Adaptive Noise Cancellation For Speech Signal

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DOI: 10.29322/IJSRP.10.09.2020.p10516
http://dx.doi.org/10.29322/IJSRP.10.09.2020.p10516

Abstract- In speech communication systems, obtaining desired signal from dialogue signal that is polluted by noise, using digital filter noise minimization is a widely known technique. This is accomplished by adaptive filter algorithms, in detail, this project focused on LMS and NLMS Algorithms. The purpose of adaptive noise drop is to get an estimation of the signal of noise and to deduct it from the noisy signal and hence upgrade the quality of the signal.

For this purpose, the filter utilizes a flexible algorithm to alter the worth of the filter coefficients, so that it obtains a good estimate of the signal after each repetitions. The performance of the system is evaluated by the impacts of different factors such as: - number of samples, amount of filter coefficients, step size, and input noise level. Finally, the performances of the algorithms in different cases is verified by simulating noise reduction ratio (NRR) by MATLAB platform.

Index Terms- Adaptive systems, Adaptive Noise Canceller, LMS, NLMS ,NRR

I. INTRODUCTION

In speech (voice) communication systems the desired signals are mixed with additive noise signals. To filter out the desired speech signal from signal corrupted by noise signal using adaptive digital filtering. The process of Extracting desired signals by this method is known as Adaptive Noise Cancellation (ANC). Noise is a public nuisance. It has an adverse psychological effect on living beings. Noise causes mental strain or tiredness, thus creating an inefficient working environment; continued noise coverage makes temporary or permanent loss of hearing.

Acoustic difficulties in the environment are gaining consideration because of the marvelous growth of technology that has led to noisy engines, heavy machinery, pumps, high speed wind buffering and a many other noise sources. Experiencing to high levels of sound causes damage to human from the physical and psychological aspects. Noise pollution is another great contributor to the environmental hazards that the world is encountering these days. Together with having a negative impact on the environment, extreme noise can cause health difficulties

The problem of controlling the level of noise in the environment has been the focus of tremendous amount of research over the years. Statutory legislations are being enforced on industries to make them strictly follow the ceiling on the maximum noise level. However, as long as the quest for larger and more powerful machinery continues, the noise pollution level will be on the rise. Due to these reasons, noise control has gained considerable importance in recent years. Acoustic Noise Control conventionally includes passive methods such as enclosures, barriers and silencers to weaken noise. These methods use either the idea of impendence change or the energy loss due to sound captivating materials.

These approaches are though not operative for low frequency noise. A technique to overwhelm this tricky is Active Noise Cancellation (ANC), which is sound field alteration using electro acoustic means. Many researchers have proposed different definitions of noise as a result of its broad category of existence. In general, the most common definition states- “Noise is arbitrary, unwanted electrical energy that enters the communications system through the communicating medium and obstructs with the conveyed message.

However, some unwanted signal is also generated in the receiver.” Before initiating the study on noise reduction, it is recommended to overview noise as the starting point. Noise can be simply stated that disturbance in the signal due to unwanted signal. The signal from any source that interfere the signal under consideration is termed as noise signal. Some common example of noise signals are the sound from mechanical devices, biological creatures, natural phenomenon (lightening, thunderstorm etc.). The noise from the surrounding mixes with the signal and disorients its information. This effect does not need noise signal to be noisy enough to be recognized by human ears. Ultrasound noise, radio waves (for example) too interferes with signal.

In contrast with human intelligence machines cannot simply deduce noise and eliminate it. The noise prevention methods cannot be very effective since, two signals of different phase for two different receivers are noise for each other. In another words, the activity for one system produce signals that are noise for another system. Some examples of noise from day to day activities .The effect of noise

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cannot be explained as the magnitude of noise is responsible for it. In this scenario, the study of noise elimination techniques becomes a crucial share of modern signal processing systems.

II. TRADITIONAL FILTERING TECHNIQUES

In communication system, commonly different transformational operations are taken place on signal during information transmission. The figures of noise corrupting signal is unknown in many conditions and varies with time. Additionally, the power of noise may be stronger relative to power of desired signal being transmitted. The unwanted signal reduction using adaptive filter is a familiar method for obtaining the desired voice signal mixed with noise

Extracting the voice signal of interest from the noise-corrupted signal is significant signal processing task in speech communication systems. In noise cancellation, signal processing operations contain to filtering out the unwanted noise or any intervention from the signal contaminated by noise so that the desired signal can be well again. In such circumstances, adaptive digital filters can express better-quality performance in cancelling background noise as related with conventional non-adaptive filters. Noise reduction is the technique of extracting noise from a signal susceptible to disturbance. Noise can be accidental or white noise with a frequency distribution, or frequency reliant on noise presented by a device's mechanism or signal processing algorithms.
In electronic devices, a main kind of noise is hiss formed by random electron motion because of thermal anxiety at all temperatures above absolute zero. These disturbed electrons quickly add and subtract from the voltage of the output signal and therefore produce noticeable noise. The known technique used to estimate the signals corrupted by noise is to pass it through the system that have a tendency to overturn the noise while leaving the signals unchanged. This type of signal estimation is known as direct filtering .The design of such filter was originated by wiener and increasingly changing to be emerged as the most important techniques in the area by the likes of Kalman and others in the domain of optimal filtering.

s + n $\hat{S}$S

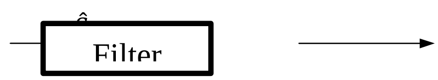

Figure 2. 1.Fundamental filtering system

Filters which are accessible for direct extracting can be fixed filter. Fixed filters: Are filters which needs previous information of both signal and noise. Which implies that if we identify properties of the signal and noise beforehand filtering, we implement the system that permits frequency that contains the wanted signal and block the frequency band taken by noise signal. This type filters are working under stationary conditions.

Adaptive filter: The filters which are categorized under adaptive filters are the ability to adjust the impulse response of a signal in order to know the statistics of the signals like mean, variance and so on by adjusting the weight of the filter and estimating the error. This kind of system has no knowledge of the statistics of the signals beforehand or no previous information of the input signals. They have a capability of adaptively tracking the signals under non-stationary conditions.

2.1 Some Common Types of Filtering Techniques:

2.1.1 Butterworth Filter

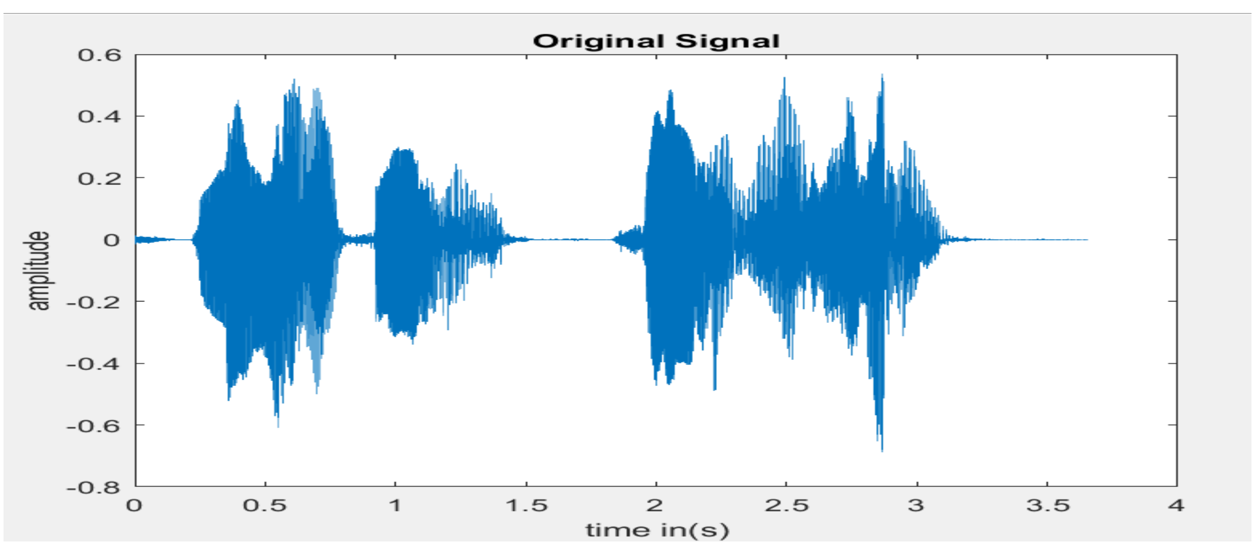

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Figure 2. 2. Original speech signal

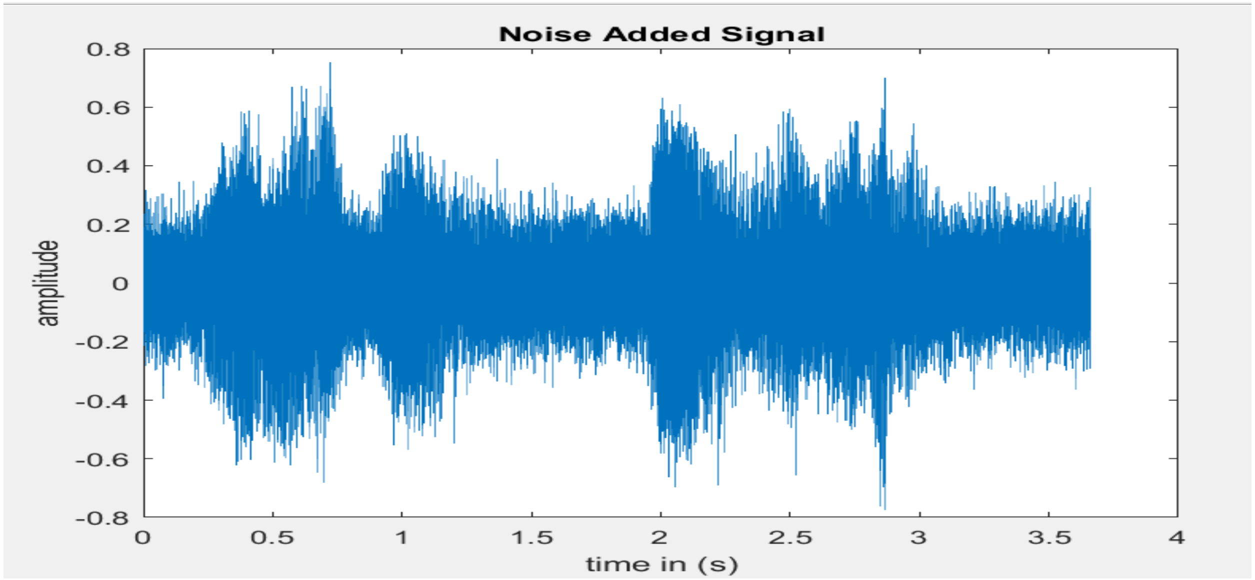

Figure 2. 3. Mixed signal

Butterworth Filter this system is a category of signal processing system implemented to have a frequency response as smooth as likely as in the pass band. It is also denoted as an extremely flat magnitude filter.

Butterworth Filter was first invented in 1930 by the British engineer. Butterworth had a standing for answering "impossible" mathematical complications. By the time, system design required for as considerable amount of designer experience because of the limitations of the theory then in use .The system was not in shared use for many years afterward its publication. The system identified that: "An ideal electrical system should not only totally block the unwelcome frequencies but should also have similar sensitivity for the wanted frequencies".

Such an ideal filter cannot be attained but Butterworth exhibited that successively closer estimates were obtained with increasing numbers of filter elements of the right values. At the time, systems generated considerable ripple in the pass band, and the high-quality of component values was highly communicating. This system showed that a low pass filter might be implemented and the frequency at which transition start is normalized to 1 and given by an equation as follows.

$$G(\omega) = \frac{1}{\sqrt{1+\omega^{2n}}} \qquad 2.1$$

Where ω is given by in standard unit of frequency response and n is the number of poles to the respective number of responsive elements in the system. If $\omega = 1$, the magnitude response of this system is in the pass band is $1//\sqrt{2} \approx 0.707$, which is half of the given power .This system is only dealt with filters with an even number of poles in proposed paper. The inventor might have been uninformed that such systems could be designed with an odd amount of poles. The engineer discovered his large order systems from 2-pole systems isolated by specific type of amplifier.

The view of frequency response of all pole systems is described as A, B, C, D, and E in his main graph. This type of system is solved the equations for two- and four-pole filters, showing how the latter could be cascaded when separated by vacuum tube and so allowing the structure of large order filters in spite of inductor losses. In 1930, best materials, that means, materials that have minimum core lose such as molypermalloy had not been exposed and vacuum-cored voice inductors stood slightly glossy.

He revealed that it was possible to modify the constituent values of the system to replace for the winding resistance of the inductors. He used coil forms of 1.25″ Diameter and 3″ Length with plug-in terminals. Connected passive elements were confined inside the wound coil form. The coil molded part of the plate load resistor. Two poles were used per vacuum tube and passive element coupling was used to the network .The inventor also has showed that the fundamental low-pass system could be adapted to give all ranges bands service.

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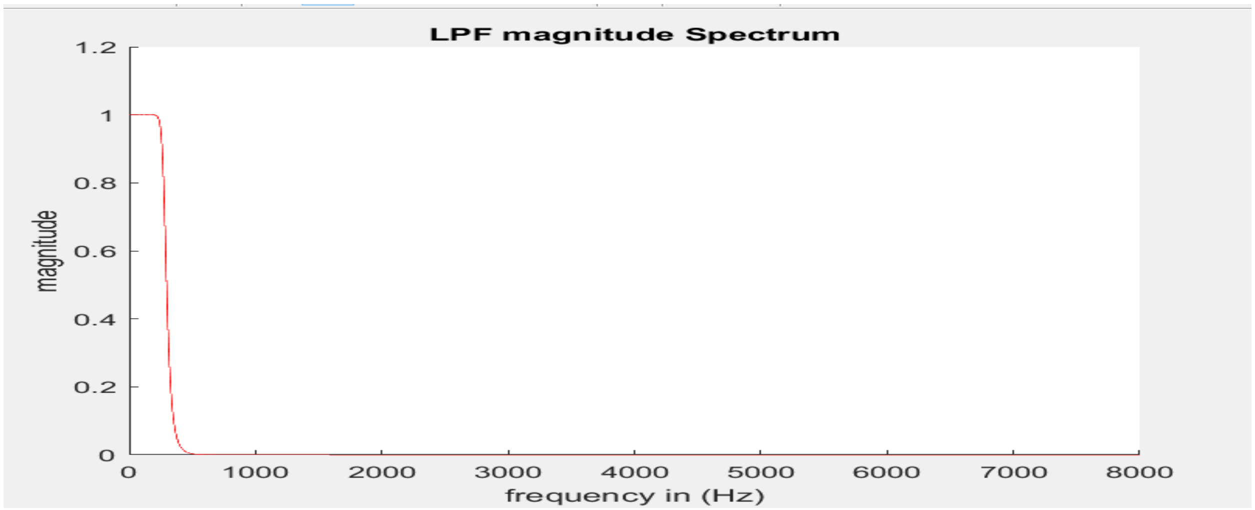

Figure.2. 4. Low Pass Filter

This filter is implemented to filter out or extract the noise part of the signal from contaminated signal adaptively as per the algorithm. The cutoff frequency (fc) where the output load voltage is equal to 0.707 of the input source, which shows the range of frequency in which our spectrum of the signal is strongly concentrated, of this designed filter is 0.035. All signals out of this range is eliminated and the signals with in this range is recovered perfectly. In many applications we want to attenuate the part of which have high frequency of signals is done by low pass filters which passes frequency below cutoff frequency and attenuates the frequency above it .So, the signal range above the turning point is one of high frequency parts which need to be eliminated, accordingly the noisy signal is processed and recovered in this thesis.

2.1.2 Chebyshev filters

Chebyshev filters this system are any type of devices having a high pitched roll-off and added pass band fluctuation (type I) or stop band fluctuation(type II) when we related to previous one . And it have the property that they minimize the error between the idealized and the true filter characteristic for the given width of the system (See references e.g. [Daniels], [Lutovac]), but with fluctuations of pass band. This type of system is comes after Pafnuty Chebyshev as its exact features are resulting from its equations. The type I systems are known frequently as just "Chebyshev filters", the type II ones are typically known as “counter Chebyshev system”. Since the pass band fluctuation characteristics in Chebyshev filters, the ones that have a flatter response in the pass band but a more uneven response in the stop band are favored for some applications. Type I system is the famous types of this filters.

The gain response, $\boldsymbol{G_n(\omega)}$ as a relation of angular frequency ω of the given level of low-pass system is equivalent to the magnitude value of its ratio of output to input.

$$\boldsymbol{G_n(\omega) = |H_n(j\omega)| = \frac{1}{\sqrt{1+\varepsilon^2 T_n{}^2\left(\frac{\omega}{\omega_o}\right)}}} \qquad 2.2$$

is calculated at s=jω where ε is the ripple factor, ω_0 is the cutoff frequency and T_n is a Chebyshev polynomial of the n^{th} order. The pass band exhibits equi ripple behavior, with the ripple determined by the ripple factor. In the pass band, the Chebyshev polynomial alternates between -1 and 1 so the filter gain alternate between maxima at $G = 1$ and minima at ,

$$\boldsymbol{G_n(\omega) = \frac{1}{\sqrt{1+\varepsilon^2}}} \qquad 2.3$$

The ripple factor ε is thus related to the pass band ripple δ in decibels by:

$$\varepsilon=\sqrt{10^{0.1\delta}}-1 \qquad 2.4$$

At the center frequency ω_0 the transfer function has the value but keeping decrease to down in to the stop band as the frequency is getting large. The collective use of defining the center frequency at basic is typically not used to Chebyshev systems; rather the center frequency is taken as the value at which the system transfer function down to the value of the ripple for the last phase.

2.1.3 Elliptical filter

An elliptic filter (also known as a Causer filter, named after Wilhelm Causer, or as a Zolotarev filter, after Yegor Zolotarev) is a signal processing filter with equalized ripple (equiripple) behavior in both the pass band and stop band. The values of fluctuations in

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each range of band is separately maintained ,and no other system of the same level can have a higher change in result among the bands, for the given values of fluctuations (whether the it is equivalent or not). In other way, one may take over the ability to maintain separately the pass band and stop band variations, and in place of implement a system that is highly exposed to component variations. When the variations in the stop band limits to zero, the system gives type I Chebyshev system. While as the variations in the pass band limits to zero, the system becomes a type II Chebyshev system and at the end, as both variations values limits to zero, the system becomes a Butterworth system.
The relationship between elliptic filter with that of angular frequency in low pass band is given by:

$$G_n(\omega) = \frac{1}{\sqrt{1 + \varepsilon^2 R^2 \left(\xi \frac{\omega}{\omega_o} \right)}} \qquad 2.5$$

Given that R_n is the given order of elliptic rational function (sometimes known as a Chebyshev rational function) and ω_o is the center frequency ε is the fluctuation parameter and ξ is the choosiness parameter.
The value of the first parameter identifies pass band fluctuation, while the two factors specify stop band ripple.

III. ADAPTIVE SYSTEMS

Adaptive system is the modern area of research in current years, it is the systems which have time varying and self-updating performance. This type of system has shown the characteristics of listed below: They can automatically adapt or self-optimize in the face changing (non- stationary) environments and changing system requirements. They can be trained to perform specific filtering and decision -making tasks. The creation of systems having these ability can be automatically implemented through training. In a logic of adaptive system can be adjusted by a repeating process.

This type of systems does not elaborate synthesis procedures usually needed for no adaptive systems. Instead, they tend to be self -designing.

They can infer a model of behavior to work with new circumstances after having seen adapted on a finite and often with minimum times of training signals or configurations.

In a limited amount, the adaptive systems can maintain themselves; means that, they can learn around an issues of internal problems. Sometimes the system can usually be defined as nonlinear systems with time-variant factors.

Its kwon that, the systems reflecting behavior like this is difficult and very complex to analyze relative with no adaptive systems however, they provide better performance when the input signal characteristics are undefined or time-variant.

And adaptive filter is a device with a linear system that has a gain managed by variable factors and a means to adapt those factors as per adaptive algorithms. Nearly, all adaptive systems are digital filters since optimization algorithms are very complex in implementation. This types of filters are important in the applications of the desired parameters in the processing operation which are not known priori or are changing like: the locations of reflective surfaces in a reverberant space. The way system uses previous result with that of current input feedback in the form of an error signal to refine its gain.

As whole, the closed loop system involves the use of a cost function, which is a standard for finest performance of the filter, to feed an algorithm, which controls how to adapt filter transfer function to minimalize the cost on the iterations

The sum of mean square of the error (MMSE), is the most famous cost function in digital signal processing applications.

As the power of digital signal processors has growing , adaptive systems have become much more familiar and are now regularly applicable in devices such as mobile phones and other communication devices, camcorders and digital cameras, and medical monitoring equipment.

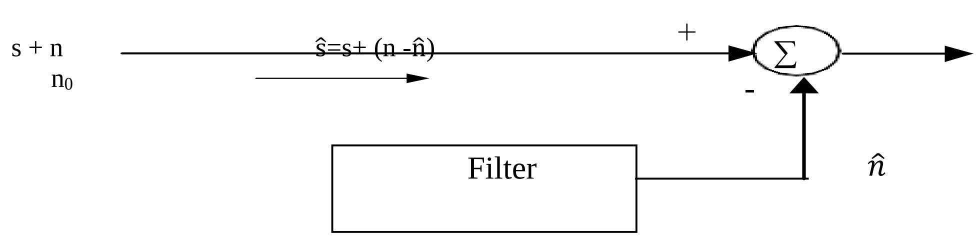

Figure 3. 1. Basics of noise estimation

Noise minimization is a deviation of the best filtering that includes creating an estimate of the noise by extracting the reference input and then deducting this noise estimate from the primary input comprising both signal and noise, simply, noisy signals subtracting noise from a received signal involves the problem of misrepresenting the signal and if done inappropriately, it may lead to an increase in the noise level. This requires that the noise estimate should be an exact duplication of n. If it were likely to know the relationship between n and $\hat{n}$, or the features of the networks conveying noise from the noise source to the noisy signal and noise inputs are known, it would be promising to make $\hat{n}$ a close estimate of n by generating a stationary filter, thought, since the behavior of the transmission

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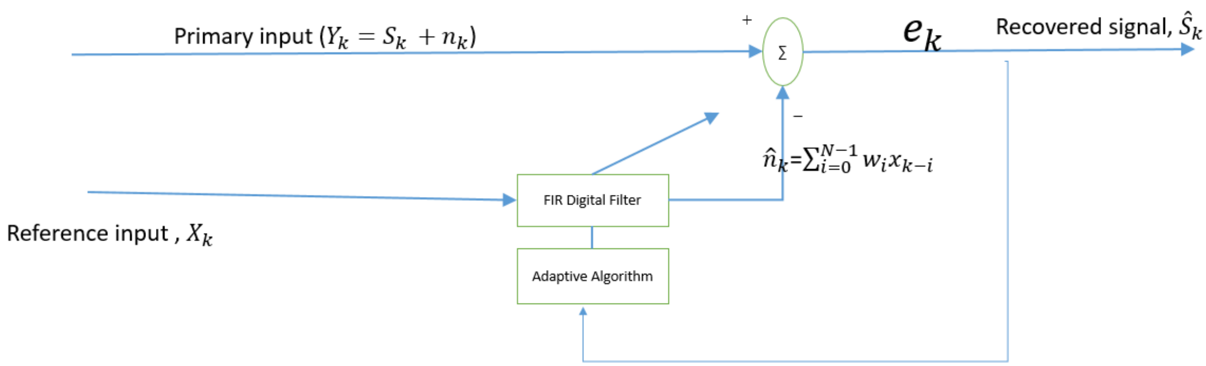
medium are not known and are random, filtering and subtraction are managed by an adaptive algorithms. Hence the self-adjusting filter is used that is capable of adjusting its parameters to minimize an error signal, which is dependent on the filter output. The updating of the filter weights, and hence the impulse response, is controlled by an adaptive algorithm. With adaptive control, noise cancellation can be adaptively done with nearly out of contaminating the signal. In fact, Adaptive Noise Cancelling is the device that makes possible accomplishment of noise elimination levels that are not possible to attain by direct filtering. The error signal to be used depends on application used.

3.1. Principles of Adaptive Noise Cancellation

General model which represent the entire analysis of this thesis is depicted below by block diagram. Each points like inputs, outputs and blocks have its features. Figure 2 3 shows the details.



Adaptive noise canceller block

Figure 3. 2. Model of Adaptive Noise Cancellation

From the above figure the system has two inputs; *the noisy signal (primary)* and the noise signal (*reference).* The primary which is the input receives a signal S_k *from* the signal source that is despoiled by the occurrence of noise n_k non similar with the wanted signal. The reference input retrieves unwanted signal X_k that *is* not similar with the signal S_k but in other direction with the noise n_k. The noise X_k goes through adaptive filter to produce an output $\hat{n}_k$ that is a very approximate of noise in contaminated signal (primary).

This noise approximate is minimized from the despoiled signal to produce the replica of the signal at $\hat{S}_k$ of the system output. In noise minimization systems a tangible objective is to get a system output $\hat{S}_k = S_k + n_k - \hat{n}_k$ which is the suitable in the optimal logic to the desired signal S_k. This objective is done by giving back the system output to the adaptive filter and updating the filter coefficients via LMS adaptive algorithm and NLMS adaptive algorithms to decrease the total system output power. Again, the system output work for as the in accuracy of the adaptive self-adjusting process.

Let , S_k , X_k, $\hat{n}_k$ and n_k are statistically stationary and have zero means. The signal S_k is uncorrelated with $\hat{n}_k$ and n_k is correlated with $\hat{n}_k$.

Mathematically, it's shown as follows

$$\hat{S}_K = S_K + n_K - \hat{n}_K \qquad 3.1$$

By squaring both sides of the equations,

$$(\hat{S}_K = S_K + n_K - \hat{n}_K)^2 \qquad 3.2$$

$$\hat{S}_K{}^2 = S_K{}^2 + (n_K - \hat{n}_K)^2 - 2\hat{S}_K(n_K - \hat{n}_K) \qquad 3.3$$

By taking the expectation of both sides,

$$E[\hat{S}_K{}^2] = [S_K{}^2] + E[(n_K - \hat{n}_K)^2] - 2E[\hat{S}_K(n_K - \hat{n}_K) \qquad 3.4$$

$$minE[\hat{S}_K{}^2] = [S_K{}^2] + minE[(n_K - \hat{n}_K)^2] \qquad 3.5$$

Signal power E [S_k2] will be unaffected as the filter is adjusted to minimize E [$\hat{S}_k$ 2], the output noise power E [(n_k –$\hat{n}_k$) 2] is also minimized. Since the signal in the output remains uniform, reducing total output power, increases the signal to noise ratio (SNR) of the system.

So,

$$\hat{S}_K - S_K = n_K - \hat{n}_K \qquad 3.6$$

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This equivalent is resulting the output $\hat{S}_k$ the best least square estimate of signal input S_k.

3.2. Algorithms

An adaptive algorithm is an algorithm that alters its features at the execution time depend on availability of information and based on previous obtained method (or criterion). This type of message is currently received data information on the available resources or execution time gained information which has relationship with that of the vicinity where it works. The famous algorithm of adaptive systems which is simple that denotes a group of stochastic gradient-descent algorithms which works in self-adjusting filter and machine learning is LMS algorithm least mean square is applicable to approximate the desired signal of the error signal by repeatedly calculating the difference of filter output and noisy signal.

3.3.1 Least Mean Square Algorithm (LMS)

Least mean square algorithm is a technique to approximate gradient vector with instantaneous point .It alters the system tap weight resulting error e(n) is reduced in the mean square logic. The predictable LMS algorithm is a stochastic operation of steepest decent algorithm. It is simply working by adjusting filter coefficients by calculating system output, desired signal and error signals. In this group of algorithm the filter is only adapted according to recent error. Stochastic gradient descent (often abbreviated SGD) is a repetitive method for enhancing (best estimate) an objective function with appropriate smoothness properties (e.g. differentiable or sub differentiable). It is called stochastic since the technique uses randomly choosing input samples to analyses the gradients, as result the gradient is called known as stochastic approximation of gradient descent. Computationally repetitive technique is a procedure that uses an initial estimation to produce a sequence of

$$e(n) = d(n) - W(n)X(n) \qquad 3.7$$

$$\hat{n}_K = W^T(n)X(n) \qquad 3.8$$

$$\xi(n) = E[e^2(n)] \qquad 3.9$$

The coefficient updating equation is,

$$W(n+1) = W(n) + \mu e(n)X(n) \qquad 3.10$$

Where, μ= is an appropriate step size, the larger step size make the coefficients to fluctuate in uncontrolled manner and at the end become unstable. Step-size is one of important parameters for LMS algorithm or other adaptive gradient descend algorithms.
If the value of step-size is fulfilled the appropriate condition which depends on the quality of recovered signal at that point, then the system will be stable. Though, under environments of having different noise, step-size may set as very small to safeguard the algorithm stable. In addition, typical LMS algorithm may not work properly in special environment, such as spontaneous noise. Hence, the only considering the parameter may not good choice to solve above difficulties.

The step size maintains the balance of the speed of adaptation and the noise in steady state. When the algorithm is in steady state it is likely to notice and decrease step size this will decrease the steady state noise.

3.3.2 Normalized least square algorithm (NLMS)

Adjusts the coefficients of W (n) of a filter in order to reduce the mean square error between the desired signal and output of the filter. Algorithm use the gradient vector of the filter tap weights.

$$W(n+1) = W(n) + \mu(n)e(n)X(n) \qquad 3.11$$

$$\mu(n) = \frac{\beta}{C + \|X_n\|^2} \qquad 3.12$$

Where, $\mu(n)$ =normalized step size
β = scaling factor
C= small positive constant
Weight vector:

$$W(n+1) = W(n) + \frac{\beta}{C + \|X_n\|^2} \qquad 3.13$$

In real scenario, input signal power not remain constant. This results changes the step- size between two consecutive coefficients of the filter which will also affect rate of convergence.

IV. SIMULATION RESULTS AND ANALYSIS

The performance estimation of adaptive noise minimization using Least Mean Square (LMS) and Normalized Least Mean Square (NLMS) algorithms are explained in detail. The performance is studied with changing some factors includes: step size, number of filter coefficients, input noise level and number of samples. The noisy signal (speech signal with random noise) is given as input to system and the adaptive noise chancellor adjusting the filter parameters to estimate the noise which is correlated to the noise corrupting signal given through primary input to the system. Finally, the output of adaptive noise chancellor is subtracted from primary output giving the signal almost equivalent to the input desired signal (recovered signal). All the outcomes are found by Mat lab simulations. The speech

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signal have the following features or properties. Those properties are number of sample, bitrate, audio sample size, audio sampling rate, audio format, and speech recording duration.

Number of samples	24000
Bit rate	64kbps
Audio sampling size	8 bit
Audio sampling rate	8000 Hz
Audio format	mono
Duration	3second

Table 4. 1 Parameters Specification

On this desired signal AWGN is added to produce noisy signal. Finally using FIR filter noise signal is filtered out. Those signals are presented in the following wave form which is obtained by mat lab simulations.

Recorded speech signal wave

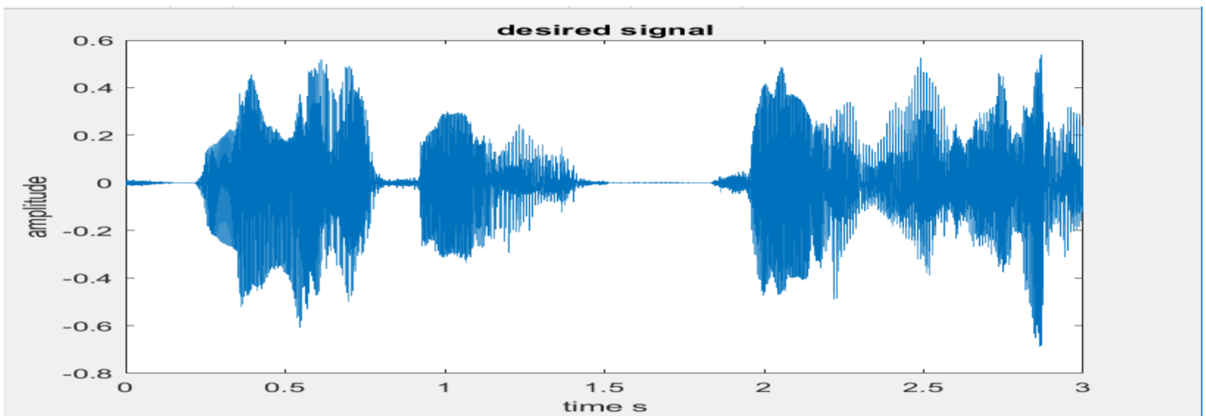

Figure 4. 1. Recorded speech signal, Input signal wave

This recorded speech signal have 24000 number of samples, bitrate (speed) 64kbps and sampling rate of 8000Hz, with a duration of 3second.

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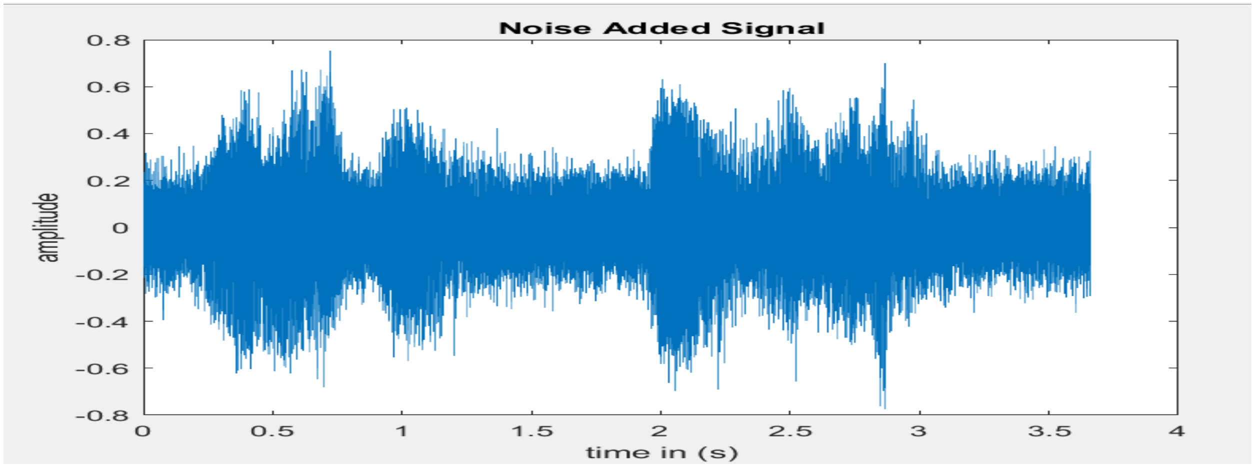

Figure 4. 2. Noisy Signal

Different observations parameters were made to evaluate the variations of the system's performance related to the results of Noise Reduction Ratio (NRR), which measures the performance adaptive filter in dB (decibel). Noise-Reduction-Ratio (NRR) is the measure of quality of the signal by evaluating the ratio of noise power to error power in noise cancelling
Mathematically given by,

$$NRR = \frac{noise\ power}{error\ power} \qquad 3.14$$

Where,
NRR= Noise Reduction Ratio.

$$NRR(dB) = 10\log_{10}(NRR) \qquad 3.15$$

Analyzing signals in different domains

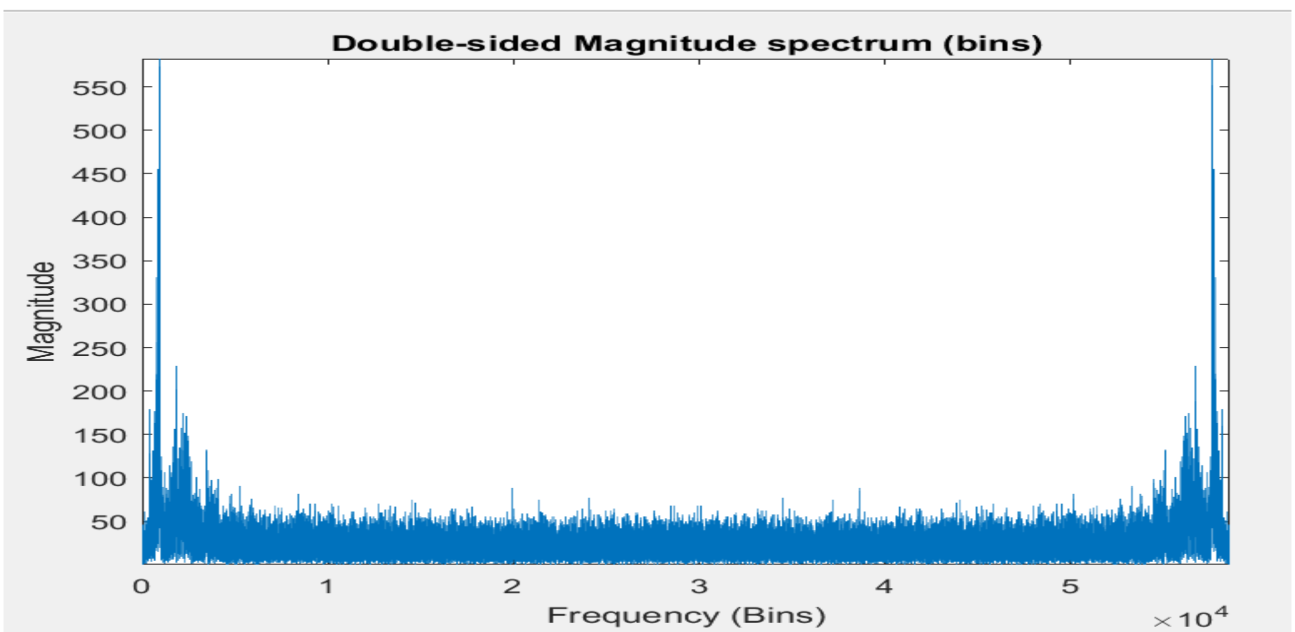

Figure 4. 3. Double Sided Magnitude spectrum in Bins

Double sided magnitude spectrum of noisy signal in frequency domain measured in Bins. Frequency in hertz (Hz) is calculated by multiplying number of Bins values with the ratio of sampling frequency of the signal (Fs) to length of the signal (N). Next, it is needed to fix an appropriate x-axis for the FFT spectrum. In this case, then put the physical frequencies in the x-axis so that we know we are getting maximum at the correct frequencies. This is a very important step. To do that, we need to understand how FFT creates "bins". For N point FFT, the number of bins created is N/2.

FFT is just an implementation of Discrete Fourier Transform (DFT), in order to discretize the continuum of frequencies, the frequency axis is consistently segmented into finite number of parts which are called bins. It can be considered as spectrum samples. In

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our example, the sampling frequency Fs = 8000 samples/second. According to Nyquist criteria, the highest physical frequency which can be characterized by its samples without aliasing is simply Fs/2 = 4000 Hz. So, basically the frequency spectrum is being segmented into tiles of Fs/N bins. We can now generate suitable frequency axis as displayed in the extract above.

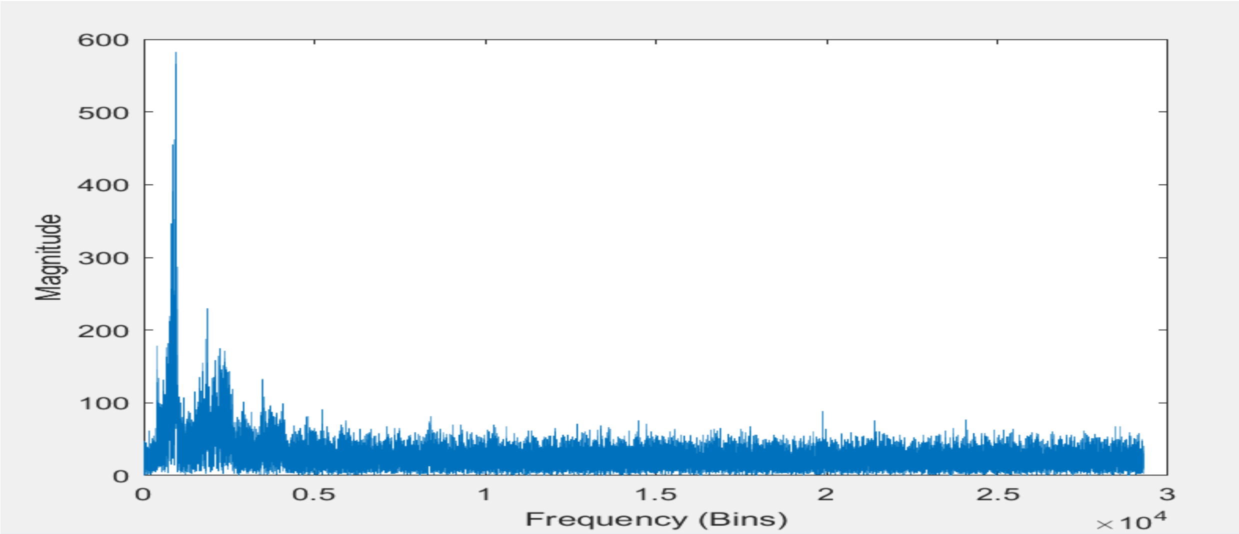

Figure 4. 4. Single sided Magnitude spectrum in Bins

By looking closely, one side of the plot given above it is the mirror of the other side, dropping the peak at 0. This is because, for real signals, the coefficients of positive and negative frequencies become complex conjugates. So, we can us one sides of the range to denote the signal. This is characterized by the type of spectrum known as Single Side Band (SSB) spectrum. This is applied to extract the signal by using Fast Fourier Transform (FFT) by not to going other transforms, which is done by taking the one side of the spectrum and multiplying by 2. In turn avoids the coefficients of complex signals for real signal. The returned vector by transform needs appropriate manage since DC component is included, so this should be fixed. At this point the frequency component is has zero value which is in reality real value.

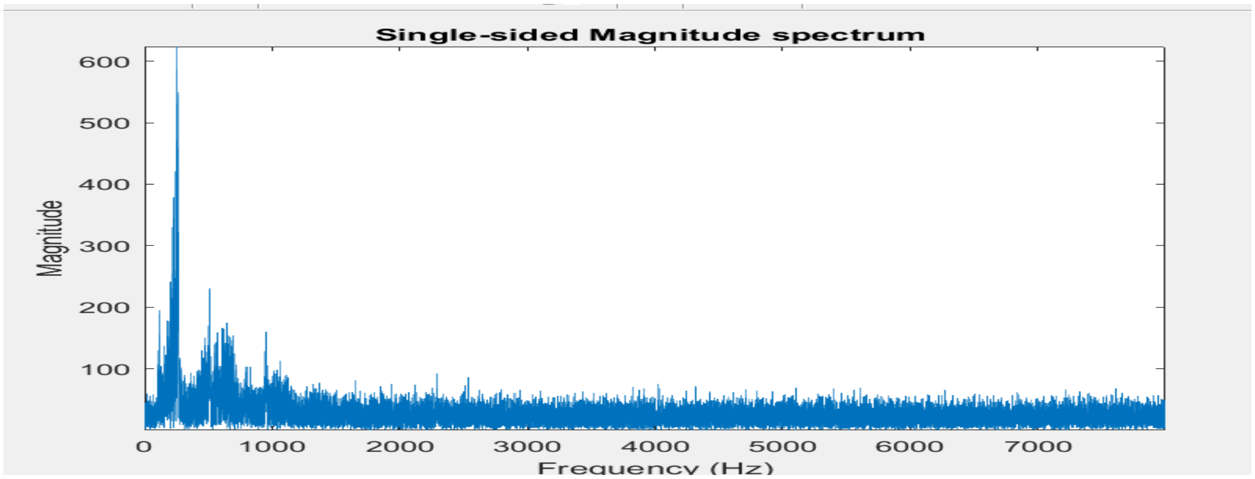

Figure 4. 5. Single sided magnitude spectrum in Hertz (Hz)

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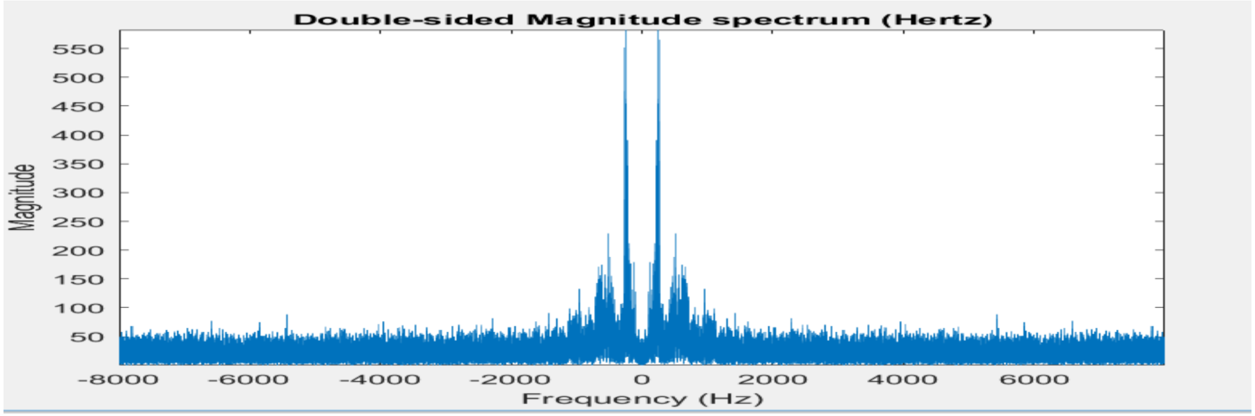

Figure 4. 6. Double sided magnitude spectrum

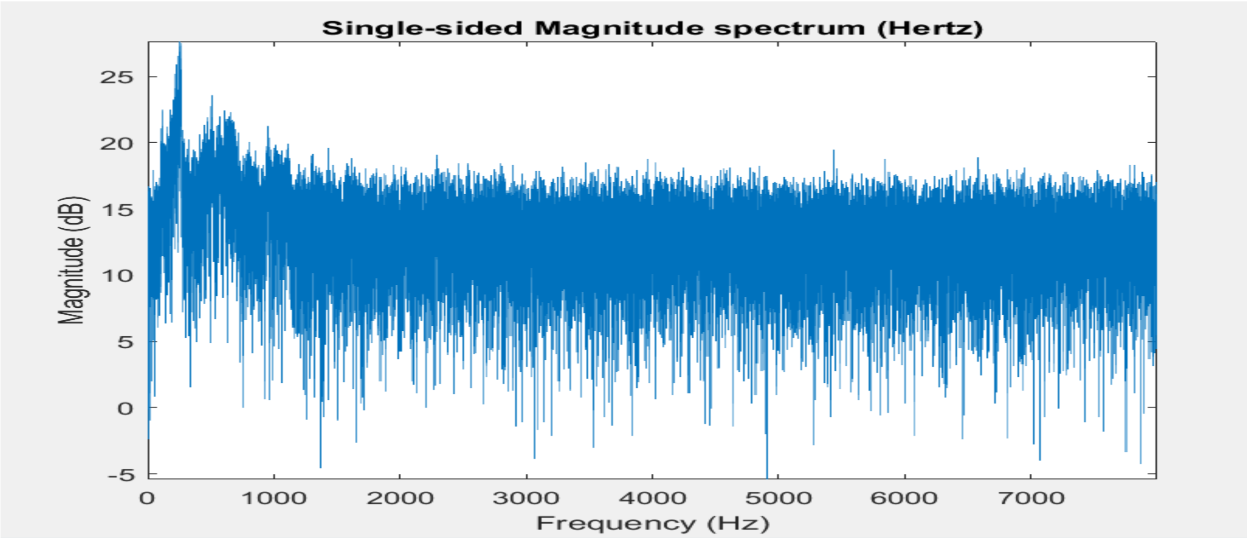

Figure 4. 7. Single sided magnitude spectrum in Hertz

And also power spectrum analysis simulation is done in both double sided and single side spectrum. Which shows the spectral strength at each bin or frequency range or slots. The following plots shows power spectral details in Decibel (dB) along y-axis and with frequency in Hertz along x-axis. The one side shows the power spectrum versus frequency in log scale.

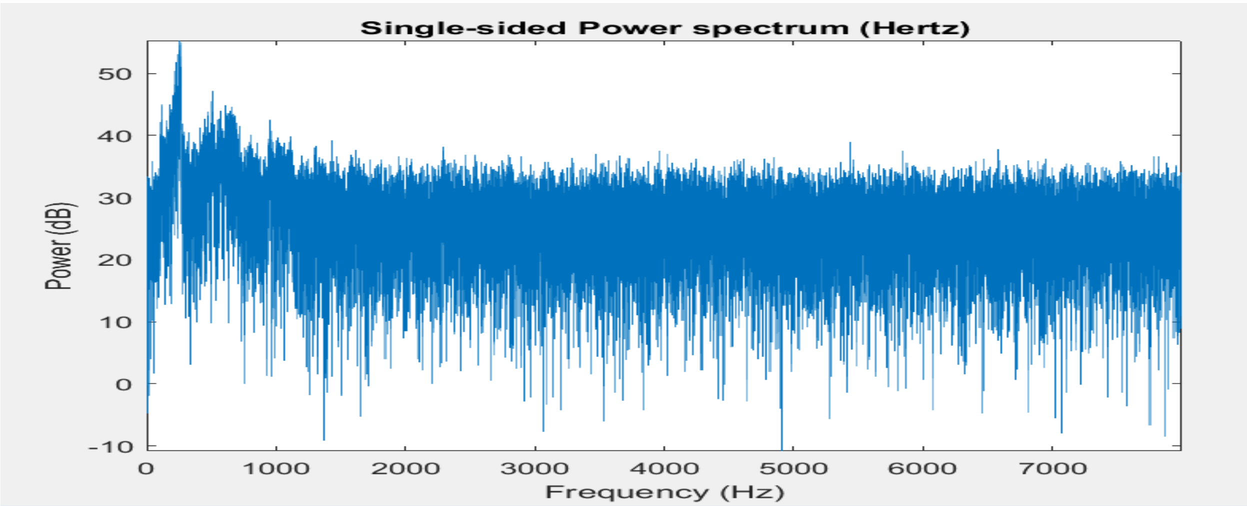

Figure 4. 8. Single Sided Power Spectrum

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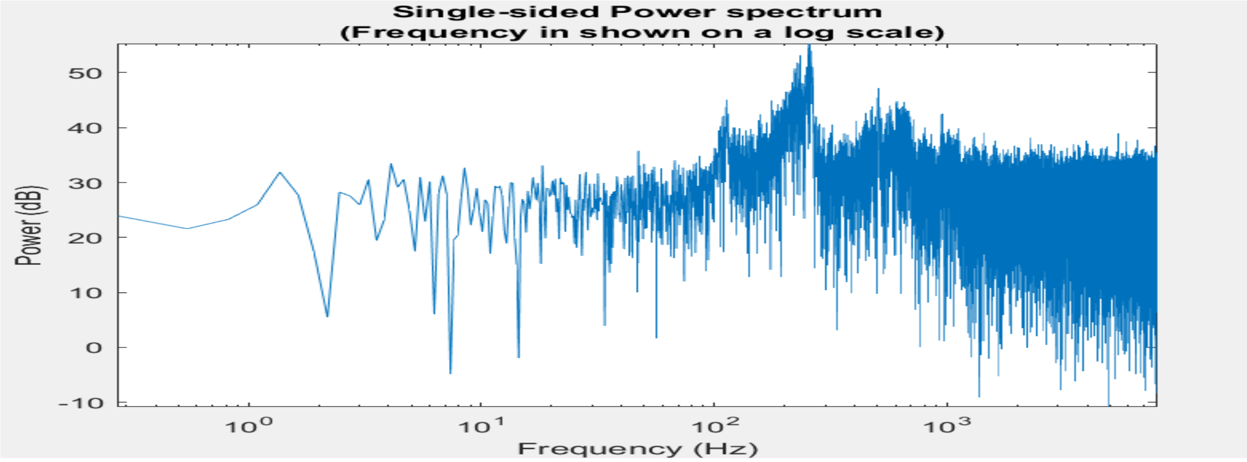

Figure 4. 9. Single Sided Lower Spectrum in Log Scale

Performance of the adaptive noise cancellation, where the value of the current output is feedback to the filter is analyzed using LMS and NLMS algorithms by varying parameters with related to noise reduction ratio.

Input signal to noise ratio (Input SNR)

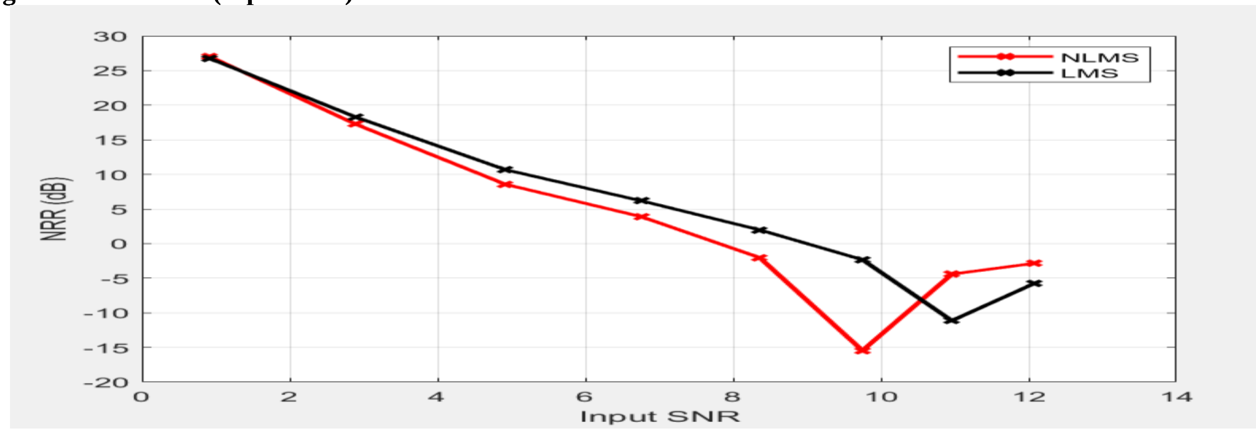

Figure 4. 10. Input SNR versus NRR (dB) for LMS and NLMS

Input SNR is the ratio of the average of signal power to noise power at the input level. High Input Signal to Noise Ratio (SNR) brings high signal quality at the output side of the digital signal processing systems. The impact of varying input SNR on the performance of adaptive noise cancellation with relation to Noise Reduction Ratio (NRR) by using both LMS and NLMS algorithms. And the simulation has taken place by fixing simulation factors such as number of samples: 20000, step size: 0.15, number of filter coefficient: 32. From figure 4.10 as Input SNR increases from 1dB to 9.75dB, the NRR decreases linearly then gradually increases.

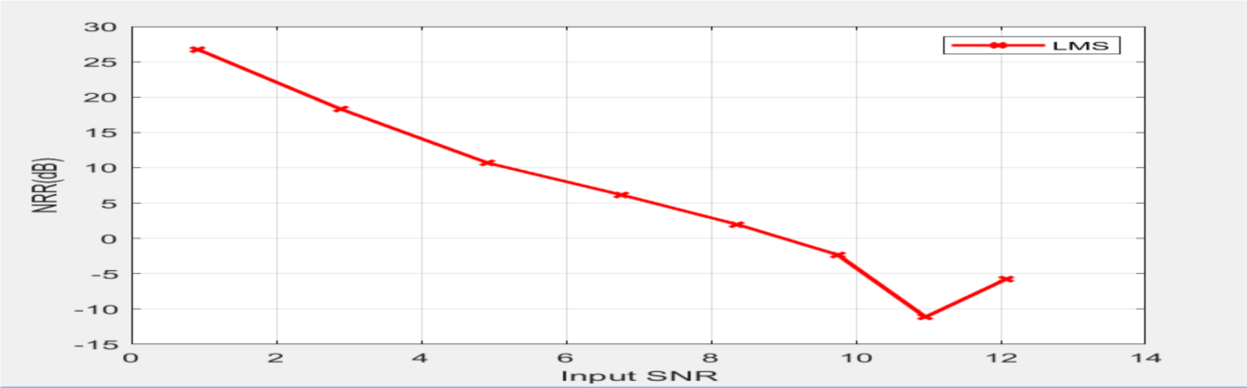

Figure 4. 11. Input SNR versus NRR (dB) of LMS

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Based on figure 4.11 input SNR increases from 1dB to 11dB with the decreasing of the respective Noise Reduction Ratio (NRR). After 11dB as input SNR slowly increasing the Noise Reduction Ratio (NRR) linearly increases. The system showed the worst performance at 11dB and gradually increases the system performance as Input SNR increases further using LMS algorithm.

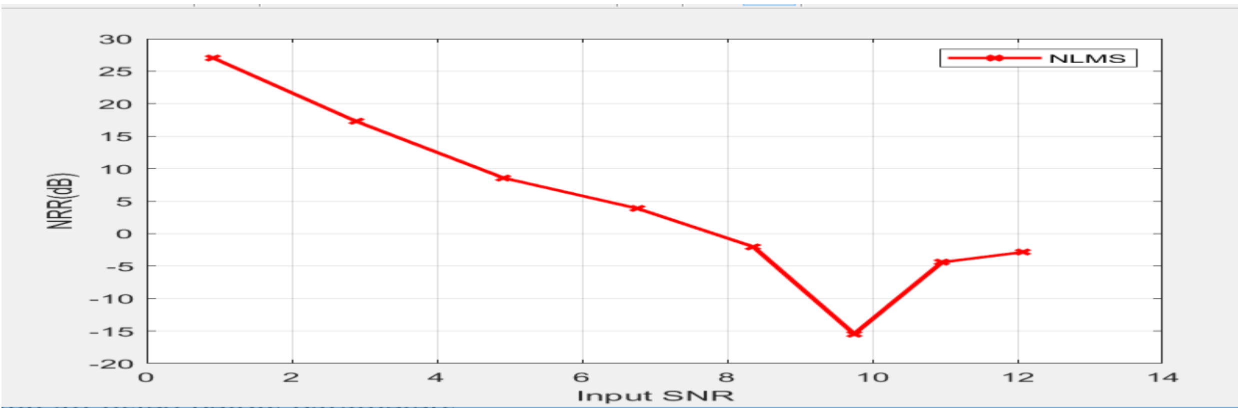

Figure 4. 12. Input SNR versus NRR of NLMS

From figure 4.12 input SNR increases from 1dB to 9.75dB with the decreasing of the respective Noise Reduction Ratio (NRR). After 9.75dB as input SNR slowly increasing the Noise Reduction Ratio (NRR) linearly increases. The system showed the worst performance at 9.75dB and gradually increasing the performance of the system as Input SNR increases further using NLMS algorithm.

Number of filter coefficients

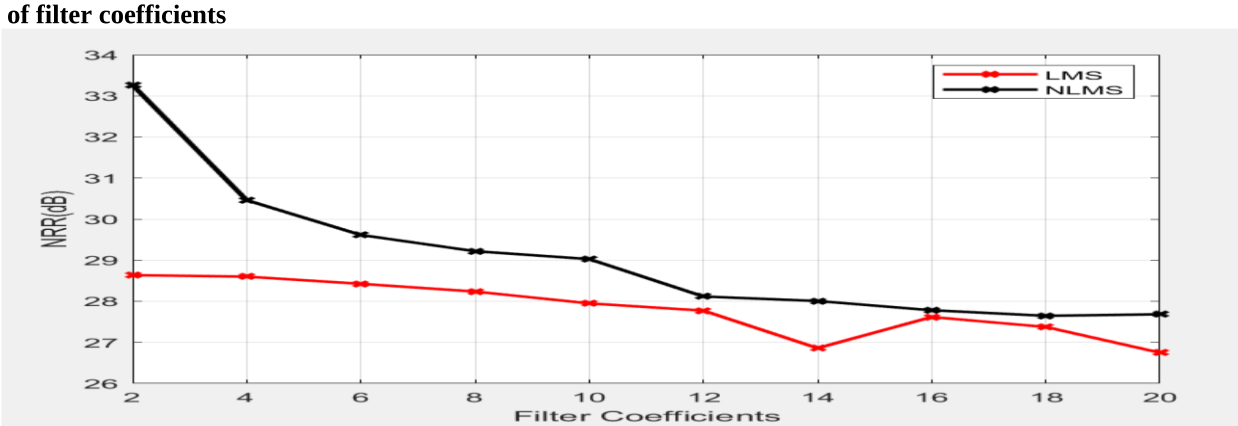

Figure 4. 13. Filter coefficients versus NRR (dB) for both algorithms

Number of observations were taken the system performance of the adaptive filter with varying number filter coefficients. Both algorithms decreases the system performance of the filter for first 10 observations as generally seen the algorithm together.

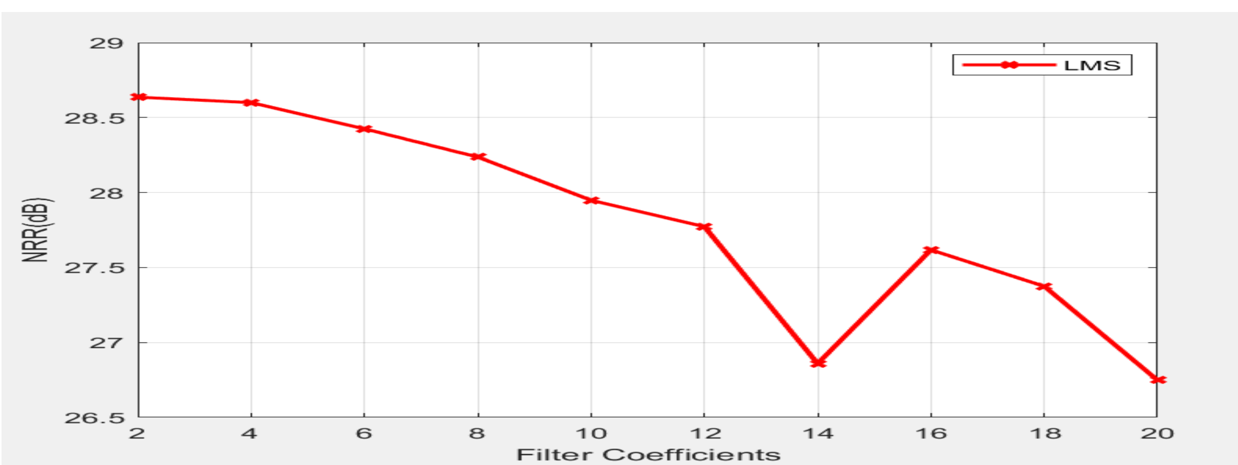

Figure 4. 14. Filter Coefficients versus NRR (dB) Of LMS

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Figure 4.14 showed the system performance decreases slowly as number of filter coefficients increasing up to 12 and sharply decreases up to 14 then increases sharply till number of coefficients to be 16, again decreases slowly using LMS algorithm of adaptive noise cancellation. When a number of filter is at 16 the system performed well that is the NRR of the system is high, which gives high quality of the signal 27.867dB of NRR within the in a filter coefficients 14 and 20. The simulation is done at the step_ size of 0.1.

Varying Step size

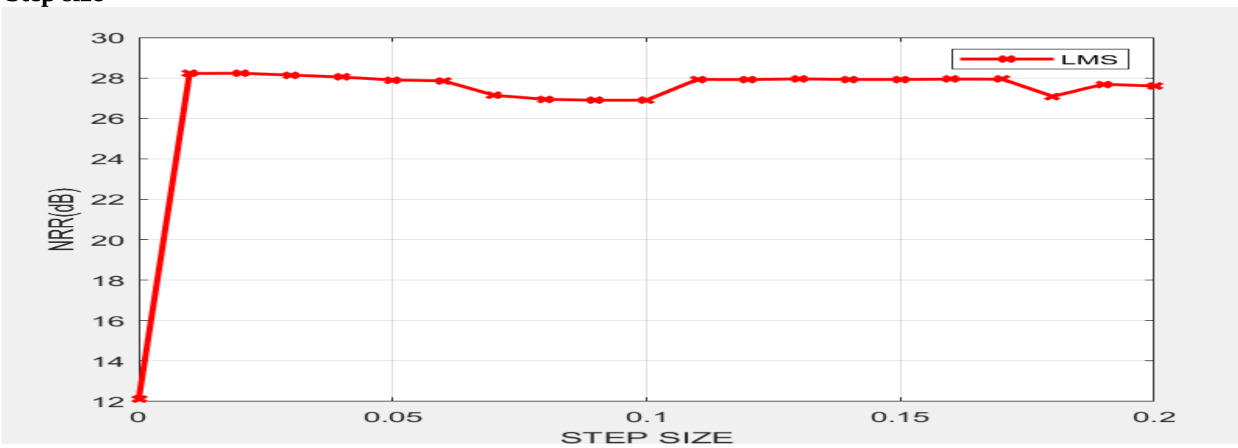

Figure 4. 15. Step size versus NRR of LMS

In above figure the step size of the algorithm changes from within a given range to evaluate the adaptive system performance on noise cancellation with respect to Noise Reduction Ratio (NRR). The system performance is increasing exponentially as number of step size gradually increases from 0 to 0.01 and climax at step size of 0.01 and 0.02 in LMS algorithm with respective Noise Reduction Ratio (NRR) of 28.65 dB and smoothly decreased till the worst performance of the system at step size of 0.1 and the NRR is 26.54dB.Again increased from 0.1 to 0.11 step size which has increased the performance as well. From step size 0.11 to 0.17 the system performance is unchanged. After that it were come to slowly declined. The signal noise power is given that -19.9972

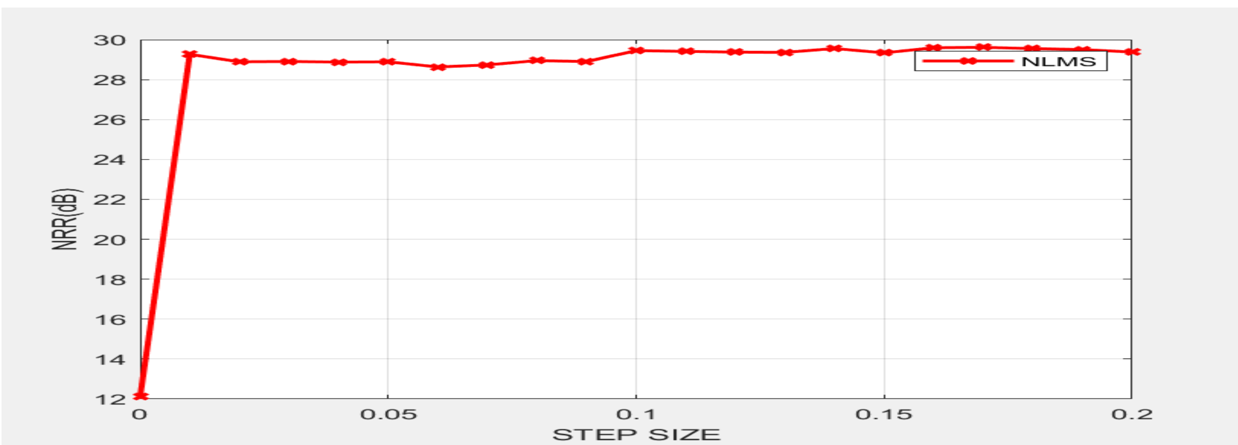

Figure 4. 16. Step size NRR of NLMS

From the above simulation figure the step size of the algorithm is changed with in a given range to evaluate the performance of the adaptive system in noise cancellation with respect to Noise Reduction Ratio (NRR). The simulation result of filter coefficient of 32 is shown above. The system performance is increased exponentially as number of step size gradually increases from 0 to 0.01 and climax at step size of 0.01 and 0.02. With respective Noise Reduction Ratio (NRR) of 28.65 dB and smoothly decreased till the worst performance of the system at step size of 0.06 and the NRR is 28.43dB. And the system is best performed at step size of 0.1 and the NRR of 29.76dB then the system is appeared to be diverged. By taking the values of step size the Normalized Linear Mean Square, NLMS, algorithm relatively brought better recovery of the wanted signal as compared to LMS algorithm.

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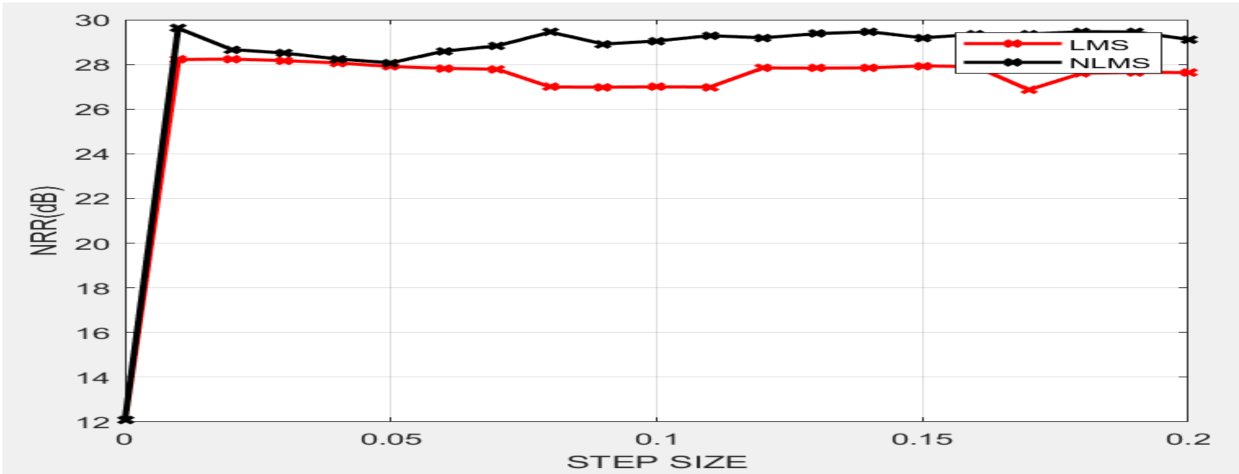

Figure 4. 17. Step size versus NRR (dB) of both algorithm

From the above simulation graph the NLMS algorithm reaches the optimum point of recovery of the signal from noisy one at the step size of 0.1.

Number of samples

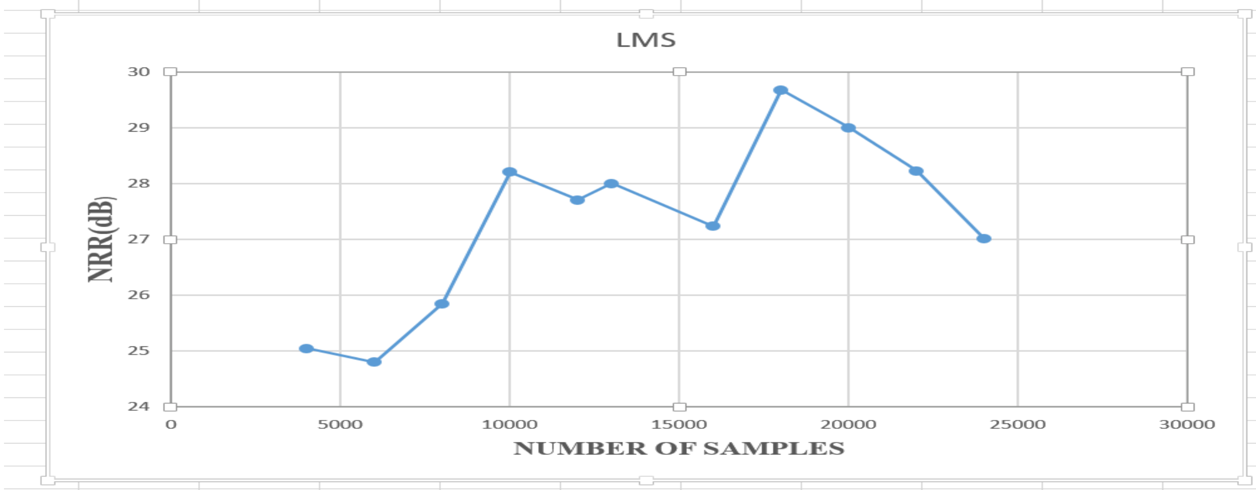

Figure 4. 18. Number of samples versus NRR (dB) of LMS

The impact of varying number of samples on the system performance to the adaptive noise cancellation is showed on this above figure. The analysis is done by making one parameter to vary while others were fixed versus noise reduction ratio. The analysis is made by increasing number of samples from 4000 up to 24000. The system has recorded the best and worst signal quality at different point of samples, at 6000 the system produced the NRR value of 24.803dB, which were the lowest quality that has recorded in the range while at 18000 number of sample point the best system performance were showed ,29.6801dB NRR. The filter system could not adapt at the first sample points because of different conditions.

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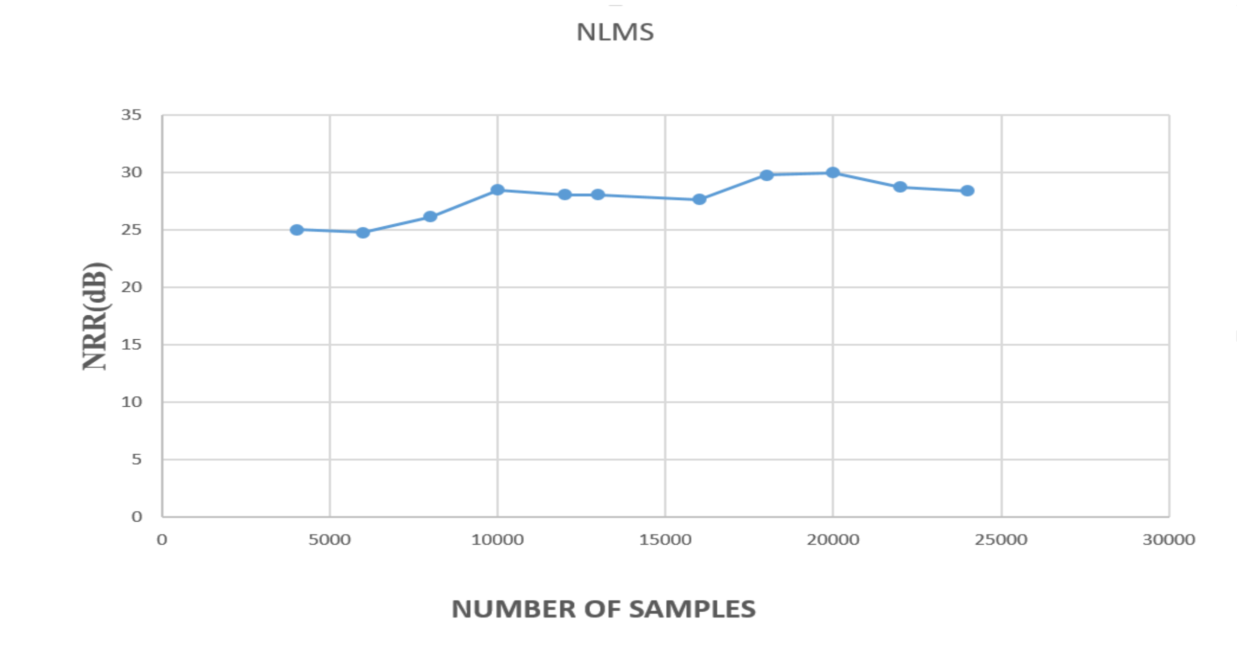

Figure 4. 19. Number of Samples versus NRR (dB) NLMS

Under NLMS algorithm the filter is performed well at the sampling number of 20000 with its respective Noise Reduction Ratio value of 29.995dB.At this point the signal is recovered perfectly. After the point of its maximum performance the quality has gone slowly as NRR decreased while number of samples increased. From NLMS algorithm the system it's showed that rapidly adapt to its input change relative to LMS for example the unexpected deviations of the signal. Has a SNR 17.4072

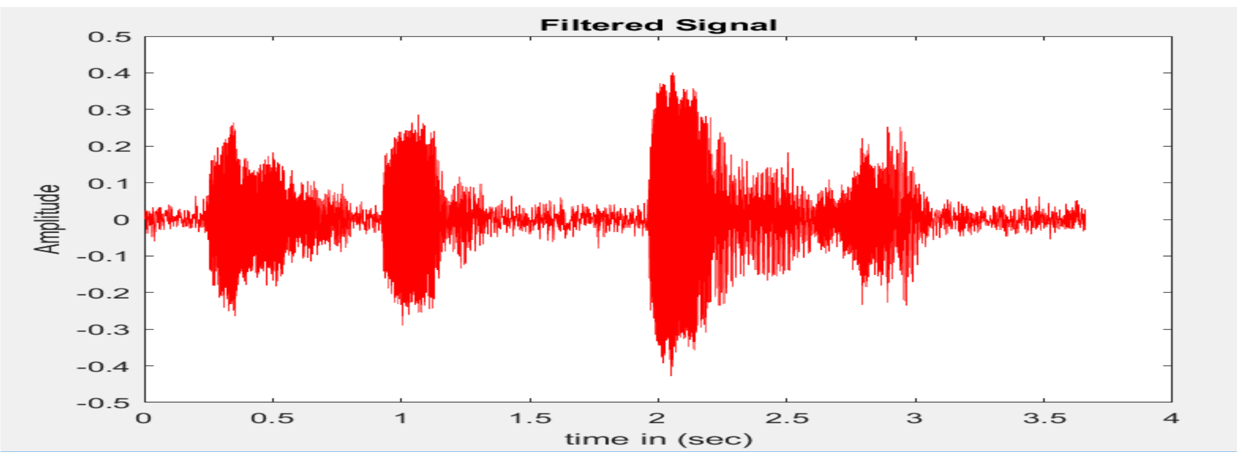

Figure 4. 20. Recovered Signal

The extracted speech signal or recovered signal at optimum step size which were different between two algorithms is simulated as shown on the above recovered speech signal. The optimum step size for NLMS algorithm is 0.15 where the best signal is extracted and the filter coefficient used is 32. This recovered wave form of speech signal above is done by NLMS algorithm because of its good performance related with LMS algorithm. The SNR of filtered signal is 26.3720 dB.

V. CONCLUSION

This paper work has concentrated on removal of noise from a particular recorded speech signal using two techniques the Least Mean Square (LMS) technique and the Normalized Least Mean (NLMS) technique. It can be seen that in LMS technique the trends of NRR with varying step size, sample number, input SNR and filter coefficients did not lead to a convincing output. But the normalized LMS method brings us a trend that helps us to analyze the variations of NRR with varying system parameters. The sound filtering is also improved giving us an increased value of NRR as compared to LMS technique.

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REFERENCES

[1] https://en.wikipedia.org/wiki/Noise_reduction.
[2] https://en.wikipedia.org/wiki/Noise
[3] Farhana Afroz1, Asadul Huq2, F. Ahmed3 and Kumbesan Sandrasegaran1 "Performance Analysis of Adaptive Noise Canceller Employing NLMS Algorithm", International Journal of Wireless & Mobile Networks (IJWMN) Vol. 7, No. 2, April 2015
[4] Chen, Yangkang; Fomel, Sergey (November–December 2015). "Random noise attenuation using local signal-and-noise orthogonalization". Geophysics. 80 (6): WD1–WD9. doi:10.1190/GEO2014-0227.1.
[5] Xue, Zhiguang; Chen, Yangkang; Fomel, Sergey; Sun, Junzhe (2016). "Seismic imaging of incomplete data and simultaneous-source data using least-squares reverse time migration with shaping regularization". Geophysics. 81 (1): S11–S20. Bibcode: 2016Geop...81S...11X. doi:10.1190/geo2014-0524.1.
[6] Chen, Yangkang; Yuan, Jiang; Zu, Shaohuan; Qu, Shan; Gan, Shuwei (2015). "Seismic imaging of simultaneous-source data using constrained least-squares reverse time migration". Journal of Applied Geophysics. 114: 32–35. Bibcode: 2015JAG...114...32C. doi:10.1016/j.jappgeo.2015.01.004.
[7] Matthaei, G. L.; Young, Leo; Jones, E. M. T. (January 1963). Design of Microwave Filters, Impedance-Matching Networks, and Coupling Structures, Volume 1 (Report). Stanford Research Institute. p. 99.
[8] Giovanni Bianchi and Roberto Sorrentino (2007). Electronic filter simulation & design. McGraw-Hill Professional. pp. 17–20. ISBN 978-0-07-149467-0
[9] Lutovac, Miroslav D.; Tosic, Dejan V.; Evans, Brian L. (2001). Filter Design for Signal Processing using MATLAB© and Mathematica©. New Jersey, USA: Prentice Hall. ISBN 0-201-36130-2
[10] Widrow, Bernard. Least-mean-square adaptive filters. Eds. Simon S. Haykin, and Bernard Widrow. Vol. 31. New York: Wiley-Interscience, 2003.
[11] Pradhan, A. K., A. Routray, and Abir Basak. "Power system frequency estimation using least mean square technique." IEEE transactions on power delivery 20.3 (2005): 1812-1816.
[12] Liu, Weifeng, Puskal P. Pokharel, and Jose C. Principe. "The kernel least-mean-square algorithm." IEEE Transactions on Signal Processing 56.2 (2008): 543-554.
[13] Jung, Sang Mok, and PooGyeon Park. "Normalised least-mean-square algorithm for adaptive filtering of impulsive measurement noises and noisy inputs." Electronics Letters 49.20 (2013): 1270-1272.
[14] Biswas, Uzzal, et al. "ECG signal denoising by using least-mean-square and normalised-least-mean-square algorithm based adaptive filter." 2014 International Conference on Informatics, Electronics & Vision (ICIEV). IEEE, 2014.
[15] Kang, B., J. Yoo, and P. Park. "Bias-compensated normalised LMS algorithm with noisy input." Electronics Letters 49.8 (2013): 538-539.
[16] S. Haykin, Adaptive Filter Theory, 4rd ed., Upper Saddle River, New Jersy: Prentice Hall, 1996.
[17] B. Widrow , J. Glover , J. R. , J. McCool , J. Kaunitz , C. Williams , R. Hearn , J. Zeidler , J. Eugene Dong , and R. Goodlin . ―Adaptive noise cancelling: Principles and applications.‖ Proc.IEEE, 63, pp.1692 – 1716 , Dec.1975 .
[18] Khanna, V. K. (2009), Digital Signal Processing, S. Chand and Company Limited, New Delhi
[19] D C REDDY, Biomedical Signal processing, Principles and Techniques, Tata McGraw ¬- Hill Publishing Company Limited, NEW DELHI.
[20] B. Widrow et al., Proc. IEEE (Letts.), vol. 65, pp.171-173, Jan. 1977
[21] D. W. Tufts, "Adaptive Line Enhancement and Spectrum Analysis", Proc. IEEE (Letts.), vol. 65, pp.169-170, Jan. 1977
[22] Messerschmitt, D.G., Echo cancellation in speech and data transmission, IEEE J. Sel. Areas Commun., SAC-2(2), 283–297, March 1984.
[23] Bernard Widrow, Fellow, IEEE, and Eugene Walach , "On the Statistical Efficiency of the LMS Algorithm with Nonstationary Inputs", IEEE Transactions On Information ' Theory, Vol. It-30, No. 2, March 1984

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