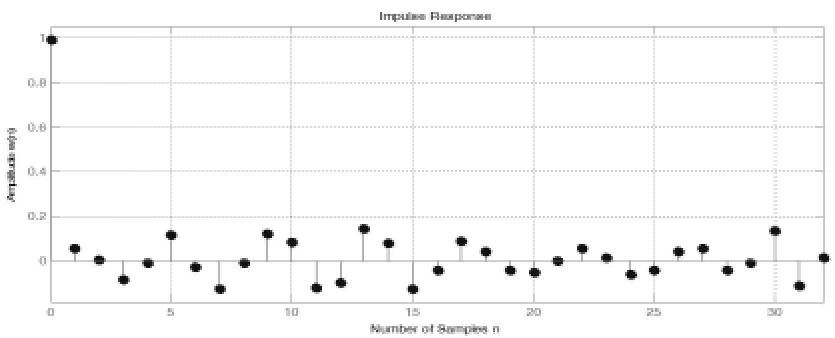
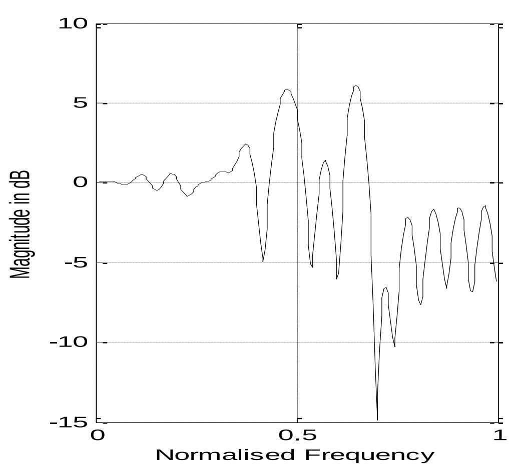


Fig. 15: Impulse Response of RLS Based Filter



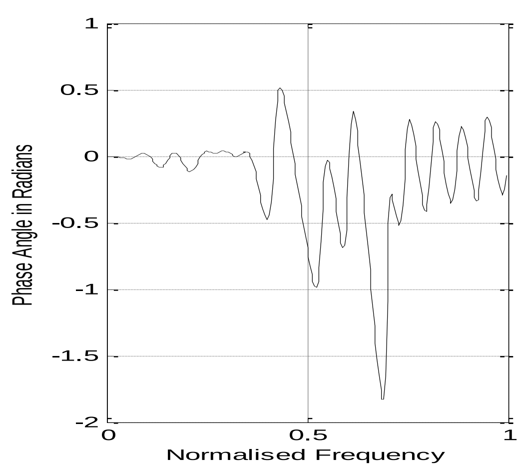


Fig. 16: Magnitude Response of RLS Based Filter Fig. 17: Phase Response of RLS Based Filter

International Journal of Electrical and Electronics Engineering Studies
Vol.6, No.1, pp. 27-42, 2020
Published by ECRTD-UK
ISSN 2056-581X (Print), ISSN 2056-5828(Online)

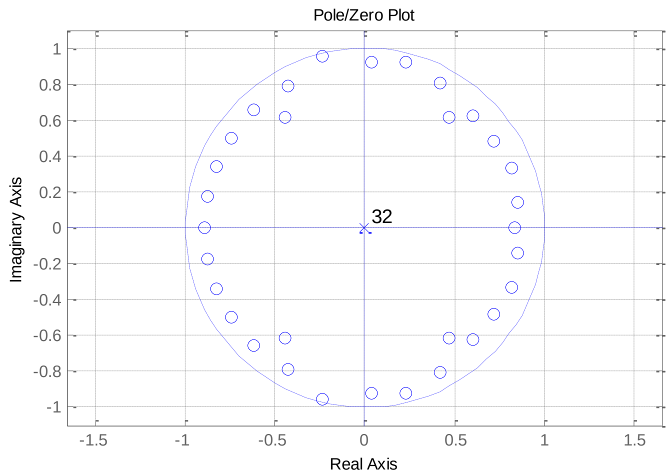
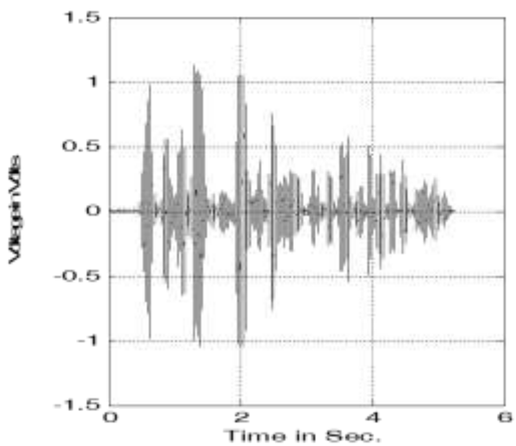


Fig. 18: z-domain Response of RLS Based Filter



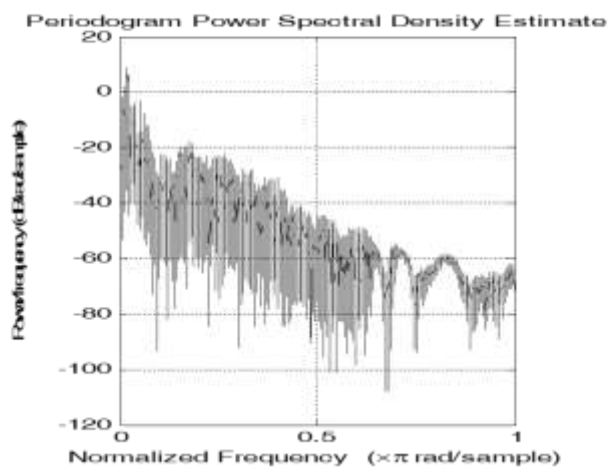


Fig. 19: RLS Based Filtered Voice Signal   Fig.20: Power Spectral Density of RLS Filtered Voice

In (a) and (b) the comparison of stability and linearity of LMS and RLS based filters is done from their instantaneous responses and presented in table 2 below. In (c) and (d) the comparison of the mean square error (MSE) and signal to noise ratio (SNR) based on the two algorithms are done from the amplitudes of the two filtered signals and presented in table 2 below.

Table 2: Comparison of Stability, Linearity, MSE and SNR in LMS and RLS Based Filtering

Algorithm	Stability	Linearity	MSE	SNR
LMS	Stable	Linear	0.0027	10.30dB
RLS	Not very stable	Not very linear	0.00004	28.55dB

From table 2, it can be seen that RLS algorithm is better than LMS algorithm in denoising voice signals of additive white Gaussian noise because it has comparatively very small MSE and very high SNR, though at the expense of stability, linearity and high computational complexity. This result agrees with the view of researchers in [7]. In (e) and (f) the comparison is done by examining the appearances of the voice signal filtered with LMS algorithm and that filtered with RLS as depicted in fig. 7 and fig. 19 respectively, and also listening them. There is no significant difference in their appearances and also in the quality of their sound or message content as both sounds are clear though the sound of the one filtered with RLS is sharper. This implies that both algorithms can reasonably denoise voice signals of noise.

CONCLUSION

From table 1, it is clear that LMS adaptive algorithm on finite impulse response filters is very effective in filtering out additive white Gaussian noise from voice signals. The optimum values of the variable parameters such as filter order and the step size depend on the type and magnitude of noise to be removed. The noise power present in the filtered signal from frequency of 0.8 and above is because it is not part of active speech signal section during recording, thus giving room for noise to cover up the section during contamination. The frequency distribution of the signals shows that original and filtered signals are almost the same in content implying high quality filtering by the adaptive filter. The design responses also indicate that the filter is stable and linear which is very desirable in processing multiple frequency signals such as voice signals.
In the comparison of LMS and RLS based filtering, from table 2, RLS is better but suffers stability, linearity and computational complexity issues.

Reference

[1]. V. K. Gupta, M. Chandra, S. N. Sharan, “Noise Minimization from Speech Signals using RLS Algorithm with Variable Forgetting Factor,” Research Journal of Applied Sciences, Engineering and Technology Vol. 4, Issue 17, Sept. 2012, pp. 3102-3107.
[2]. Y. T. Ting, D. G. Childers, “Speech Analysis using the Weighted Recursive Least Squares Algorithm with Variable Forgetting Factor,” ICASSP, Albuquerque, NM, 1990, pp. 389-392.
[3]. S. H. Leung, C. F. So, “Gradient-based Variable Forgetting Factor RLS Algorithm in Time-varying Environment,” IEEE Transactions on Signal Processing, Vol. 53, No. 8, 2005, pp. 3141-3150.

[4]. J. Wang, “A Variable Forgetting Factor RLS Adaptive Filtering Algorithm,” International Symposium on Microwave, Antenna, Propagation and EMC Technologies for Wireless Communications, Beijin, China, 2009, pp. 1127-1130.
[5]. M. Z. A. Bhotto, A. Antoniou, “Robust Recursive Least Squares Adaptive Filtering Algorithm for Impulsive-noise Environments. IEEE Signal Processing Lett., Vol. 18, Issue 3, 2011, pp. 185-188.
[6]. A. K. Sahu, A. Hiradhar, “Noise Cancellation Using Adaptive Filters of Speech Signal by RLS Algorithm with Matlab.
[7]. V. R. Vijaykumar, P. T. Vanathi, “Modified Adaptive Filtering Algorithm for Noise Cancellation in Speech Signals,” Electronics and Electrical Engineering, No. 2(74), 2007, pp. 17-20.
[8]. G. Iliev, N. Kasabov, “Adaptive Filtering with Averaging in Noise Cancellation for Voice and Speech Recognition,” Department of Information Science, University of Otago, 2001.
[9]. V.M. Kaine, S. Oad, “Noise Cancellation in Voice Using LMS Adaptive Filter,” International Journal of Emerging Technology and Adavanced Engineering, Vol. 4, Issue 10, October, 2014, pp. 656-659.
[10]. G. K. Girisha, S. L. Pinjare, “Performance Analysis of Adaptive Filters for Noise Cancellation in Audio Signal for Hearing Aid Application,” International Journal of Science and Research, Vol. 5, Issue 5, May 2016, pp. 364-368.
[11]. P. Rakesh, T. K. Kumar, “A Novel RLS Based Adaptive Filtering Method for Speech Enhancement,” International Journal of Electrical, Computer, Electronics and Communication Engineering, Vol. 9, No. 2, 2015, pp. 153-158.
[12]. M. T. Afolabi, C. B. Mbachu, “Windowed Adaptive Filtering for Reducing Noise in Audio Signals During Transmission to Remote Locations,” International Journal of Innovative Research and Development, Vol. 8, Issue 6, June 2019, pp. 265-271.
[13]. R. Martinek, J. Zidek, “Use of Adaptive Filtering for Noise Reduction in Communication Systems,” Department of Measurement and Control, Technical University of Ostrava-Poruba.
[14]. V. Thakkar, “Noise Cancellation Using Least Mean Square Algorithm,” IOSR Journal of Electronics and Communication Engineering, Vol. 12, Issue 5, Ver. I, Sept.-Oct. 2017, pp. 64-75.
[15]. E. A. Oni, I. D. Olatunde, K. O. Babatunde, D. O. Okpafi, “Improvement of Audio Signal Quality Using Adaptive Filtering and its Performance Advantage Over Non-Adaptive (Linear) Filtering,” International Journal of Electrical and Electronic Science, 5(2), 2018, pp. 39-45.
[16]. J. Jebastine, B. S. Rani, “Design and Implementation of Noise Free Audio Speech Signal Using Fast Block Least Mean Square Algorithm,” Signal and Image Processing: An International Journal (SIPIJ), Vol. 3, No. 3, June 2012, pp. 39-53.
[17]. Rajni, I. Kaur, “Electrocardiogram Signal Analysis- An Overview,” International Journal of Computer Applications, Vol. 84, No. 7, December 2013, pp. 22-25.
[18]. S. Y. Zaw, A. M. Aye, “Performance Comparison of Noise Detection and Elimination Methods for Audio Signals,” International Journal of Engineering and Technology, Vol. 03, Issue 14, June 2014, pp. 3069-3073.
[19]. B. A. Shenoi, Introduction to digital signal processing and filtering design, USA, Canada: John Wiley and Sons, 2006.

[20]. P. K. Dar, M. I. Khan, "Design and Implementation of Non Real Time and Real Time Digital Filters for Audio Signal Processing," Journal of Emerging Trends in Computing and Information Sciences, Vol. 2, No. 3, 2011, pp. 149-155.
[21]. G. Kadam, P. C. Bhaskar, "Reduction of Power Line Interference in ECG Signal Using FIR Filter," International of Computational Engineering Research, Vol. 2, Issue No. 2, Mar.-Apr. 2012, pp. 314-319.
[22]. B. Chabane, B. Daoued, "Enhancing Speech Corrupted by Colored Noise," WEAS Transactions on Signal Processing.
[23]. G. Srika, R. Prasad, "An Enhanced Audio Noise Removal Based on Wavelet Transform and Filters," Adavances in Computational Sciences and Technology, Vol. 10, No. 10, 2017, pp. 3111-3121.

APPENDIX

Matlab Program

```
clc,clear
[y,Fs]=audioread('C:\Users\Test\Desktop\LMSVOICE.wma');%loads voice signal
sound(y,Fs)
pause(6)
d=awgn(y,10.5);%Voice signal contaminated with 10.5dB AWGN
sound(d,Fs)
k=231349;%Length of the voice signal
t=1/Fs:1/Fs:1/Fs*k;%Time range and incremental value
figure(1)
subplot(1,2,1);
plot(t,y,'k');%plots original voice signal in black
grid on
ylabel('Amplitude in Volts')
xlabel('Time in Sec.')
subplot(1,2,2)
plot(t,d,'k');%plots contaminated voice signal in black
grid on
ylabel('Amplitude in Volts')
xlabel('Time in Sec.')
L=32;%Order of the filter
mu=0.0002;%Step size for the adaptation process
ha=adaptfilt.lms(L+1,mu);%Creats the adaptive filter object
[y1,e]=filter(ha,y(:,1),d(:,1));%Filters the contaminated voice signal
pause(2)
sound(y1,Fs)
[h,w]=freqz(ha,256);%Returns 256 samples of filter vectors
HdB=20*log10(abs(h));%Magnitude response of the filter
Phaseangle=unwrap(angle(h));%Phase response of the filter
```

```
impz(ha);%Plots the instantaneous impulse response of the filter
grid on
ylabel('Amplitude w(n)')
xlabel('Number of Samples n')
figure(3)
subplot(1,2,1);
plot(w/pi,HdB,'k')%Plots the magnitude response of the filter in black
grid on
ylabel('Magnitude in dB')
xlabel('Normalised Frequency')
subplot(1,2,2);
plot(w/pi,Phaseangle,'k')%Plots the phase response of the filter in black
grid on
ylabel('Phase Angle in Radians')
xlabel('Normalised Frequency')
zplane(ha)%Plots the pole-zero response of the filter
grid on
ylabel('Imaginary Axis')
xlabel('Real Axis')
figure(5)
subplot(1,2,1);
plot(t,y1,'k')%plots filtered voice signal in black
grid on
ylabel('Voltage in Volts')
xlabel('Time in Sec.')
subplot(1,2,2)
plot(t,e,'k');%plots estimated noise in black
grid on
ylabel('Amplitude in Volts')
xlabel('Time in Sec.')
figure(6)
subplot(1,2,1);
periodogram(y(:,1))%Plots power spectral density of the original voice
subplot(1,2,2);
periodogram(d(:,1))%Plots power spectral density of the contaminated voice
figure(7)
periodogram(y1)%Plots power spectral density of the filtered voice signal
n=1:k;%Ploting range for frequency domain
x1=fft(y,k);%Transform original voice signal to frequency domain
x2=fft(d,k);%Transform contaminated voice signal to frequency domain
x3=fft(y1,k);%Transform filtered voice signal to frequency domain
figure(8)
subplot(1,2,1);
plot(n,abs(x1),'k')%Plots the original voice in frequency domain
```

```
grid on
ylabel('Amplitude in Volts')
xlabel('Frequency')
subplot(1,2,2);
plot(n,abs(x2),'k')%Plots contaminated voice in frequency domain
grid on
ylabel('Amplitude in Volts')
xlabel('Frequency')
figure(9)
plot(n,abs(x3),'k')%plots the filtered voice in frequency domain
grid on
ylabel('Amplitude in Volts')
xlabel('Frequency')
```