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FACULTY OF ELECTRICAL ENGINEERING

DEPARTMENT OF ELECTRICAL AND COMPUTER ENGINEERING

Comparative Analysis of Adaptive Filters for Removal of Pink Noise from a Corrupted Speech Signal

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A Thesis Submitted to the Department of Electrical and Computer Engineering in Partial Fulfillment of the Requirements for the Degree of Masters of Science in Communication Engineering and Networking

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COMPARATIVE ANALYSIS OF ADAPTIVE FILTERS FOR REMOVAL OF PINK NOISE FROM A CORRUPTED SPEECH SIGNAL

SURAFEL DEMEKE YIMER

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This is to certify that the thesis entitled **COMPARATIVE ANALYSIS OF ADAPTIVE FILTERS FOR REMOVAL OF PINK NOISE FROM A CORRUPTED SPEECH SIGNAL** submitted in partial fulfillment of the requirements for the degree of masters of science in communication engineering and networking, the graduate program of the department of electrical and computer engineering and has been carried out by **SURAFEL DEMEKE YIMER** Id. No. PGComW/015/09 under our supervision. Therefore, we recommend that the student has fulfilled the requirements and hence hereby can submit the thesis to the department.

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Declaration

I, the undersigned, declare that this MSc. thesis is my own original work and has not been presented for a degree in this or any other university and any materials used from other sources has been clearly identified, properly acknowledged and cited.

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Abstract

Noise affects different communication systems during transmission, on channels or reception processes and hence signal quality improvement is required when it is degraded due to various background noises. In this thesis work, Least Mean Square (LMS), Recursive Least Square (RLS), Wiener and Kalman filters are compared for removal of pink noise from a corrupted speech signal to improve some speech qualities using filter length, Signal to Noise Ratio (SNR) and Mean Square Error (MSE), computational complexity, stability and convergence speed parameters.

A pure speech signal and pink noise are generated separately, added together and produce a noisy speech signal having different signal to noise ratio levels and then feed to the adaptive filters as an input. The filters then estimate the distorted speech signal and produce a mean square error that has a significant difference for the same input noisy signal. Based on the simulation results obtained, it is concluded that Kalman filter has better MSE performance in terms of filter length, signal to noise ratio and mean square error metrices, since it produces the smallest mean square error followed by wiener, LMS and RLS filters. In terms of computational complexity, stability and convergence speed metrices, Kalman is computationally more complex and has faster convergence rate but LMS is more stable. Hence, we can conclude that, in removing pink noise from a corrupted speech signal Kalman filter has better MSE and faster convergence speed performances even if it is computationally more complex and less stable.

Keywords: *Adaptive filter, Kalman filter, Least Mean Square, Pink noise, Recursive Least Square, Wiener filter*

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Acronyms

ADC	Analog to Digital Converter
ANN	Adaptive Neural Network
ANC	Active Noise Control
ANFF	Adaptive Neuro Fuzzy Filter
AWGN	Additive White Gaussian Noise
CD	Compact Disk
DAC	Digital to Analog Converter
dB	Decibels
DSBF	Delay and Sum Beam Former
DSP	Digital Signal Processing
EBF	Elko’s Beam Former
LMS	Least Mean Square
LTI	Linear Time Invariant
ND	Noise Distortion
MAE	Maximum Absolute Error
MSE	Mean Square Error
NLMS	Normalized Least Mean Square
PSNR	Peak Signal to Noise Ratio
RLS	Recursive Least Square
RMSE	Root Mean Square Error
SNIR	Signal-to-Noise Interference Ratio
SNR	Signal to Noise Ratio
PC	Personal Computer
PESQ	Perceptual Evaluation of Speech Quality
PSD	Power Spectral Density
USB	Universal Serial Bus
VoIP	Voice over Internet Protocol
WBF	Wiener Beam Former

Symbols and Mathematical Notations

A, B, C	State transition (Adaptation) matrices used to convert one state matrix to next.
H	Observation (Measurement) matrix of Kalman filter
I	Identity matrix
K	Kalman gain
N	Filter length
Q	Process noise covariance matrix of Kalman filter
R	Measurement noise covariance matrix for Kalman filter and Auto-correlation matrix in case of wiener filter
μ	Convergence constant or the step size of LMS algorithm
n	Time Index for each iteration
p	Cross-correlation vector
u	Control variable matrix of Kalman filter
w	Predicted state noise matrix of Kalman filter
ψ_λ	Correlation matrix for RLS algorithm
δ	Small positive constant
λ	Forgetting factor of RLS algorithm which has value near to but less than one
ξ	Performance function for wiener filter
P_k	Process covariance matrix which represents the error in the estimate
X_k	State matrix of Kalman filter
Y_k	Measurement value of specific state for Kalman filter
Z_k	Measurement noise for Kalman filter
$x(n)$	Distorted speech signal, an input to adaptive filters
$y(n)$	Output speech signal
$d(n)$	Desired signal
$e(n)$	Error signal
$w(n)$	Filter coefficient (adaptive filter tap weights)
$\hat{w}^T$	Transpose of vector filter tap weights

R^{-1}	Inverse of Auto-correlation matrix
$\hat{y}_{n-1}(n)$	Filter output vector
$u(n)$	Intermediate vector
$k(n)$	Gain vector for recursive least square algorithm

CHAPTER ONE

1. INTRODUCTION

1.1 Background

Human beings have been using different ways of getting information from the outside world to create an efficient communication with one another. Communication via voice, images and text has been used as most significant sources of information. speech is one of the necessary functions of human beings for many reasons and it stands out as the most effective, efficient and comfortable way for transmitting linguistic contents and communicating other useful information like the feeling of the speaker [1].

Speech signal processing is the study of speech signals and their processing methods. It is a part of Digital Signal Processing (DSP) that is applied to speech signals. It is the most significant process that allows humans to communicate in a natural way through speech. When a person talks air vibrations are created and these vibration results in a sound. This sound is then digitized by Analog to Digital Converter (ADC) taking precise measurements of the wave at frequent intervals [2].

Since the environments we live are noise inevitable, the speech signals can be contaminated everywhere by acoustic natural background noises. The quality of speech has great necessity for accurate and liable information transfer in many speech communication systems. There are systems that are used for speech processing to communicate or store the speech. But these systems are usually designed for noise-free environment and the presence of natural and man-made interferences in the form of additive background and channel noise drastically degrades the performance of these systems and causes incorrect information exchange and listener fatigue in real-world environment [1].

Pink noise is one of the most common natural noises which degrades the quality of speech signal. it has a frequency spectrum of the form that the Power Spectral Density (PSD) or power per frequency interval is inversely proportional to the frequency of the basic signal. In pink noise the octaves (half or double frequency) carry equal amount of noise energy [3].

Noise affected audio signals have to be cleaned using the digital signal processing algorithms before they stored, transmitted or played. Hence speech signal improvement has been a significant area of signal processing in the past years which was aimed to supply an increment on understandability and acceptability of a speech signal by approximating the noise characteristics of the corrupted signal and removing the noise parts and come up with a clean speech signal. At different times different noise remover algorithms had been used to enhance the performance of the speech signal throughout the communication. Adaptive filters are best selected algorithms for audio signal noise reduction applications.

Using fixed filters is absolutely failed circumstance for a continuously changing noisy speech signal since noise is a bit similar with the randomly generated signal and it is very difficult to estimate its statistical value. Hence the use of self-regularizing algorithms that can handle some of the signal changes with a very fast rate and enables the process of noise cancellation converge rapidly [4]. Least mean square, Recursive least square, Wiener and Kalman filters are adaptive filters that can be used for removal of pink noise from a corrupted speech signal.

In speech signal enhancement the adaptive filters are used to de-noise the corrupted signal by determining the input signal and decreasing the noise level in the system output. it can adjust its parameters automatically and it requires almost no prior information both on signal and noise characteristics. In this thesis work a pink noise and clear audio signals are added and an affected speech signal is feed to these filters so that the noisy signal can be enhanced.

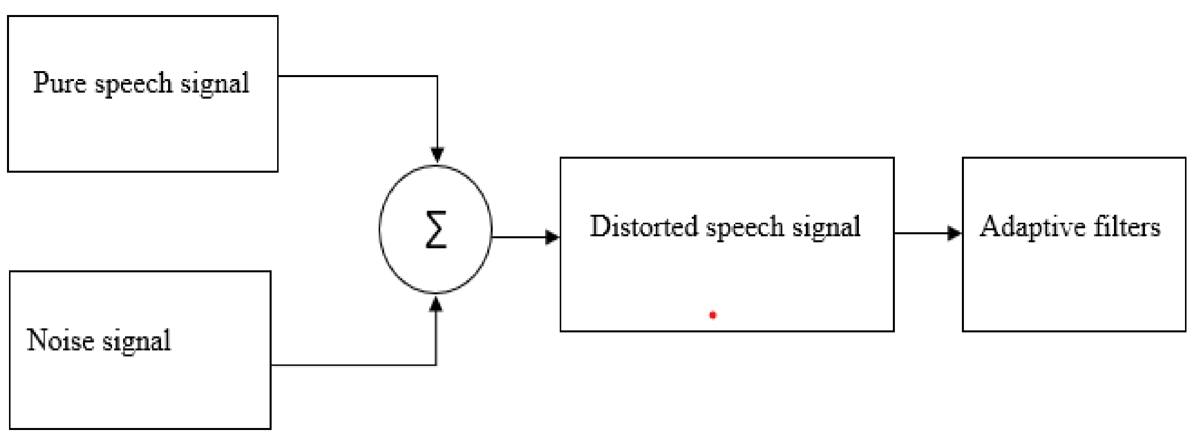

Figure 1.1: Speech signal enhancement system using adaptive filters

A self-regularized filter is demanded when the time invariant filters can't handle the randomly changing characteristics of noise. It may also be seen of as a system that strives to change its measurements on a regular basis in order to achieve a clearly defined goal. The performance evaluation of adaptive filters can be determined by examining the convergence rate, complexity, stability and other speech signal quality measures that a filter can accomplish for removing the noise signal [5].

By automatically adjusting their coefficients and changing their characteristics adaptive filters achieve certain goals. There are many adaptation algorithms designed for different purposes in various architectures. In performing adaptation these filters comprises of two different parts. These are the digital filters which performs filtering process and an adaptive algorithm that modfies the filter tap weights (coefficients).

In this Thesis the performance of adaptive filters is evaluated by minimization of the mean square error between filtered output speech signal and the noisy input speech signal, their computation complexity, stability and convergence speed measures. Each of these metrics are used to show how the adaptive filters perform on the common noisy input speech signal.

1.2 Statement of the Problem

Even if speech is the most natural and effective way of communication between human beings the signals may be affected by different noises generated from different sources during communication. These sources of a noise can be natural or man-made and its effects on speech signal varies significantly. Pink noise is a natural noise that occurs most usually and affects speech signal and leads to an error.

Noise reduction is a highly challenging issue since noise features may vary in time. Hence it is very tiresome to choose an algorithm that works in varying environments. Appropriate selection of the algorithm may lead to proper ways for eliminating the additive noise from corrupted speech signal by keeping the appearance and features of the original signal.

Hence the existence of pink noise that affects a speech signal communication and selection of an optimal and efficient adaptive filter to eliminate this noise from a corrupted speech signal are the main challenges and concerns that initiate us to do this work.

1.3 Objective of the Thesis

1.3.1 General objective

- The general objective of this thesis is to evaluate and compare the performance of adaptive filters for removal of pink noise from a corrupted speech signal.

1.3.2 Specific objectives

- ✓ To analyze the characteristics of pink noise and generate a pink noise corrupted speech signal at different SNR levels.
- ✓ To analyze the mathematical models of LMS, RLS, Wiener and Kalman filters.
- ✓ To evaluate filters on the generated corrupted speech signals.
- ✓ To compare filters based on filter length, signal to noise ratio and mean square error metrics on the same noisy speech signal.
- ✓ To analyze the computational complexity, stability and convergence speed of each filters.

1.4 Thesis Contribution

Many thesis works have been done on comparative analysis of adaptive filters for noise removal from a corrupted speech signal. But if it is asked "What would be the contribution of this particular thesis on the completion?"

Some of the main contributions of this paper would be, Make a comparative analysis of adaptive filters (LMS, RLS, Wiener and Kalman) in a way that is different from other works (specifically done on pink noise by generating both the noise and speech signals). This thesis evaluates the effect of signal to noise ratio and filter length on adaptive filters to their mean square error, stability, computational complexity and convergence speed to come up with the filter of better performance.

1.5 Scope of the Thesis

The general scope of this thesis is making a comparative performance analysis of adaptive filters namely (LMS, RLS, Wiener and Kalman) for removal of pink noise from corrupted a speech signal using filter length, signal to noise ratio, mean square error, computational complexity, stability and convergence speed parameters.

1.6 Thesis Organization

As stated above on the objective section, the main goal of this work is to compare different adaptive filters on a corrupted speech signal by pink noise. To achieve these general and specific objectives the thesis is divided in to different chapters and different procedures were followed in each chapter.

The first chapter presents the basic concepts on speech signal, adaptive filters and noise as introduction and thesis objectives, problem statements, scopes of thesis and contributions. On the second chapter different papers written related with the title are reviewed by reading books, articles, journals, referring simulation tools and other resources.

The third chapter discusses about the theoretical analysis, the basic ideas on speech signal, noise and filters. The fourth chapter of the thesis is on the mathematical modeling of the system including speech signal, pink noise, mixing speech and noise, adaptive filters (LMS, RLS, Kalman and Wiener). It states how the mathematical procedures of the adaptive algorithm processes to remove the pink noise from a corrupted speech signal.

In chapter five simulation results are evaluated, analyzed and disscussed. The simulation results (from MATLAB and MS. Excel) of different algorithms are used in order to compare the adaptive filtering techniques. In the last section, the thesis work is concluded and future tasks are recommended.

CHAPTER TWO

2. LITREATURE REVEIEW

So far, many researches have been conducted on removal of various background noises from a corrupted speech signal using adaptive filters, a short summary of some of the researches are reviewed here below.

In [6], Wiener filter and LMS algorithms were compared to remove a real-time noise within the real time recorded speech signal and performance comparison was made using minimum mean square error, convergence speed, computational complexity, stability, signal to noise ratio and filter length as a parameter. They found out as LMS algorithm has low cost and complexity than wiener filter but has low convergence speed and MSE. The gap on the thesis was that it only compared LMS algorithm and wiener filter and the noise type was not specifically stated.

An inclusive comparison of LMS and RLS adaptive filters were presented in [7] for speech noise cancellation. LMS was found computationally less complex, stable, more reliable as compared to RLS. The LMS algorithm was comparatively easy to execute and has practical benefits on the adaptivity of the problems at hand. In this paper only two adaptive filters were compared based on computational complexity, stability, reliability and convergence rate parameters.

Minajul Haque and Kaustubh Bhattacharyya [8] have done a comparison of different speech processing and noise reduction techniques. The techniques discussed were LMS algorithm, Kalman filter, Adaptive Neural Network (ANN) and Adaptive Neuro Fuzzy Filter (ANFF). LMS adaptive filter performance was better in linear noise condition but in nonlinear noise condition Kalman filter gives better result compared to LMS. The adaptive neural network and adaptive neuro-fuzzy filter gives the optimal results in non-stationary noise condition. The comparison was basically made depending on linearity/nonlinearity and stationary/non stationary conditions of noise and filter order metrics.

In [9] a comparative analysis of spectral subtraction and Kalman filtering techniques was done. It was found that spectral subtraction technique was highly capable for noise removal at high SNR conditions but performance degrades with reduction in SNR. Kalman filter was found efficient in noise reduction at low SNR levels. The two algorithms were compared on different background noise types and SNR levels.

According to [10], the least mean square error, convergence speed and filter order metrics were used to compare adaptive filters least mean square, normalized least mean square, and recursive least square. The least mean square method takes more iterations to reach the steady state condition, while the normalized least mean square and recursive least square algorithms need less iterations. Compared to LMS and NLMS, the RLS method provides faster convergence and lower error. The MSE, convergence speed, and filter order parameters were utilized to compare these methods, however the noise type used for comparison was not specified.

Adaptive filters LMS and NLMS were evaluated in [11] for noise removal from distorted speech signals and improves speech signal quality. Different background noises (like machinegun, factory, car and traffic noises) were added to clean speech signals at different SNR levels for comparison. The parameters used were signal to noise ratio, mean square error and Root Mean Square Error (RMSE). The NLMS method was determined to be a better optimum adaptive noise canceller for speech signal based on the performance evaluation. Only two adaptive filters were covered on the listed parameters and noise types.

The performance of LMS, RLS and delta rule algorithm was compared on a white gaussian noise in [12]. It was concluded that RLS algorithm were better in performance than other two algorithms. The comparison was basically depend on computational complexity, convergence speed and mean square erro metrics. RLS algorithm was found more complex than the other two algorithms followed by delta rule and LMS algorithm respectively. RLS algorithm converges very quickly with less error than the two algorithms. Comparison was done on white gaussian noise and noise removal was based on Active Noise Control (ANC) which is principle of superposition and the adaptive filters were used to control the noise. Three filters were used on electro accoutic signals.

In [13], the performance of two adaptive filters LMS and NLMS was studied. The parameters of the filters used were signal to noise ratio, mean square error value, step size and filter order. LMS adaptive filter shows better noise cancellation in lower step size and higher filter order, whereas NLMS adaptive filter shows better noise cancellation in higher step size and higher filter order. Overall based on the performance of these two filters, it was concluded that the NLMS adaptive filter had better noise cancellation capability at higher filter order but LMS adaptive filter was found the simplest and reliable filter. The noise type used was not specified and the values of SNR and MSE was evaluated by varying step size and filter order values.

The removal of various background noise was the main focus in [14] which presented different beamforming concepts for reducing noise in speech signal that affects hands-free speech communication. The background noises were suppressed using adaptive beam formers like Wiener Beam Former (WBF), Elko's Beam Former (EBF), Maximum Signal-to-Noise Interference Ratio (SNIR) Beamformer and Delay and Sum Beam Former (DBF) as they have the ability to enhance the desired speech signals while suppressing the noise sources assumed from other directions. The performance of these Beamformers is evaluated by considering the objective measure parameters such SNR, Speech Distortion (SD), Noise Distortion (ND) and Perceptual Evaluation of Speech Quality (PESQ) under different noisy environments.

As we have seen on the literatures reviewed, comparative analysis of adaptive filters was done only on two or three filter types and the parameters used were not common on different researches. The performance of adaptive filters (LMS, RLS, Wiener and Kalman) has not been studied yet for removal of pink noise from a corrupted speech signal. Therefore, this thesis work is done on comparative analysis of LMS, RLS, Wiener and Kalman filters using filter length, signal to noise ratio, mean square error, computational complexity stability and convergence speed parameters.

CHAPTER THREE

3. SPEECH NOISE AND ADAPTIVE FILTERING TECHNIQUES

3.1 Speech signal

Speech is the most natural and preferred way of communication among humans and also begins to be the favorite means of communication between machines and humans. The sound waves can be produced by the human mouth and heard through ears [15]. The study of human speech production and perception is crucial for the increment of speech signal quality by using voice production, modeling and improvement processes.

Speech events can be classified as silent, unvoiced and voiced depending on the power of the speech signal caused by air pressure. when there is no speech signal generated in the spectrum the event is called silent, unvoiced when the vocal cords are not vibrating which results in time varying or random speech waveform and voiced when air moves from lung and the tightened vocal cords vibrate at regular intervals resulting in a periodic speech waveform.

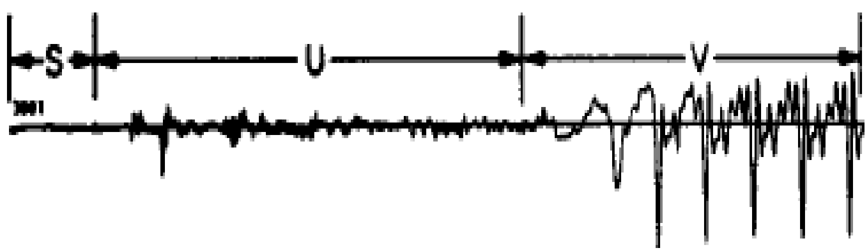

Figure 3.1 Waveform of various speech events [15]

When the speech signals are examined over a short period of time (between 5 and 100ms), the characteristics of the signals are fairly stationary**.** However, when examined over a long period of time (more than 100ms), the characteristics of the signals reflect the characteristic change of different sounds being spoken [15]. An audio signal is produced by the changes in air and the wave shape of a speech signal will have varying amplitudes depending on the level of air pressure of the sound at any given moment.

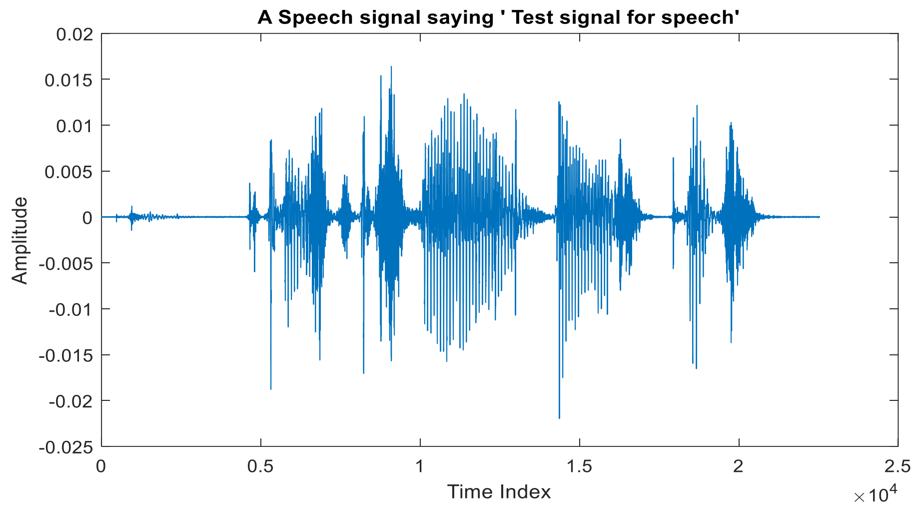

Figure 3.2: A speech signal representing a phrase ‘Test signal for speech”

The figure above (Figure 3.2) shows an example of an audio signal saying "Test signal for speech" and the spectral arrangement of speech signal is generated and traveled through a vocal tract tube with variable cross-sectional area, where there are silent, unvoiced and voiced events that describes the spectrum of the voice signal. For speech signal, these vibrational modes are referred to as formants. The formant frequency representation is a very effective way of representing time-varying speech characteristics [15].

Speech processing is the study of speech signals and their processing techniques. The signals are often processed in digital format, so speech processing can be assumed as a one of the digital signal processing parts applied to speech signals. Some features of speech processing include the acquisition, manipulation, storage, transfer and output of speech signals.

Most audio signals are stored in digital format (for example, on a Compact Disk (CD), digital audio player, hard drive, or Universal Serial Bus (USB) flash drive), and these signals must be transformed into analog signals in order to be heard through speakers. As a result, digital to analog converters (DACs) are found in CD players, digital music players, and Personal Computer (PC) sound cards.

In Voice over Internet Protocol (VoIP) applications, the source must first be digitized for transmission, so it undergoes through Analog to Digital Convertsion (ADC) and reconstructed into analog using a DAC on the receiving end. Considering a phone call, a microphone converts the caller's speech into an analog electrical signal, which is subsequently transformed to a digital stream by an ADC. After then, the digital stream is broken into network packets and delivered together with other digital data. The packets are subsequently sent to their final destination, but each one may travel an entirely different path and may not even arrive in the proper sequence. After that, the digital voice data is taken from the packets and put together into a digital data stream. A digital-to-analog converter (DAC) transforms this to an analog electrical signal, which drives an audio amplifier, which drives a loudspeaker.

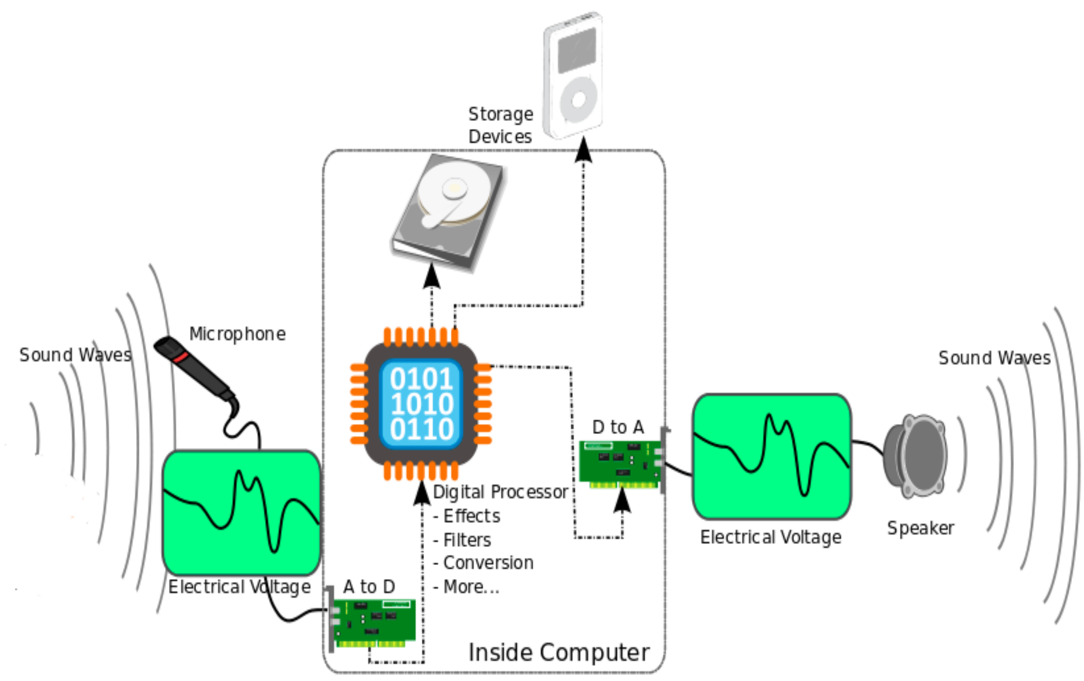

Figure 3.3: The lifecycle of sound from its source through an Analog to Digital Converter (ADC), digital processing, a Digital to Analog Converter (DAC) and finally as sound again [16]

Audio signals are digital representations of sound waves that compress and refract as they pass through air. Processing can take place in either the digital or analog domains since audio signals can be represented in either. Digital processors operate mathematically on the digital representation of the analog electrical signal, whereas analog processors operate directly on the analog electrical signal.

Speech analysis technique is the basic of the signal processing which is concerned with the electrical representation of audio signals. The amount of energy contained in audio signals is typically measured in decibels [15]. Speech is often corrupted by acoustic background noises that degrades the perception of the signal measured in terms of quality and intelligibility. Background noises are broadband and non-stationary and affects audio signals which results in low signal to noise ratio or reduced the speech quality and intelligibility [14].

3.2 Noise

In any communication system, some unwanted signal is introduced into the original message either during transmission, on channels, or during reception, making the desired signal unpleasant for the receiver and leading to doubts about the communication's quality [17]. This type of disturbance is known as noise.

It can also be defined as any unwanted signal that interferes with the desired signal, whether random or deterministic and it usually has a fluctuating frequency, amplitude, and does not have a form, making it utterly unpredictable. Although it cannot be completely eliminated, some de-nosing actions are often used to decrease it.

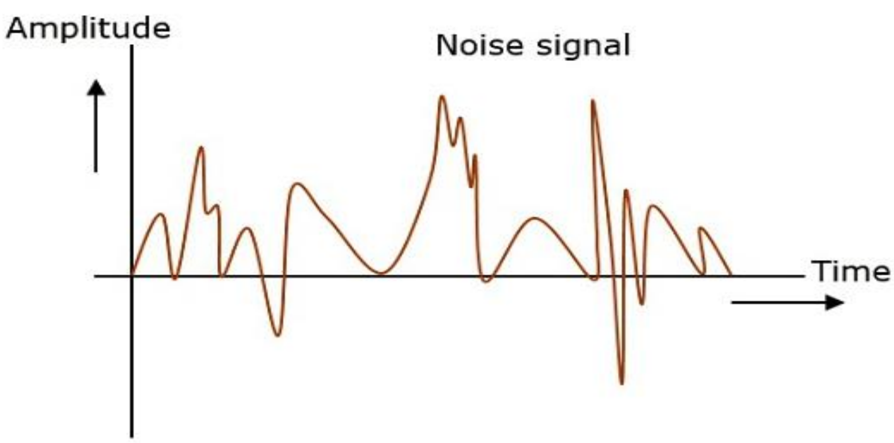

Figure 3.4: A noise signal [18]

In speech communication, noise disrupts the direct connection between human beings by masking some acoustical characteristics and speech becomes distorted and the information value of speech signal gets reduced.

Acoustic noise is the most common type of noise and it usually comes from moving, vibrating, or colliding sources. It may be found in different intensities on various situations such as moving automobiles, air conditioners, computer fans, traffic, people chatting in the background, wind, rain and other sources of acoustic noise contributes to the overall noise level.

These undesired signals come from different sources which can be classified as man-made or natural [17]. The noise type that come from man-made sources arise due to any piece of electrical or electronic equipment issues during communication and their effects can be removed or at least reduced by careful engineering design and practice.

Interference caused by natural sources are not manageable in such a direct way and their features can't best be expressed statistically. Some of the natural sources of noise arise from random thermal movement of electrons, atmospheric absorption and cosmic sources. Colored noise is the one which affects speech signal communication on different situations.

Colored noises

In audio signal processing the color of noise indicates the power spectral arrangement of noise signal (a signal created by a random process) [19]. The color of a noise signal tells as divergent colors of noise have observably different properties. For example, as images have a visually distinguishable appearances similarly in speech signal colored noises sound different to human ears. Therefore, every application usually requires noise of a particular color.

In most of the communication systems white noise is considered as usual and most commonly modeled noise and if there exists a white noise then the colored noise must also exist since white noise has unchanging power spectral density across the whole frequency spectrum and it includes of all colored noise spectrums.

A colored noise is said to be produced when there exists a non-uniform power spectral arrangement of the noise across the entire frequency spectrum. In these noise types, there exist a non-zero values for auto correlation or auto covariance at different time instances and they also have a rough frequency arrangement and some examples of this type of noises are pink, red, black, violet and brown noises [17].

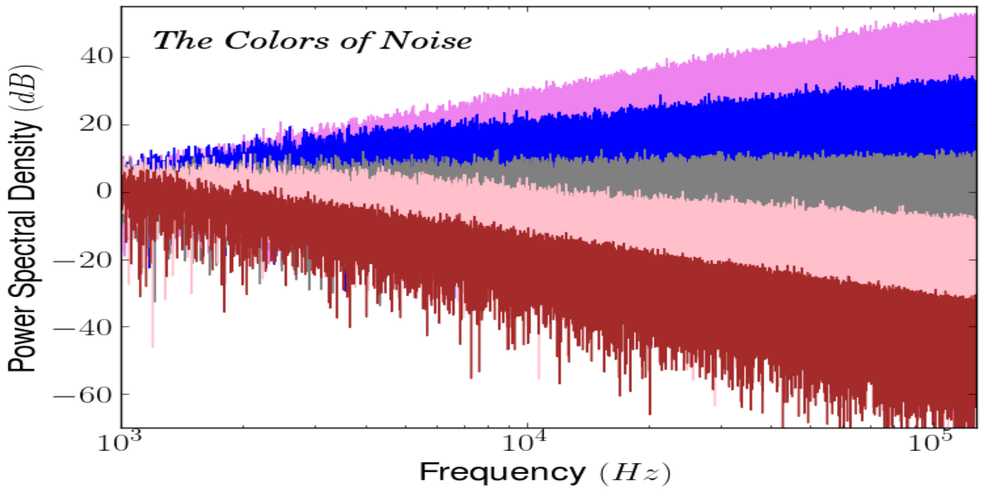

Figure 3.5: Power spectral densities of the colored noise for different colors [19]

The figure above (Figure 3.5) shows the power spectral density arrangement of various colored noises (violet, blue, white, pink, brown/red) respectively as a function of frequency. The power spectral densities are arbitrarily adjusted so that the spectral values are roughly equivalent nearly to 1 kHz [19]. The slope of each spectrum's power spectral density describes the framework for the associated electromagnetic/color analogies. A noise signal can be called colored noise, which is just to say that it is not a pure white noise. In audio signals the most common colored noise encountered is pink noise.

Pink noise

Pink noise is a type of colored noise that gets its name from the pink color of visible light in its power spectrum as well as the random signals that have constant power per percentage bandwidth for all frequencies in an octave. The color of the noise is identified by the energy of the sound signal on how energy is distributed over various frequencies.

It is a random signal with an equal power spectral density per octave (a frequency that is the half or double of basic frequency). It is one of the most common types of noise that occurs naturally, lowers the quality of voice signals, and has a frequency spectrum that is inversely proportional to the basic signal frequency.

Each octave (half or double in frequency) in pink noise carries equivalent amount of noise energy. For instance, the energy in the frequency interval between 10 Hz and 20 Hz there is one octave which is equivalent to the energy in the frequency interval between 100 Hz and 200 Hz. But, in absolute frequency case the frequency interval between the first two is 5 Hz while the interval between the second two is 100 Hz [20].

In white noise case the difference between two frequency levels is obvious but in pink noise the interval between two frequencies that are half or double to one another are considered as octave and for the above case both of the two (10 Hz to 20 Hz and 100 HZ to 200Hz) frequencies are one octave apart and they are functionally the same. When frequency increases the intensity of the noise signal gets smaller and hence at higher frequencies sound gets softer.

The power of the speech signal determines the color of the noise depending on how energy is distributed over different frequencies or the speed of sound. Pink noise comprises of all frequencies that a human can hear though the energy is not uniformly distributed across the entire spectrum. It has a high power at smaller frequencies which generates a deep sound [20].

In pink noise, the intensity within each consecutive octave is the same but each octave has half the power of the preceding one. This is the same as light spectrum that tends toward the red or lower end of the visible light spectrum. It gives more power to the smaller frequencies for compensation since at higher frequencies each octave will be getting wider in bandwidth. Unlike white noise, which represents all the frequencies equally, the higher frequencies of pink noise are less intense.

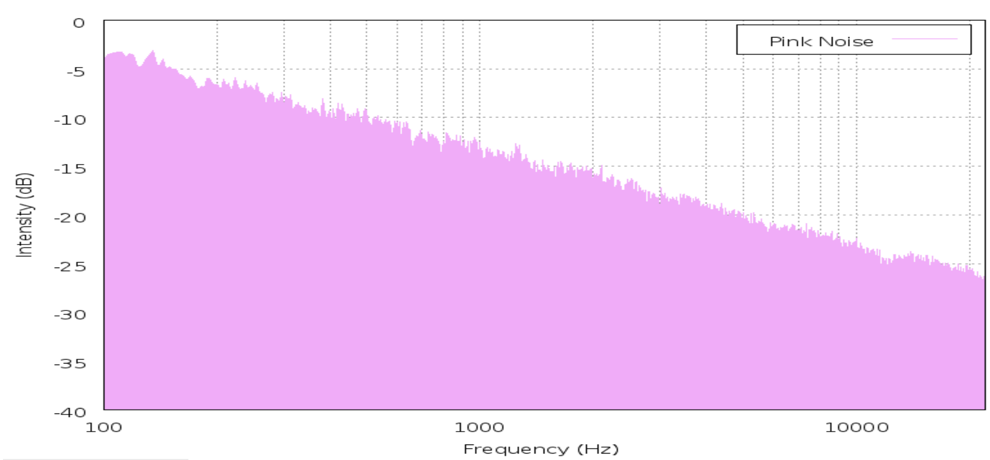

Figure 3.6: Pink noise frequency profile [21]

Octaves are frequency groupings that enables to measure how the human hearing system takes up various frequencies. Each octave indicates the total amount of sound energy in a certain frequency range. At higher frequencies, octave bands cover a wider frequency range than octave bands at lower frequencies. That's because, at lower frequencies, the human ear can simply differentiate between them, but as they go higher, even high frequencies that are far apart, it becomes increasingly difficult [22].

Hence, lower frequencies have smaller octave bands, whereas higher frequencies have broader octave bands. The frequency range encompassed in each of the usual octave bands used in acoustics is shown in the table below.

Table 3.1: Octave bands and their frequency groups [22]

Octave band center frequency (Hz)	Lower frequency	Higher frequency	Octave range
63	44	88	44
125	88	177	89
250	177	355	178
500	355	710	355
1000	710	1420	710
2000	1420	2840	1420
4000	2840	5680	2840
8000	5680	11360	5680

As shown on the table above, there is one octave band between frequencies 88 Hz and 177 Hz, which is t 125 Hz band, and there’s another octave band between 177 Hz and 355 Hz, that’s 250 Hz band. The 250 Hz octave band contains 178 invididual frequencies while the 125 Hz octave band only contains 89 invididual frequencies. The 250 Hz octave band is therefore wider than the 125 Hz band [22].

3.3 Filters

A filter is a tool that takes a number of discrete segments from an input and processes them in a certain order to generate an output segment. It might also be regarded of as a system that selects components with the needed characteristics from a larger pool of options. When it comes to signals, the segments are thought of as frequency components of the basic signals, and filters are employed to maintain all of the frequency components that fall within a particular range of frequencies while leaving as much of the rest as possible [23].

Most usually the term is used to describe a system that reshapes the frequency components of an input signal to produce an output signal with desired properties. The signal may be thought of as a collection of frequency components with varying frequencies and amplitudes. The filter will choose components based on the frequencies we wish to reject, keep or enhance. To put it another way, the filter will change the amplitude of the components based on their frequency [23].

Filters are used in a number of applications to decrease the influence of additive noise or interference in a signal, allowing the valuable signal component to be separated more clearly in the filter output.

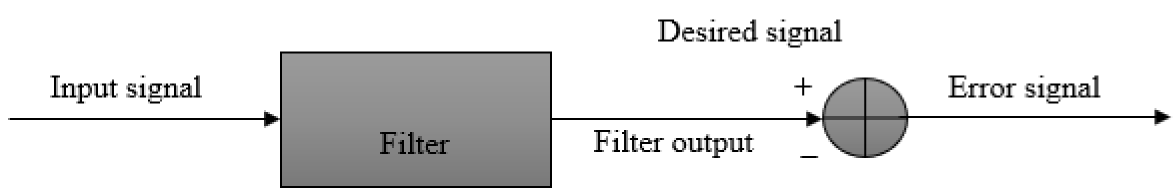

Figure 3.7: Schematic diagram of a filter [23]

When a corrupted signal passes through a filter, it estimates a signal corrupted by additive noise and tries to reduce the noise while keeping the desired signal relatively unchanged, the filtration process that follows this procedure is known as direct filtering.

Filters used for direct filtering can be either Fixed or Adaptive [23].

Fixed filters: A priori knowledge is mandatory for both the signal and noise, if the signal and noise are already identified, then we can design a filter that can allow frequencies contained in the signal to pass and reject the frequency band occupied by the noise. It is used when the metrics of both signal and noise are known.

3.4 Adaptive filters

An adaptive filter is a self-modifying filter that uses an algorithm to study the initial input statistics and track them if they are time varying. These filters estimate the deterministic signal while filtering out noise that isn't correlated with it. The adaptation algorithm is used to monitor the environment and adjust the filter transfer function accordingly. The algorithm starts from a set of initial conditions that may correspond to complete ignorance about the environment and based in the actual signals received, attempts to find the optimum filter design [24].

An adaptive filter is a self-adjusting tool that takes the help of iterative algorithm for signal processing and uses some training vector that provides different understanding of a desired response and can be combined with reference to incoming signal. First input and training are compared consequently, error signal is created and that is used to modify some previously supposed filter parameters under effect of incoming signal.

These type filters can be recognized in two interrelated systems. The simplest way comes straight from its name which says an adaptive filter gets information from the environment and the signal that it is operating to change itself so as to best perform its task. The information from the surrounding may be taken as actual signal (so-called desired signal) or may be supplied a prior in the form of early knowledge on the statistical features of the input signal [25].

Else ways, we can think as an adaptive filter is an algorithm which is used to isolate the combination of two signals. The filter must have some information about the signals in the form of a reference signal to be able to isolate them. Then the filter will have two outputs corresponding to each signal in the mixture as a consequence of isolating the signals the reference signal is processed in functional ways [25].

The self-modifying features of an adaptive filter makes it capable of arranging its filter coefficients automatically to adapt the input signal through an adaptive process. It has a great role in Digital Signal Processing (DSP) results, in telephone voice repetition avoidance, noise reduction, communication channel equalization, signal improvement, Active Noise Control (ANC) and adaptive control system and other many areas.

Generally adaptive filters are used for the adapting the signal varying conditions and environments, checking the spectrum mixing between noise with signal and change the filter coefficients and make the filter converge to an optimal state.

The fundamental criteria for optimization is a cost function which is usually the mean square error between the output of the adaptive filter and the desired signal. when the filter becomes adapted to its coefficients the mean square error converges to its smallest value and at smallest value of the mean square error the filter will said to be adapted and the coefficients have become finally converged.

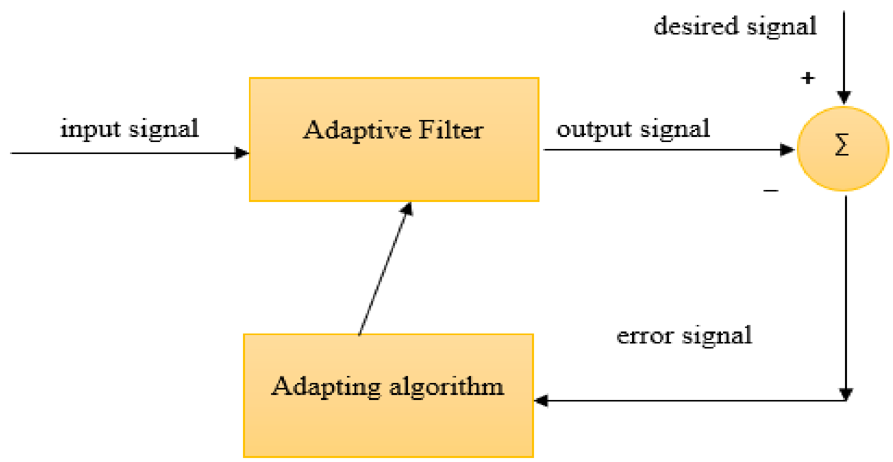

Figure 3.8: General adaptive filter structure [23][24]

For reducing pink noise from a distorted speech signal, various adaptive filters (LMS, RLS, Wiener, and Kalman) are employed in this thesis work. These filters are used to repair a noisy speech signal using a way that ensures the output is a better representation of the desired signal. Choosing filter coefficients to achieve a good match between the target signal and the filter output is normally done by optimizing a well-defined performance function. These performance functions can be defined statistically or deterministically.

In statistical framework, mean square error value of the error signal which is the difference between the desired signal and the filter output is usually used as a performance function. In deterministic approach the most common option of performance measure is a weighted sum of the mean squared error and reducing this function yields a filter that is optimal for the given information [27].

Hence, for evaluating the desired signal the adaptive filter is required to be designed using either stochastic or deterministic approaches. Deterministic approach follows averaging of some quantities that the filter must do on the specified set of data. The stochastic approach needs the previous knowledge on the data of the underlying signals.

There are two basic operational processes in adaptive filter, these are filtering process which are used to generate an output signal in response to the specified input signal and adaptation processes used to modify the filter parameters to the environment. This process is guided by an error signal that describes how effectively the filter output is correlated with the desired response.

An adaptation process aims to modify the filter parameters (filter transfer function) to the (possibly time-varying) environment. The adaptation is controlled by an error signal that indicates how well the filter output matches with the desired response an adaptive filtration process can be implemented as an analog or digital component.

An adaptive filter modifies various criteria for the goal of accomplishing some well-specified objective or target that is dependent on the system's condition as well as its environment and filter parameter adjustment will continue until steady state condition. Depending on how these parameters can be adjusted and the adaptation process is done, there are various adaptive algorithms and filter structures.

3.4.1 Least Mean Square Algorithms (LMS)

The Least Mean Square (LMS) algorithm is the most widely used adaptive algorithm firstly found in the year 1959 by Widrow and Hoff. It uses a gradient-based method of steepest decent and the estimates of the gradient vector from the available data. It is used to get the estimated signal by updating the filter coefficients that creates the least mean square error of the signal (difference between the desired and the output signal) [31].

LMS has a repetitive approach that makes consecutive adjustment to the weight vector in the direction of the negative of the gradient vector which finally leads to the minimum mean square error. Matrix inversions and correlation functions are not needed in LMS algorithm working processes [24]. It is the most common adaptation algorithm that works by moving to the minimum error evaluated at every repetition for a time varying signal feature. It is the basic element of various stochastic gradient algorithms in signal processing.

It follows two basic operation processes in reducing the noise from a corrupted signal. These are, filtration and adaptation processes [26]. In filtration process, the filter output and error signals are determined by making a comparison of the output signal with the desired signal and in adaptation process, the filter tap weights (coefficients) are updated depending on the determined error signal.

3.4.2 Recursive Least Square (RLS) Algorithm

Recursive least square (RLS) is an adaptive algorithm which iteratively tries to obtain the filter coefficients that reduces the mean square error relating to the input signals. it uses a prior information with new obtained information and replace its model parameters to minimize the error between the real data and the evaluated data. This algorithm is needed if the required outcome is obtained in real time or to take decision about time with new observed data [31].

RLS algorithm solves the least square problems iteratively and at each repetition when new data sample gets accessible the tap weights of the filter get updated. In processing the input signal, the algorithm goes through multiple iterations and processes the data sequentially as it is obtained, this nature of the algorithm makes its name recursive. It can also be called real-time identification or on-line identification process [26].

It works on all the data gathered and weighs it optimally and accounts for past data from the beginning to the current data point and its objective is to minimize the total weighted squared error between the desired and output signals.

3.4.3 Wiener Filter

The wiener filter is the most crucial and valuable algorithm to learn and understand adaptive filters well. It is most significant to many operations that indicates the evaluation of a desired signal order from another related order. It can be used on applications such as prediction, smoothing, joint process estimation, channel equalization and signal processing [27].

It is used to generate an evaluated clean speech signal from a given noisy speech signal. It is developed to map an input signal to an output that is as nearer as likely to the desired signal. It is a category of optimum linear filter that indicates linear evaluation of desired signal by modifying the weights to minimize the mean square error between the desired signal and the filter output [27]. In wiener filters, the basic signals are supposed to be random processes and the filter design is done using the statistics obtained by averaging.

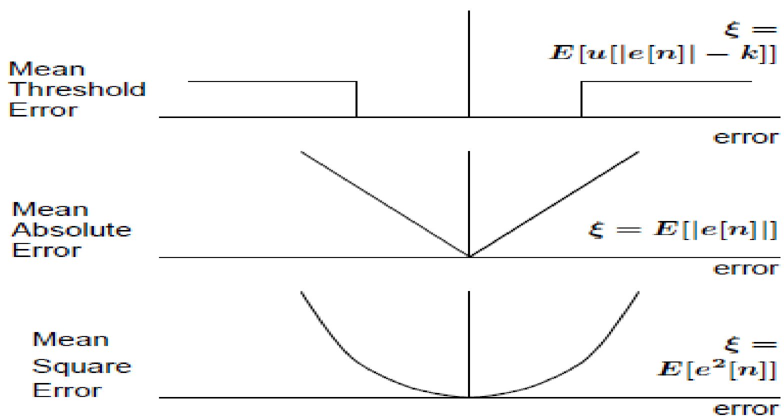

Figure 3.9: Cost function representations for wiener filter [27]

The fundamental idea behind wiener filter is obtaining the optimum mean square error called cost function and this cost function is used to decide on the performance of the filter.

Wiener filter is characterized by:

- ✓ The assumption that both the signal and the noise are processed randomly with known spectral characteristics, in other words known as auto and cross-correlation functions.
- ✓ Minimum mean-square error is the requirement for optimum performance. (This is partly to make the issue more adjustable mathematically.
- ✓ it is a linear and time-variant filter and it takes the signal and noise as an input additively.

3.4.4 Kalman Filter

Kalman filter is one of the adaptive algorithms which is named after Rudolf E. Kalman in 1960’s. it uses a mathematical method to compute estimation values that can be seen over time which consists of the main speech signal and noise (random variations) and generate an output that are closer to the actual measurement and their related values [28].

Kalman filter generates estimates of the true value of measurements and their related computed values by predicting a value and evaluates the weighted average of the predicted and measured values. More weight will be given to the value with the minimum uncertainty. The estimated values generated by this process tend to get closer to the accurate values, because the weighted average has best estimated uncertainty than either of the values that went into the weighted average.

It is a capable iterative filter that evaluates the internal condition of a linear dynamic system from a sequence of noisy estimations and used in many engineering areas such as radar communication**,** vehicle speed and direction control, space and military technologies, positioning of ships, aircraft and spacecraft and signal processing (both for image and speech signals).

The design of Kalman filter is in a way that can evaluate the preceding process by using a feedback control. it computes the process over time and gets feedback through the observed data. It has two basic steps in estimating the possible values [28]:

- ✓ Derive equations for prediction (Prediction step)
- ✓ Update the observed data (Correction step)

In the first step, Kalman filter produces estimates of the current state variables along with their uncertainties by driving equations and taking the preceding state as a reference. In the second step, corrections are made using measurement update and the equations are concerned on the feedback that adds a new data to the previous estimation so that the proposed estimated state can be achieved.

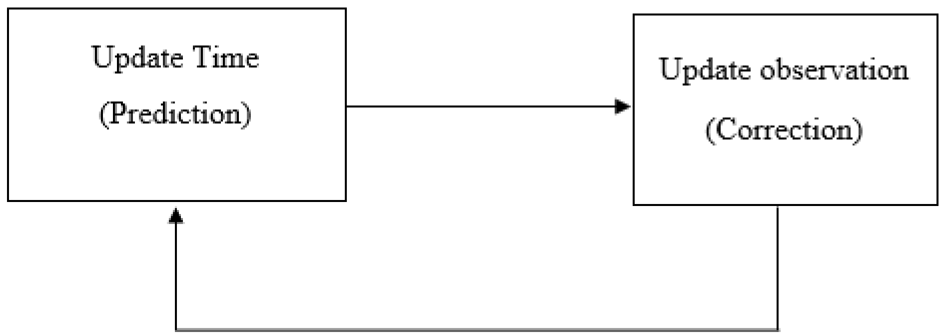

Figure 3.10: Prediction and correction steps of Kalman filter [29][30]

It is one of the most important and common estimation algorithms, produces estimates of hidden variables based on inaccurate and uncertain measurements and provides a prediction of the future system state based on past estimations.

CHAPTER FOUR

4. SYSTEM AND MATHEMATICAL MODEL

Speech signal improvment is the process of increasing the value or quality of a deteriorated speech signal by reducing the noise components using signal processing tools. It can also indicate the separation of the independent signals (clean and noise signals) in addition to reduction of various noises. In removing noise from distorted speech signal predicting the noise feature is the fundamental procedure which helps to reduce the unwanted signal components and get a pure speech signal.

4.1 System Model

A system model is designed to remove pink noise from a corrupted speech signal, which includes the processes of generating a clean speech signal and pink noise, mixing the pure speech signal with pink noise to produce a speech signal corrupted by pink noise, and filtering the distorted signal using adaptive filters least mean square, recursive least square, wiener and kalman filters. In this section, the general system model is introduced and each components of the system are analyzed mathematically in detail on subsequent parts.

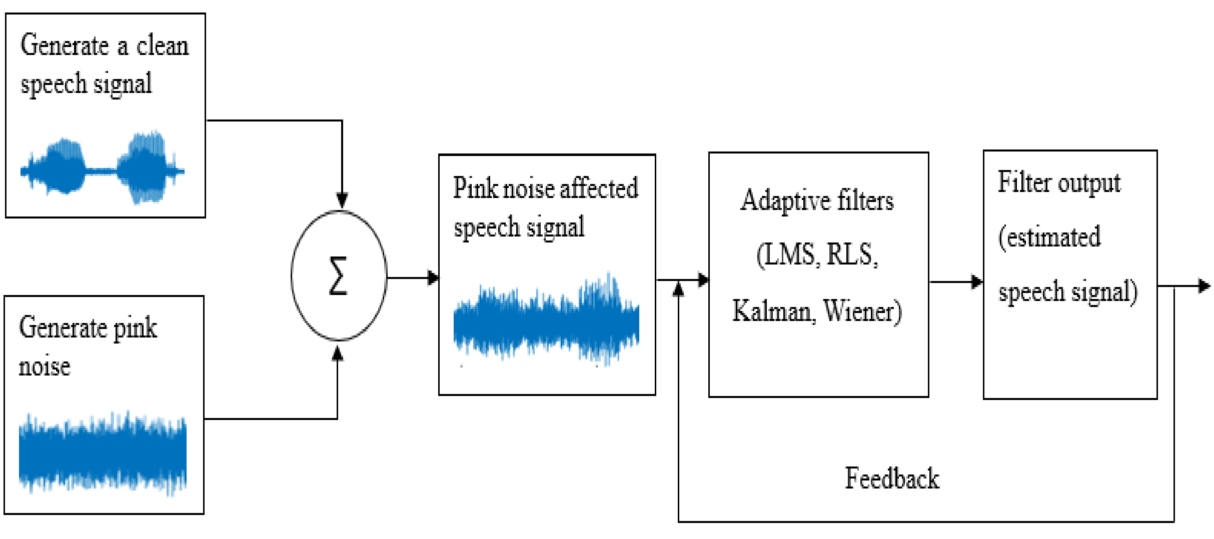

Figure 4.1: System model for speech signal improvement using adaptive filter

4.1.1 Speech signal

Sound signals can be represented using an acoustic signal in terms of variation in electrical voltage levels for analog signals or a sequence of binary numbers for digital signals. It has a frequency range of 20 Hz - 20kHz which is identical with lower and upper boundaries of human hearing. It can be generated from various sources, processed in electrical form and converted back from electrical signal in to sound by loudspeakers or headphones [34].

A sound signal represents alterations in air pressure over time and it has a waveform that has the same shape as the trigonometric sine wave function. Since sinusoidal signals have a defined operating character which can be described using the trigonometric function, the simplest model of a sound can be stated as the most general sinusoid function of the form [34].

$$P = \text{Asin}\big(2\pi(ft + \phi)\big) \tag{4.1}$$

Where P is the sound pressure in decibels (dB), t time in seconds, A is amplitude of the sound signal, f defines frequency in hertz and ϕ defines its phase. Period usually represented by T describes the time in seconds, where T= $\frac{1}{f}$ and the sinusoid starts at time t = 0.

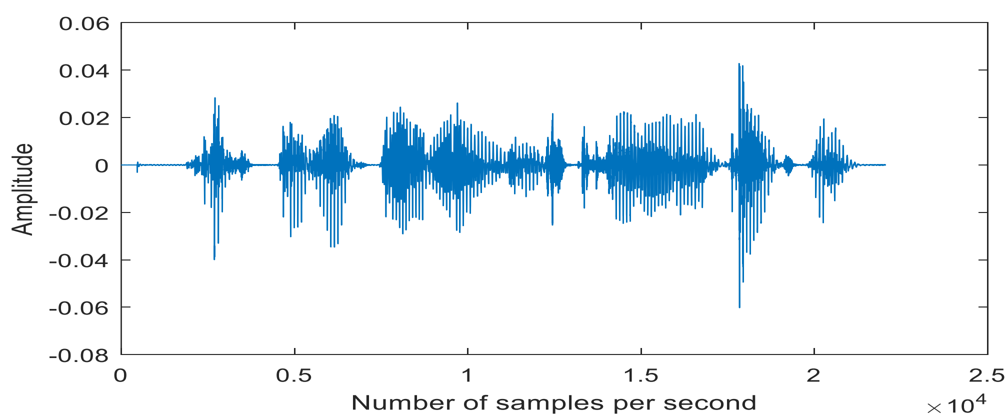

Figure 4.2: A speech signal waveform saying " The sky that morning was clean and bright blue"

The figure (Figure 4.2) shows a speech signal which has the form of sound stated in eq (4.1) with a sound pressure having variable amplitude and frequency at different times and phases.

In order to process speech signals in digital form, the analog version of the signal produced at the microphone output must be sampled. In digitizing an audio signal stream, frequency and bit rate (number of bits per sample) are the factors to be considered. The sampling process is controlled by sampling frequency and bit rate controls the bit resolution. These two factors can have influence on speech intelligibility, information content and perceived quality.

The analog audio signal is sampled based on sampling theorem which states that, if f_m is the maximum frequency component in the analog signal, then the information present in the signal can be represented by its sampled version provided that the number of samples taken per second is greater than or equal to twice the maximum frequency component. The number of samples per second is more commonly termed as sampling frequency f_s . Hence, according to the sampling theorem, f_s should be greater than or equal to $2f_m$ [34].

The speech signal has frequency components in the audio frequency range (20 Hz to 20 kHz) of the electromagnetic spectrum. This is the reason for perceiving the information present in the speech signal by human ears. The standard sampling frequency to sample audio signal is in the range of (8kHz to 96 kHz) but the most commonly used sampling frequency is 44.1kHz [34][36].

4.1.2 Pink Noise

Pink Noise causes interference and other form of inconveniences in speech signals. It is also called as $\frac{1}{f}$ noise since, its power spectral density is inversely proportional to the frequency of the basic signal. It usually occurs in biological systems and has identical amount of noise energy in each octave in contrast with white noise and commonly happens in almost all electronic devices and reduces the quality of the desired signal [35].

Power spectral density (PSD) analyzes the way how power of a signal is distributed over its frequency elements. It is a very useful analysis system that decomposes a signal into its frequency components and gives a hint on how the signal operates and how its frequency components are primarily made, whether it is from high or low frequencies. For example, if a signal has level spectral density it means an even power distribution over all frequencies.

The spectral density S(*f*) of white, pink and brown noises can be calculated using the form

$$S(f) = \frac{1}{f^a} \quad (4.2)$$

Where *f* is the frequency of the basic signal and *a* is constant value ($0 \le a \le 2$), when $a = 0$ it is a white noise, for $a = 1$ it is called pink noise and for $a = 2$ it is known as brown noise [35].

4.1.3 Mixing the clean speech signal with pink noise

Following the generation of both the clean speech signal and pink noise, mixing these signals will be the next step, which results in a pink noise affected (corrupted) speech signal. Since the noise generated is additive, the corrupted speech can be expressed as [29]:

$$x(n) = y(n) + z(n) \quad (4.3)$$

where $y(n)$ is clean speech signal, $z(n)$ is the noise signal (a pink noise in this case) and $x(n)$ is the pink noise affected (corrupted) speech signal.

Using discrete Fourier transform, the power spectrum of the corrupted speech can be approximately expressed as [29]:

$$|x(k)|^2 = |y(k)|^2 + |z(k)|^2 \quad (4.4)$$

Where $x(k), y(k)$ *and* $z(k)$ are the amplitude spectra of the corrupted speech signal, pure speech signal and noise signal respectively [29].

$$SNR(dB) = 10 \log_{10} \frac{|x(k)|^2}{|z(k)|^2} \quad (4.5)$$

The equation above (eq 4.5) can be used if the signal strength measurements are in voltage. However, if the signal measurement is in watts, SNR calculations can be:

$$SNR(dB) = 20\, log_{10} \frac{|x(k)|^2}{|z(k)|^2} \quad (4.6)$$

But, if the signal and noise measurements are in decibel form, we can directly subtract the noise quantity from the input affected signal as:

$$SNR(dB) = x(k)(dB) - z(k)(dB) \quad (4.7)$$

4.1.4 Least Mean Square Algorithm

After the corrupted speech signal is generated, it will be taken as an input to the adaptive filters so that noise components can be reduced. Least mean square algorithm is one of these adaptive filters that is used to obtain an output signal closer to the desired signal by finding the filter coefficients that helps to minimize the error signal (difference between the desired and the output signal). It uses a probabilistic gradient descent technique and it only adapts based on the error at the current time [38].

The main assumption behind least mean square filter is updating the filter weights to converge the optimum filter weight and estimate the results using only the current updates continually. The algorithm begins by assuming small weight (zero in most cases) and at every step the weights are updated by finding the gradient of the error signal. if the mean square error gradient is positive, it means the error is increasing positively, so it is needed to reduce the filter weights further until the mean square error gradient gets negative [39].

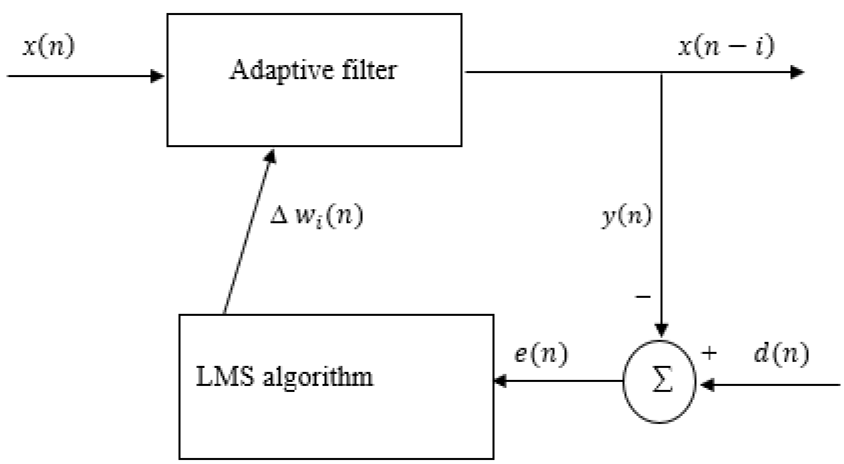

Figure 4.3: LMS Algorithm [40][41]

In filtering and updating the weights LMS has the following three basic steps as a working principle [40],

- ✓ Compute the predicative output which is the filtered output signal.
- ✓ Calculate the estimation error.
- ✓ Set the order of the filter and initialize the filter weights(coefficients).

$$y(n) = w^T(n)x(n) \tag{4.8}$$

Where $x(n)$ is the input signal, $y(n)$ the filter output, $d(n)$ desired signal, $e(n)$ is the error signal, $w(n)$ the filter coefficients and N is filter length.

The filter coefficients $w_0(n)$,$w_1(n)$ ..., $w_N(n)$ are chosen in a way that the difference (error) between filter output and desired signal is reduced in some sense. The filter weights are directly related with the functions in time. This reveals the fact that in adaptive filters, tap weights are updated in time as they are continuously adapting so that any variations in the signal statistics could be tracked.

The least mean square algorithm adapts the filter coefficients, so that the error signal $e(n)$ is reduced, thus we can find the error signal as [40]:

$$e(n) = d(n) - y(n) \tag{4.9}$$

and the filter coefficients can be updated as:

$$w(n+1) = w(n) + \mu e(n)x(n) \tag{4.10}$$

where μ is the convergence constant or the step size of the least mean square algorithm which determines the convergence speed of the filter. It is a smaller positive constant that affects the performance of the algorithm in speed of convergence and stability issues. If μ is selected to be very small, then the algorithm converges very slowly and a large value of μ may lead to a faster convergence speed but less stable around the minimum values [41].

The above three equations can generally express the least mean square iterative algorithm. It signifies a simple procedure for iterative update and adaptation of the filter coefficients after arrival of every new input sample $x(n)$ and its corresponding desired sample $d(n)$. equation (1) is performed to obtain the filter output and it is known as filtering, equation (2) is used to find the estimation error and equation (3) finds the filter coefficients update at every iteration [41]. The flatness of the underlying process's spectral content has a direct impact on the LMS algorithm's convergence behavior.

Mean Square Error of least mean square algorithm

The mean square error estimator calculates the average of the squares of the errors that is the mean squared value of the difference between the desired signal values and the filter output values. It is a measure of the performance quality of a filter obtained from the square of Euclidean distance concept, and always positive with decreasing value and approaching zero as the error gets decreased. The reason that mean square error is almost always strictly positive and not zero is because of randomness or the estimator does not account for information that could produce a more accurate estimate [46].

The mean square error is the second moment (about the origin) of the error and thus it includes both the variance of the estimator (how the estimates are broadly spreaded from one data sample to another) and its bias (how the average estimated value is far from the true value).

The cost function or mean square error value of least mean square algorithm can be calculated as [46]

$$\begin{aligned} \mathrm{MSE}_{\mathrm{LMS}} &= \mathrm{E}\,[\text{desired signal} - \text{filter output}]^2 \\ &= \mathrm{E}\,[\mathrm{e}^2(n)\ ] \end{aligned} \tag{4.11}$$

The $\mathrm{MSE}_{\mathrm{LMS}}$ defines the performance function of the least mean square algorithm. hence, for a given noisy speech signal which is affected by pink noise at different signal to noise ratio levels, the mean square error value will show how the filter performs on the signal at different iterations.

4.1.5 Recursive Least Square Algorithm

Recursive least square algorithm finds the filter coefficients recursively that optimizes the performance function related to the input signal and planned to reduce the mean square error. In the derivation of recursive least square algorithm the input signals are considered deterministic while for least mean square algorithm and it is considered stochastic [46].

Because it needs all past samples of the input signal and intended output to be accessible at every repetition, the least square determination technique has relatively little demand in the actual implementation of adaptive filters. It follows the time variation of the process to the optimal filter coefficient.

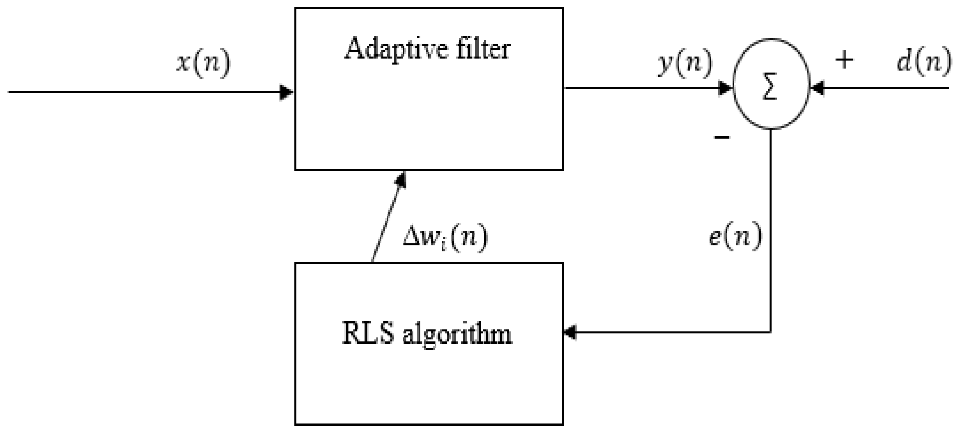

Figure 4.4: Adaptive filter recursive least square algorithm [47][48]

It operates using Kalman filtration theory, time averaging, and the least squares approach. Recursive least square method has its unique statistic formulation as compared to least mean square algorithm. It operates with average values computed from several time outputs [48].

Recursive least square algorithm has two basic stages:

- ✓ Initialization and operation stages

In the initialization stage an easy and most usaully used solution is to begin the recursive least square algorithm with an initial value of

$$\psi_{\lambda}(0) = \delta I \tag{4.12}$$

Where $\psi_{\lambda}(0)$ is the initial correlation matrix, δ is a small positive constant and I is an identity matrix, the RLS algorithm's convergence characteristic can be decreased by selecting a relatively small value for δ [48]. At the same initialization stage, it is a usual procedure to set the filter coefficients as $w(0) = 0$.

The operation stage of recursive least square algorithm has five steps in doing its filtration process recursively. It takes the following steps in to consideration to perform its task [49]:

- ✓ Calculate the filter output using filter coefficients from the previous iteration and the present input vector.

- ✓ Estimate the vector of mean gain.
- ✓ Calculated the value of the estimated error.
- ✓ Calculate the filter coefficients vector is updated and the vector of the gain.
- ✓ Compute the inverse matrix.

The output of the filter [48][49] can be obtained as

$$\hat{y}_{n-1}(n) = = \hat{w}^T(n-1)\ x(n) \tag{4.13}$$

where $\hat{w}(n-1)$ is the filter tap weights vector estimate, $\hat{y}_{n-1}(n)$ is the filter output and $x(n)$ is an input vector.

The estimation of the vector mean gain [20] will be

$$u(n) = \psi^{-1}{}_{\lambda}(n-1)x(n)$$

$$k(n) = \frac{u(n)}{\lambda + x^T(n)u(n)} \tag{4.14}$$

where $\psi^{-1}{}_{\lambda}(n-1)$ is inverse matrix, $u(n)$ is intermediate vector $k(n)$ is a gain vector and λ is a positive constant called forgetting factor which is close to but smaller than 1.

The estimation error of the filter can be obtained using the form [49]

$$\hat{e}_{n-1}(n) = d(n) - \hat{y}_{n-1}(n) \tag{4.15}$$

It indicates how much the output speech signal of filter deviates from the desired signal.

The update of the tap-weight vector adaptation or filter coefficient can be calculated as

$$\widehat{w}(n) = \widehat{w}(n-1) + k(n)\hat{e}_{n-1}(n) \tag{4.16}$$

The inverse matrix update will be

$$\psi_{\lambda}{}^{-1}(n) = \lambda^{-1}(\psi_{\lambda}{}^{-1}(n-1) - k(n)\,[x^T(n)\,\psi_{\lambda}{}^{-1}(n-1)\,]) \tag{4.17}$$

This filtration process will proceed recursively following the steps listed above until a steady condition or the mean square error minimized to the optimum level.

The mean square error that determines the performance of recursive least square algorithm can be calculated as

$$\mathrm{MSE}_{RLS} = \frac{1}{N}\sum_{i=0}^{N-1}(\lambda^i(\text{desired signal} - \text{output signal})^2$$

$$= \frac{1}{N}\sum_{i=0}^{N-1}(\lambda^i e^2(n-i)) \tag{4.18}$$

where N is the filter length, *i* and n are iteration and time indexes respectively.

4.1.6 Wiener Filter

In signal processing, the wiener filter is used to find the estimate of a desired or target random process by LTI filtering an observed noisy process, assuming known stationary signal, additive noise, and noise spectral arrangement. It lowers the mean square error between the estimated and desired random processes. The wiener filter is a general-purpose filtration approach that recommends linear estimation of a desired signal sequence from a related sequence. It includes techniques like as prediction, smoothing, joint process estimation, and channel equalization [48][49][[50].

Its purpose is to compute a numerical estimate of an unknown signal utilizing a related signal as an input and filtering that known signal to get the estimate as an output. The known signal, for example, may be made up of an unknown signal of interest that has been corrupted by additive pink noise. As a result, it is utilized to apply a statistical technique to filter out noise from the distorted signal and give an approximation of the basic signal of interest.

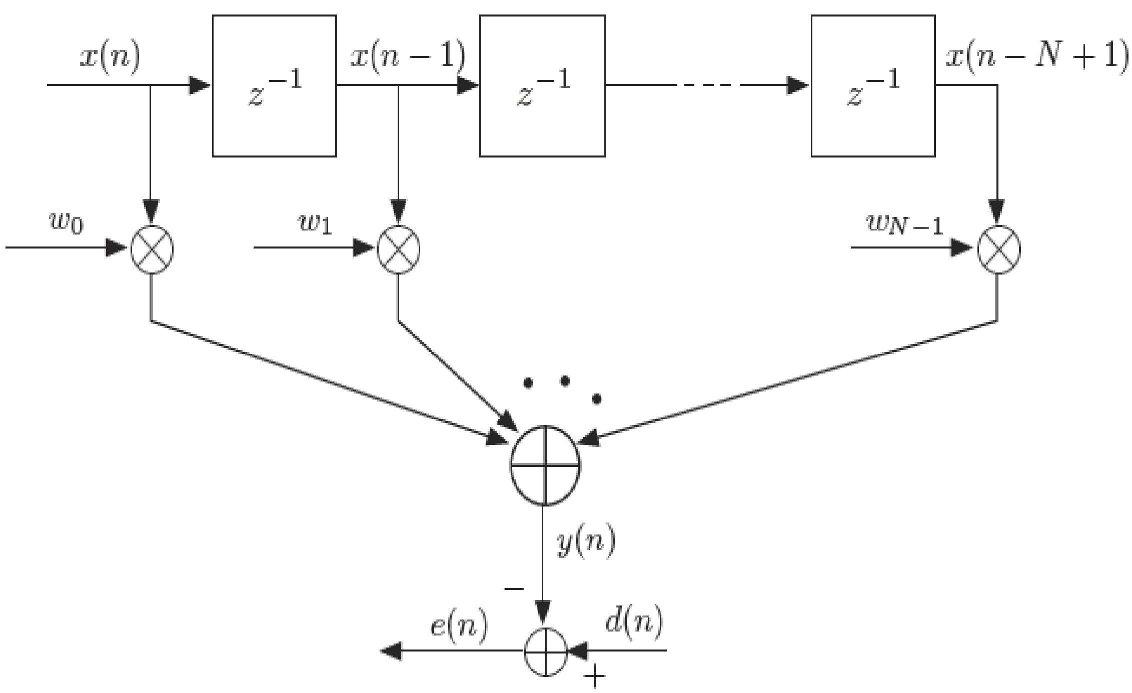

Figure 4.5: Transversal wiener filter [50]

The above figure (Figure 4.5) shows a transversal wiener filter of estimating a desired signal $d(n)$ based on an input signal $x(n)$. it is assumed that both $x(n)$ and $d(n)$ are samples of infinite length random processes, $y(n)$ and $e(n)$ are filter output and estimation error respectively. When the estimation error is smaller the performance of wiener filter becomes better. Hence, as the error approximates to zero, the output of the filter approximates the desired signal $d(n)$ [51]. Filtering a signal $x(n)$ and adjust it in a way that it approaches some other signal $d(n)$ in some statistical sense is the objective of wiener filter. That is, the output of the filter $y(n)$ is a good estimate of $d(n)$. The output error signal $e(n)$ represents the mismatch between $y(n)$ and $d(n)$.

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

where $y(n) = \sum_{i=0}^{N-1} w(n)x\,(n-i)$

For example, assume that $x(n)$ represents the price of a certain stock on day n and $d(n)$ represents the price of that stock one day in the future. The objective is to find a filter that can predict $d(n)$ from $x(n)$. To discover the best linear predictor or optimum filter, we need a way to measure how well the filter performs, which is called a cost function. The cost function is used to assess the performance and may take many various forms [51].

The performance function in Wiener filters is determined to be [51]

$$\begin{aligned} \xi &= \mathrm{E}[|d(n - y(n)|^2] \\ &= \mathrm{E}[|e(n)|^2] \end{aligned} \tag{4.19}$$

where, ξ is the performance function and E [·] denotes the statistical expectation.

The performance function (ξ), commonly known as the mean square error criterion, must fulfill the following two requirements:

- ✓ it must be mathematically easy
- ✓ It should have a single minimum or maximum point that enables the best set of filter parameters to be chosen without ambiguity [50].

The possible generalization of the mean square error criteria will be

$$\xi_p = \mathrm{E}[|e(n)|^p]$$

Where, p is an integer 1, 2, 3… N and when p = 2 it leads to the Wiener filter performance function, which is described above, and when p >2 and even it may result in more than one minimum or maximum point, but when p is odd it is difficult to handle computationally due to the modulus sign on $e(n)$[49].

In wiener filter, the performance function can be evaluated using different approaches. The most usually used approaches are transversal real valued case, principle of orthogonality, normalized performance function, extension to complex valued case and unconstrained wiener filter case. In this thesis scenario transverasl real valued case is selected for measuring the performance function of the filter on speech signal improvemnt.

Transversal real valued case

Consider the transversal filter in Figure 4.5, where the filter input $x(n)$ and the desired output $d(n)$ are considered to be real valued stationary processes. The weights of the filter taps w_0, w_1,..., w_{N-1} are likewise considered to be real-valued. The column vectors define the filter tap-weight and input vectors respectively [49].

Since the filter tap weights w_0,w_1, . . .,w_{N-1}, are assumed to be real valued, the filter tap weight and input vectors are defined the column vectors as follows.

$$w = [w_0, w_1, \ldots, w_{N-1}]^T \text{ and}$$

$$x(n) = [x(n)\ x(n-1) \ldots x(n-N+1)]^T$$

Then the filter output $y(n)= \sum_{i=0}^{N-1} w(n)x\,(n-i) = w^T\, x(n) \;=\; x^T(n)\, w$, because $w^T\, x(n)$is a scalar and thus it is equal to its transpose, that is [48][49][50]:

$$w^T\, x(n)= [w^T\, x(n)]^T= \; x^T(n)\, w \text{ Thus, we may write}$$

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

$$= d(n) - w^T\, x(n)$$

$$w^T\, x(n) = \; d(n) \;-\; x^T(n)\, w \qquad (4.20)$$

We already know that ξ= E$[|e(n)|^2]$, so by substituting we will get

$$\xi = \mathrm{E}\,[d(n)^2] - w^T\mathrm{E}\,[x(n)d(n)] - \mathrm{E}\,[d(n)x^T(n)]\boldsymbol{w} + w^T\mathrm{E}\,[x(n)x^T(n)]\boldsymbol{w}$$

Next, if we define the *N*-by-1 cross-correlation vector

$$\mathrm{p} = \mathrm{E}[\boldsymbol{x}(n)\mathrm{d}(n)] = [p_0, p_1, \ldots, p_{N-1}]^T$$

and the *N*-by-*N* autocorrelation matrix

$$\mathbf{R} = \mathrm{E}\,[x(n)x^T(n)] = \begin{bmatrix} r_{00} & r_{01} & r_{02\ldots} & r_{0N-1} \\ r_{10} & r_{11} & r_{12\ldots} & r_{1N-1} \\ r_{20} & r_{21} & r_{23\ldots} & r_{2N-1} \\ .. & .. & .. & .. \\ r_{N-10} & r_{N-11} & r_{N-12\ldots} & r_{N-1N-1} \end{bmatrix}$$

$$\text{So, } \xi = \mathrm{E}[\mathrm{d}^2(n)] - 2w^T\mathbf{p} + w^T\mathbf{R}\boldsymbol{w}$$

The optimum set of the Wiener filter tap weights can be obtained using [50]

$$Rw_0 = p \tag{4.21}$$

This equation is called Wiener–Hopf equation and the subscript “0” to ***w*** is to emphasize that it is the optimum tap weight vector. Then we will have

$$w_0 = R^{-1}\mathbf{p}$$

assuming that **R** has an inverse. Therefore, the minimum mean square error that can be achieved by the transversal real valued case for a wiener filter is [4]:

$$\xi_{min} = \mathrm{E}[\mathrm{d}^2(n)] - \mathrm{p}^T R^{-1}\mathrm{p} \tag{4.22}$$

4.1.7. Kalman Filter

When the measured values contain unexpected or random error, uncertainty or variation, Kalman filter provides a series of equations and sequential data inputs to quickly estimate the true value of a signal contaminated by noise using iterative mathematical techniques. It offers a solution by using a recursive least squares technique and has the ability to estimate past, present and even future conditions.

It is a collection of mathematical equations that performs a predictor-corrector type estimator which is optimum in a sense that minimizes the estimated error covariance when a certain presumed criterion is satisfied [53]. It is proposed to estimate the unknown states of a dynamic system using a series of iterative equations that predict the state of a system by reducing the mean square error. It has prediction and correction steps for estimating the clean part from a corrupted speech signal. In the prediction stage the filter generates an estimate in consideration of current state variables and their instabilities. Because of the recursive nature of the computation, the system may operate indefinitely using the current data estimates and no further historical data is required. It uses a feedback control to compute the preceding process, then estimates the process over time and receives feedback from observed data. So, in step one the equation is derived in order to update the time or forecast and in step two, the observed data is updated [53].

By using the covariance matrix of the previous and intermediate states as a reference, the prediction step equations are utilized to establish the state. The feedback, which adds new information to the prior estimates must be taken into account in the correction stage so that the desired estimated state may be reached. prediction-correction algorithms are a kind of estimate algorithm that has been used to address a variety of problems [52].

The measurement noise covariance and process noise covariance are the two filter parameters that need to be evaluated for the optimal Kalman filter estimation. The accurate estimate of these two filter parameters which must be adjusted can significantly improve filter performance [53].

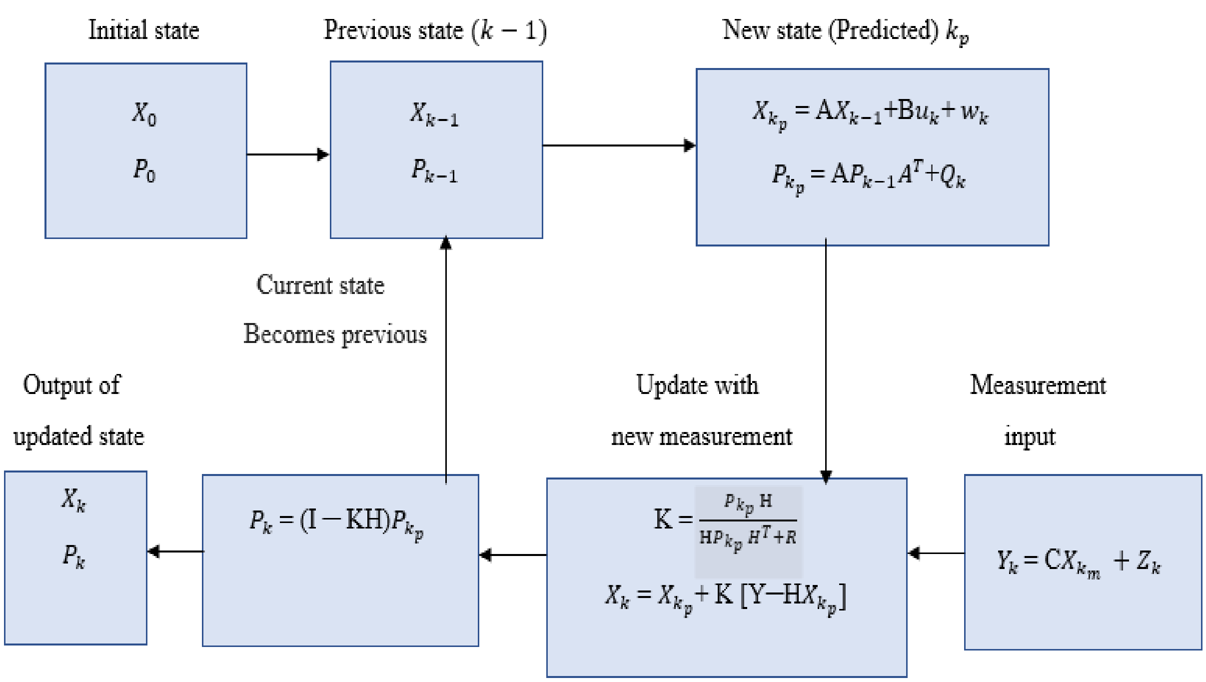

Figure 4.6: Kalman filtering algorithm [49][50][53]

Where X is state matrix which represents the state of input signal in the process, P is process covariance matrix or error in the process and the predicted state is based on previous state. The symbols u, w and Q are control variable matrix which controls the flow of air pressure on the speech signal, predicted state noise matrix and process noise covariance matrixes respectively. A, B and C are adaptation matrices which are used to convert one state to another [53]. In the correction (measurement) state K is the Kalman gain and identity matrix I, R is measurement noise covariance matrix, Y is measurement of the state, Z_k is the measurement noise and H is the observation (measurement) matrix.

The mean squared error of Kalman filter is given by

$\mathrm{MSE}_{Kalman} = \frac{1}{N}\sum_{k=0}^{N-1}[\mathrm{e}_k]^2$, where by the error signal for Kalman filter is equivalent to (I-KH) P_{kp} = P_k.

Hence, the mean square error of Kalman filter will be:

$$\mathrm{MSE}_{Kalman} = \frac{1}{N}\sum_{k=0}^{N-1}[(\mathrm{I}-\mathrm{KH})\ \mathrm{P}_{kp}]^2$$

$$= \frac{1}{N}\sum_{k=0}^{N-1}[\mathrm{P}_k]^2 \tag{4.23}$$

CHAPTER FIVE

5. SIMULATION RESULTS AND DISCUSSION

The comparison of LMS, RLS, Kalman and Wiener adaptive filters are presented in this section of the thesis work. The table below (Table 5.1) shows the simulation parameters used in this work and performance evaluation is done using MATLAB and Microsoft Excel.

Table 5.1: List of parameters used for simulation

Parameters and inputs used for simulation	**Values**
Audio input (using two SNR levels)	5dB, 10dB
Filter length (Number of Iterations)	10, 15
Sampling rate of the generated audio signal	11,025 Hz
The length of the generated Audio signal (Time in seconds)	2 Seconds
Input audio signal saying in words	“The bird was flying on the smooth plane”

5.1 Comparison of Adaptive Filters in terms of Filter length, SNR and MSE

In this section of the thesis work simulation result of adaptive filters (LMS, RLS, Kalman and Wiener) are evaluated using filter length, signal to noise ratio and mean square error parameters on a noisy speech signal affected by pink noise. The performance of these algorithms is compared by changing filter length (10 and 15 iterations) and signal to noise ratio (5dB and 10dB) values.

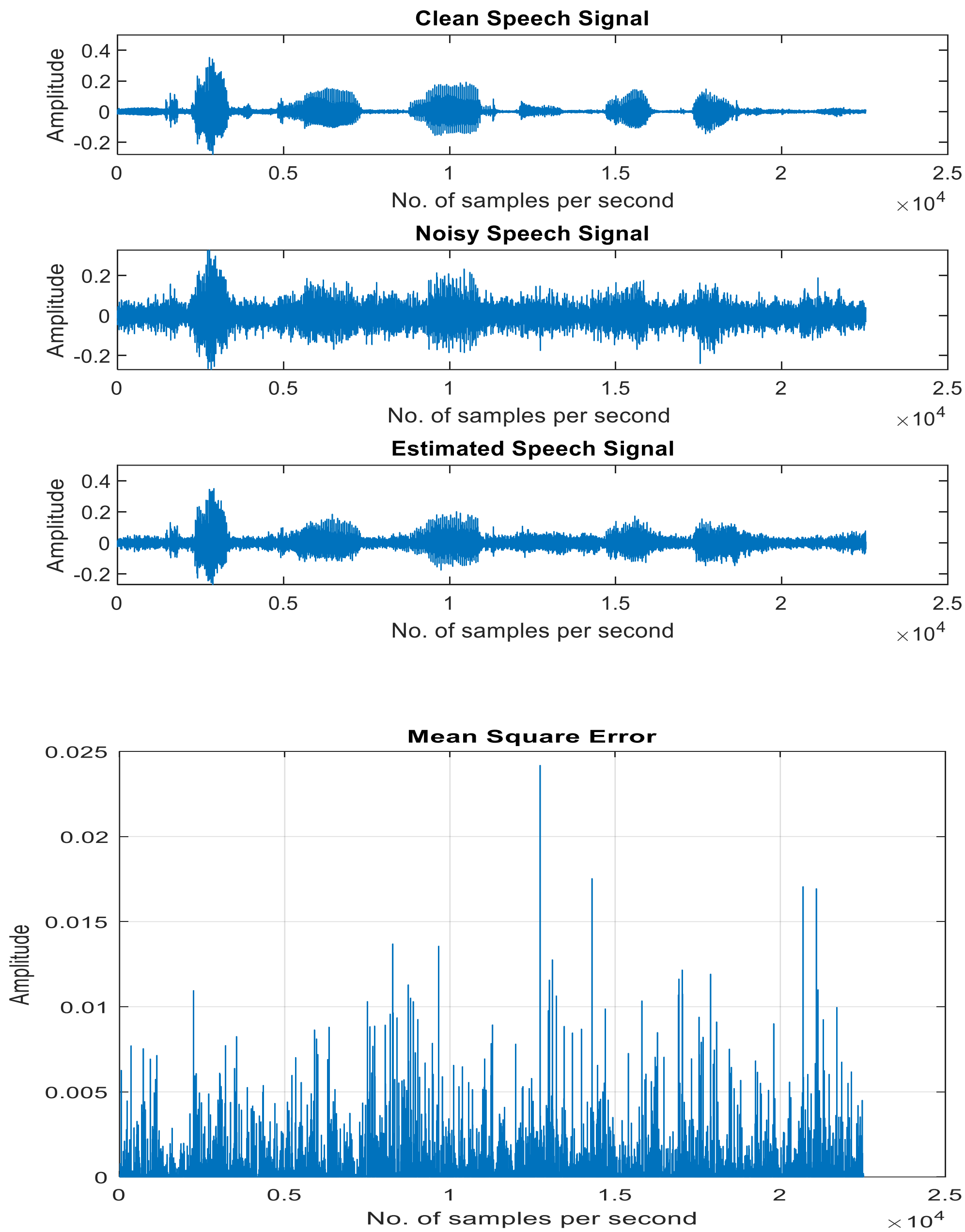

Figure 5.1: Kalman filter on noisy speech signal of SNR 5dB and 10 iterations

As we can see on the Figure (Fig. 5.1), the speech signal affected by pink noise having SNR value of 5dB is feed into Kalman filter as an input and filtered using 10 iterations. The filter has two inputs, a clean audio signal as desired signal and a pink noise affected speech signal of 5dB and one estimated (filtered) output speech signal.

The estimated output has some spectral improvements which indicates as the noise from the speech signal is reduced and mean square error shows how the filter performs on the given input speech signal using error values.

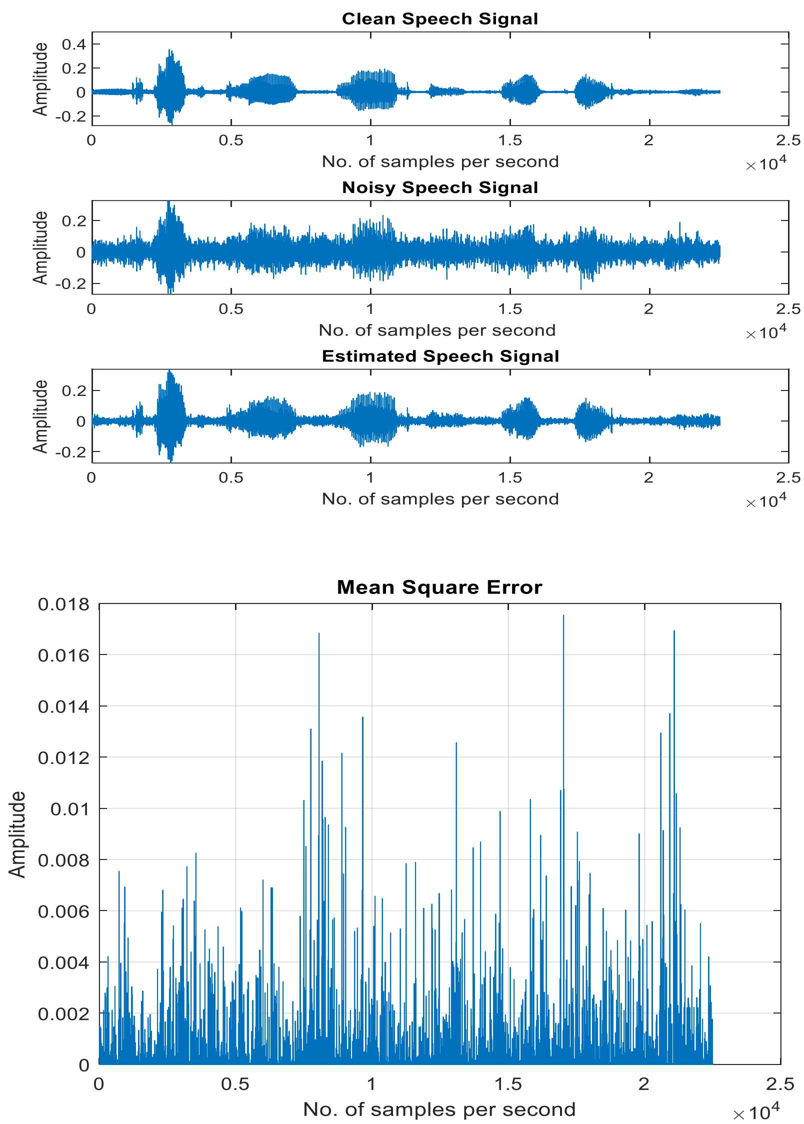

Figure 5.2: Kalman filter on a noisy speech signal of 5dB SNR level and 15 iterations

The figure above shows estimation of distorted speech signal having SNR level of 5dB by kalman filter using 15 iterations. As we can see from two figures (Figure 5.1 and 5.2) the filter has a common input noisy speech signal of 5dB and different number of iterations (10 and 15), and we can observe as there is a visible difference on their MSE performance, as number of iterations are increased the MSE performance of the filter becomes enhanced.

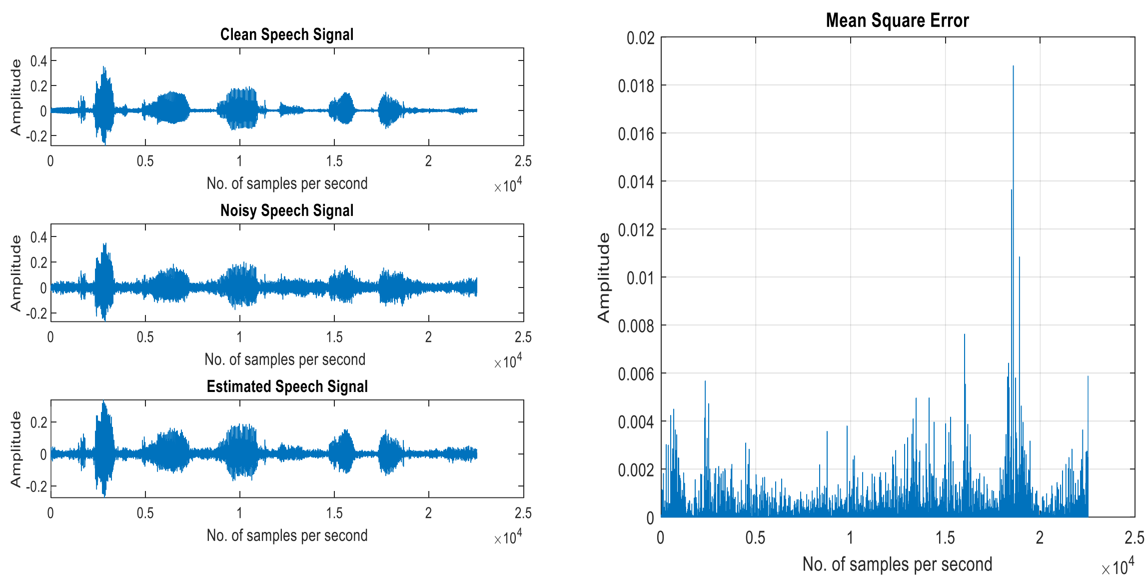

Figure 5.3: Kalman filter on a noisy speech signal having SNR value of 10dB and 10 iterations

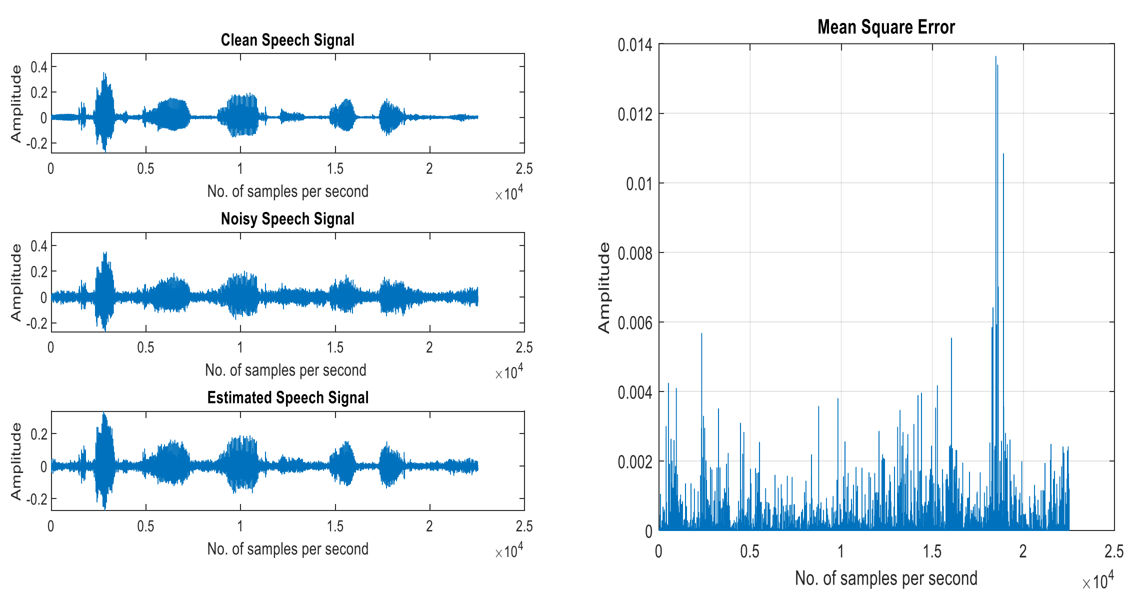

Figure 5.4: Kalman filter on a noisy speech signal of 10dB SNR level and iteration of 15

The results above (Figure 5.3 and 5.4) show outputs of Kalman filter on a speech signal having SNR level of 10dB, and filter lengths of 10 and 15 respectively. From the figures we can observe that the mean square error has a significant difference at various sample points and times for each iteration, which shows that in filtration process, as SNR values and iterations are increased the MSE performance of the filter is improved.

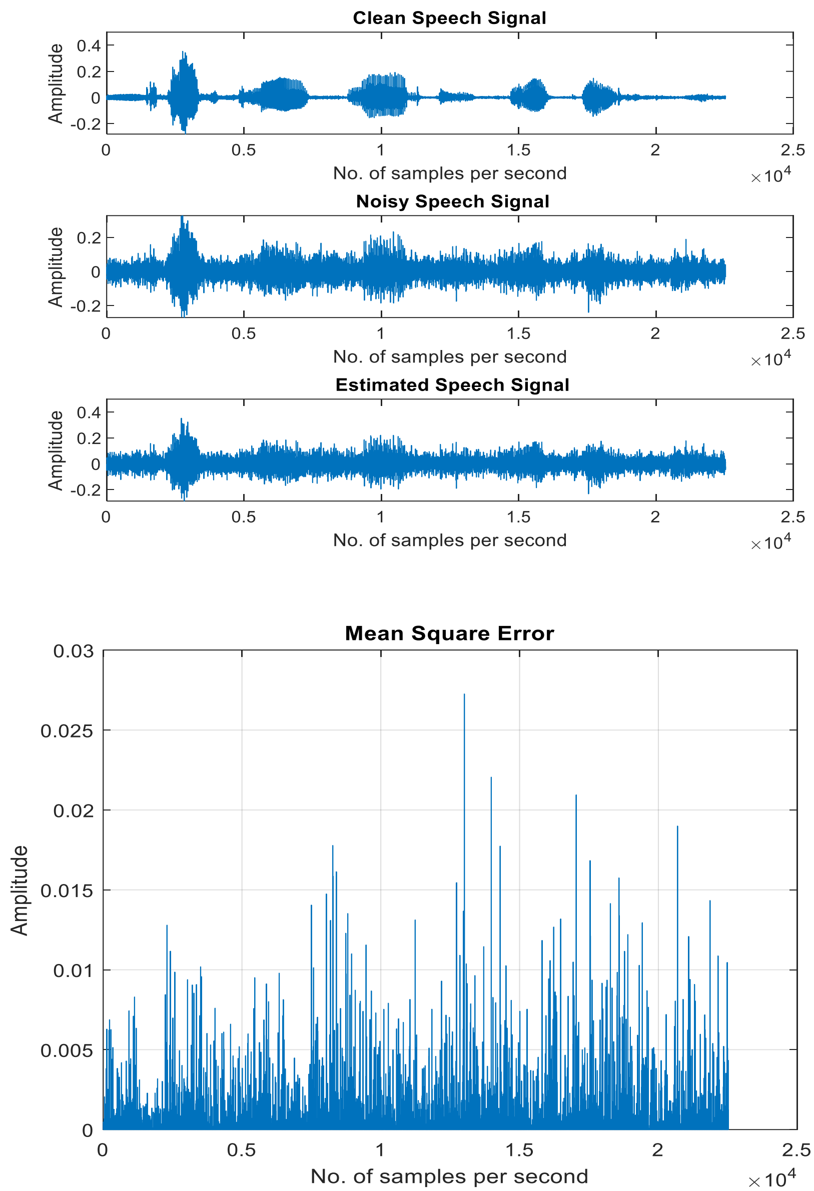

Figure 5.5: LMS algorithm on a noisy speech signal of 5dB SNR level and 10 iterations

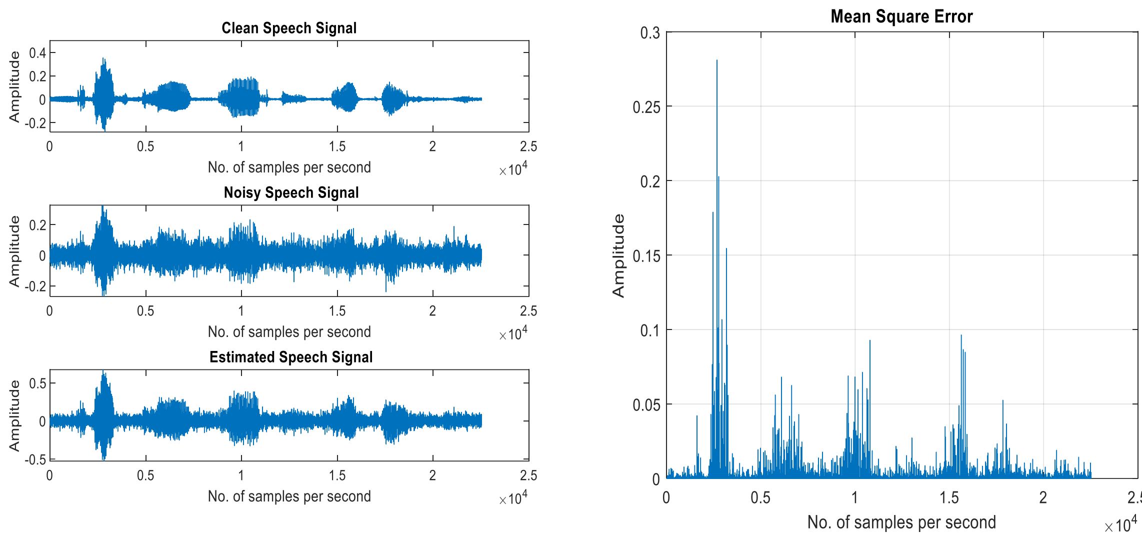

Figure 5.6: LMS algorithm on a noisy speech signal having 5dB of SNR and 15 iterations

The figures (Figure 5.5 and 5.6) show the output of LMS algorithm on a noisy speech signal of 5dB and iterations of 10 and 15. The distorted signal is cleaned using LMS algorithm at different number of iterations and a reduced mean square error is produced.

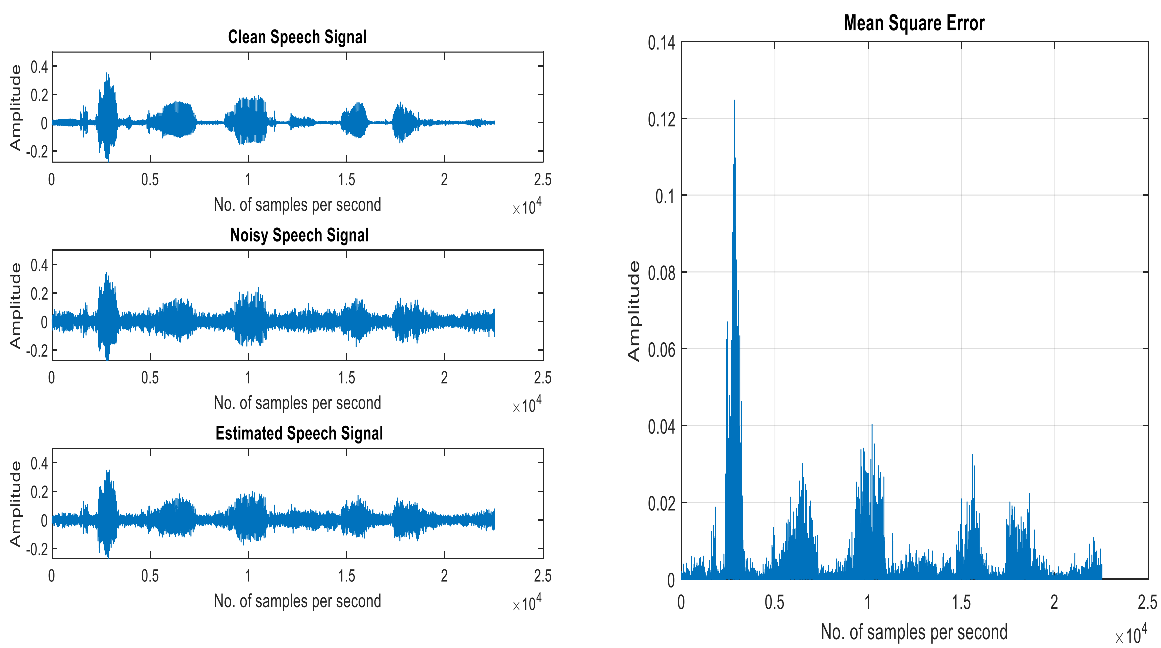

Figure 5.7: LMS algorithm at pink noise affected speech signal of 10dB and iterations of 10

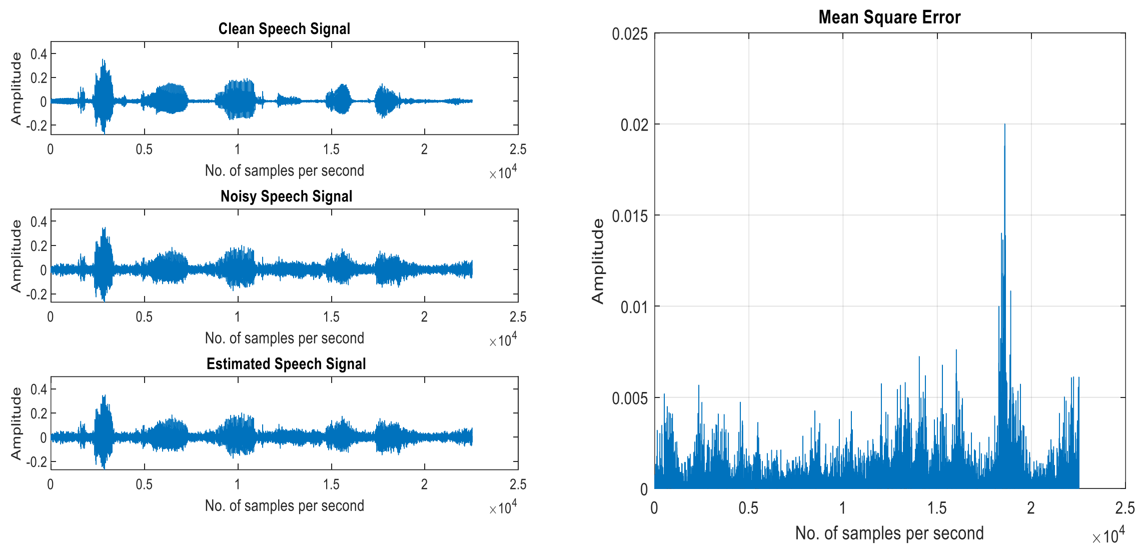

Figure 5.8: LMS algorithm on a noisy speech signal of 10dB SNR level and at iteration of 15

The simulation result on the figures above shows the output of LMS algorithm for a noisy speech signal of 10dB and a filter length of 10 and 15. As we can see as there are differences on MSE performance level even if the input speech signal is the common.

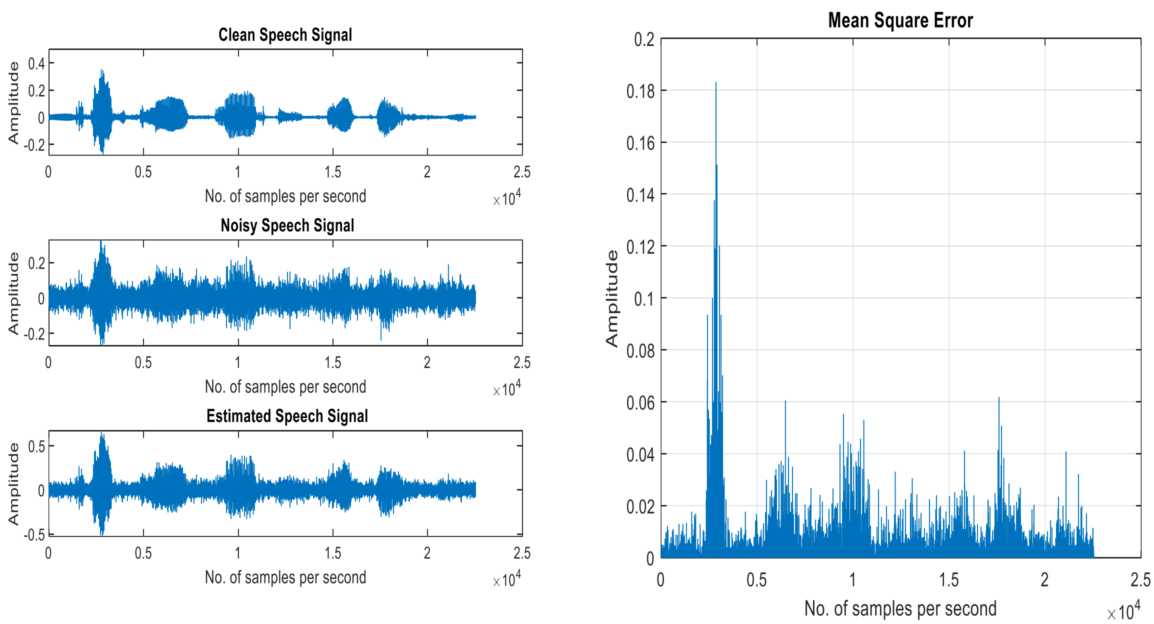

Figure 5.9: Wiener filter on a pink noise affected speech signal at SNR level of 5dB using 10 iterations

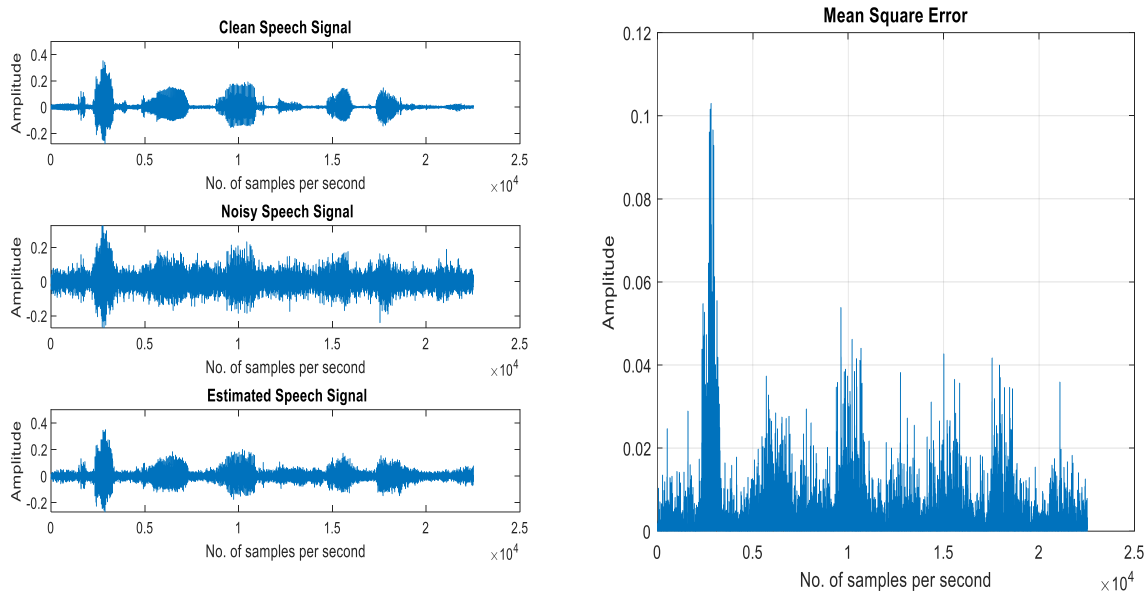

Figure 5.10: Wiener filter at 5dB SNR level of pink noise affected signal and iterations of 15

The results above on figures (Figure 5.9 and 5.10) shows the performance of wiener filter on a speech signal affected by pink noise of 5dB using 10 and 15 iterations respectively. A common input signal corrupted by pink noise was feed to wiener filter and estimated using different iterations which showed reduction of mean square error levels.

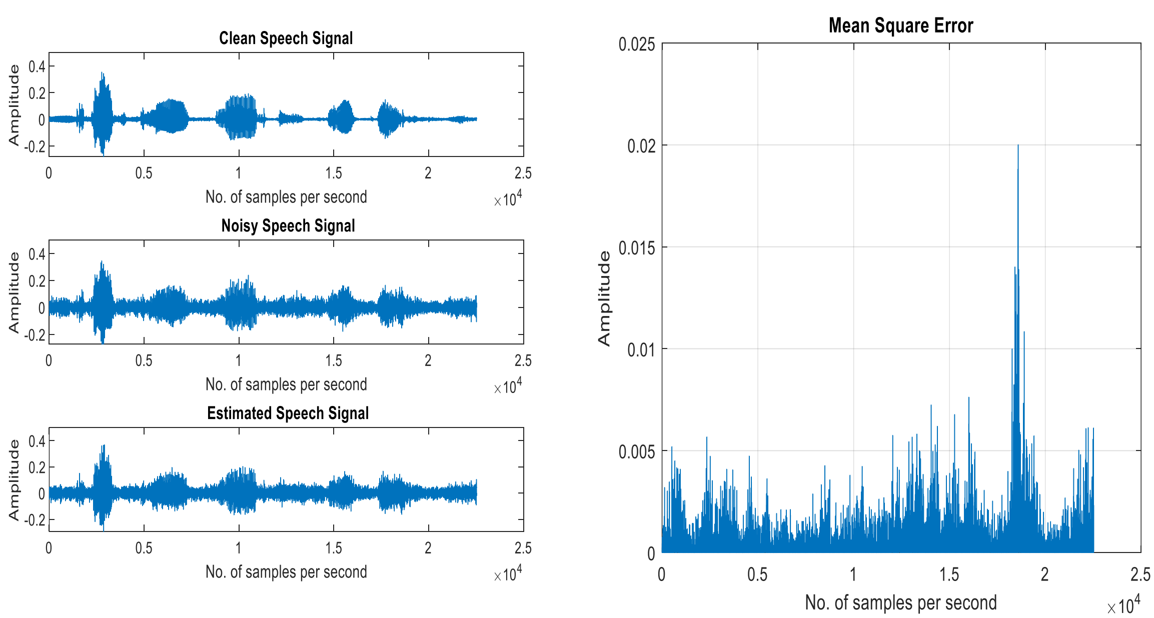

Figure 5.11: Wiener filter at 10dB SNR level of pink noise affected signal and 10 iterations

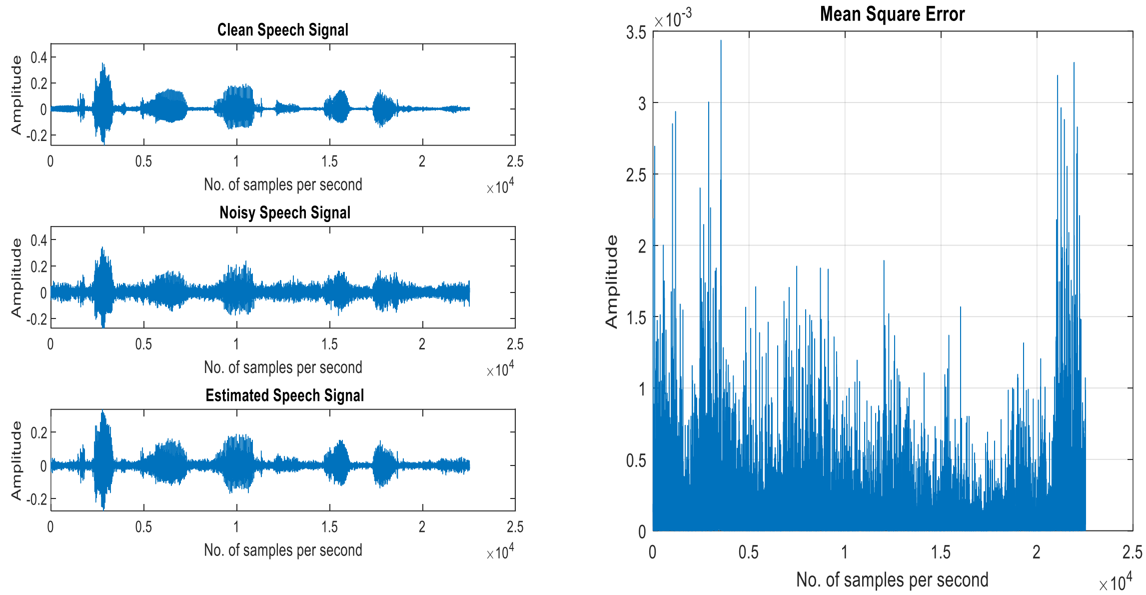

Figure 5.12: Wiener filter on a noisy speech signal at SNR level of 10dB and 15 iterations

As shown on the figures above the wiener filter has different performance levels at different iterations on the same input signal. The output shows MSE with different signal amplitude values for the clean input signal, noisy and estimated signals. The filter has done its filtration process on the same input signal at iterations of 10 and 15.

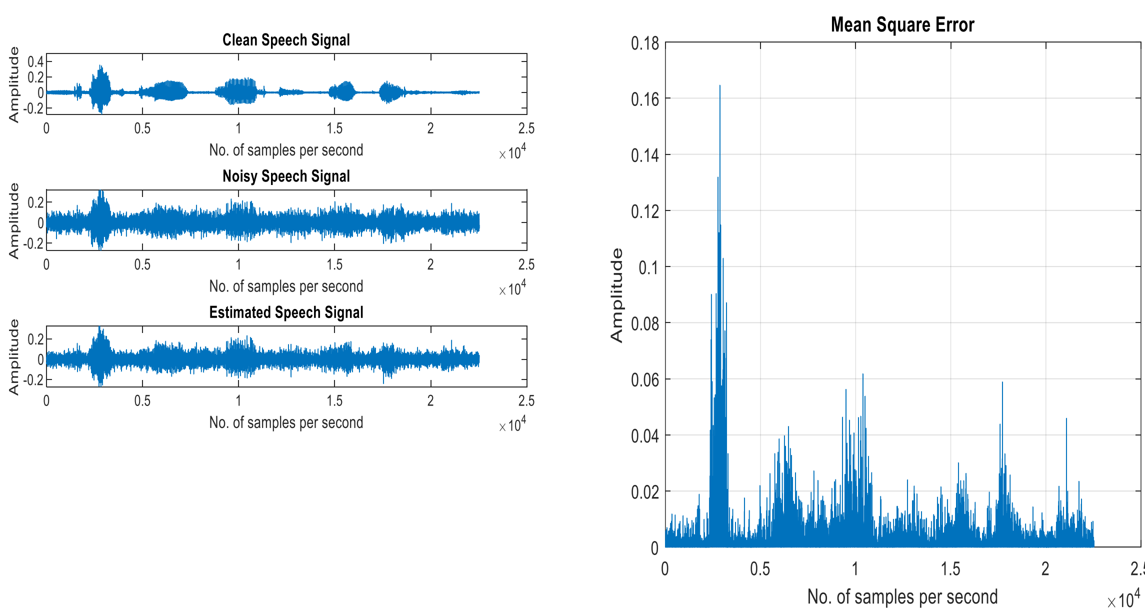

Figure 5.13: RLS algorithm at 5dB SNR Level of pink noise affected signal and iterations of 10

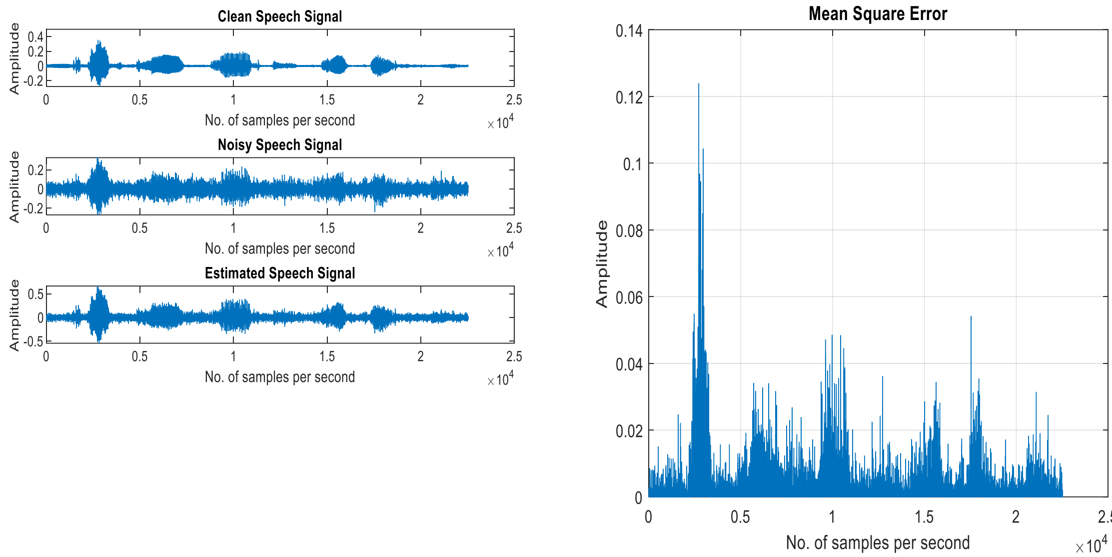

Figure 5.14: RLS algorithm at 5dB SNR level of pink noise affected signal and iterations of 15

The figures (Figure 5.13 and 5.14) show the output of RLS algorithm on noisy speech signal of 5dB and iterations of 10 and 15 respectively. At different iterations the RLS algorithm has different MSE values on the same input signal.

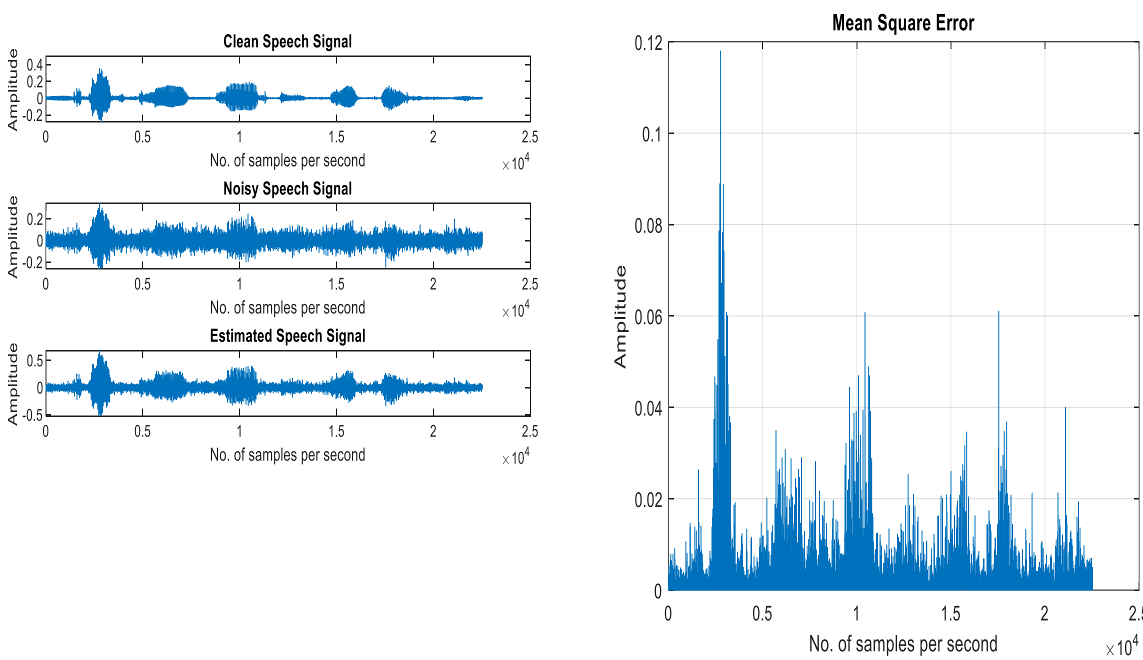

Figure 5.15: RLS algorithm at 10dB SNR level of pink noise affected signal and iterations of 10

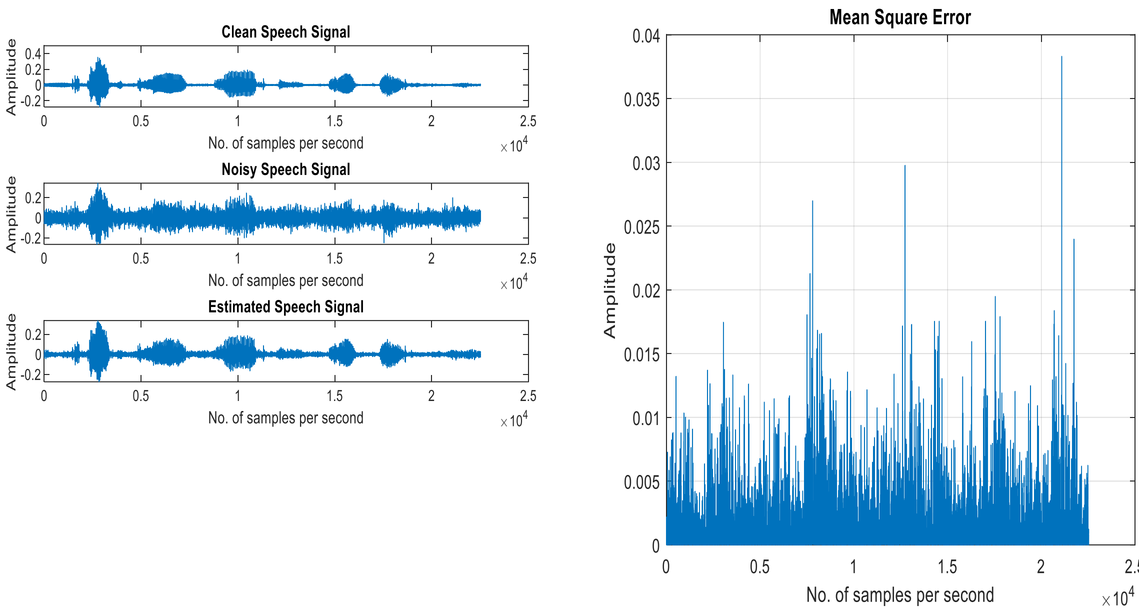

Figure 5.16: RLS algorithm at 10dB SNR level of noisy speech signal and iterations of 15

As shown on the figures above the RLS algorithm has different MSE performance levels at different iterations for a common input noisy speech signal. The estimated speech signal has different signal amplitude values which describes MSE effectiveness at various iterations and input signal values. When the input noisy speech signal has relatively higher SNR level and the number of iterations is increased the MSE performance of each filter become enhanced.

From all of the above simulations, the results can be described in tabular form by taking samples from all adaptive filters (Kalman, LMS, wiener and RLS). It evaluates all the corresponding values of MSE at different SNR values (5dB and 10dB) and number of iterations (10 and 15). The table shows the mean square error values of audio signal samples of each adaptive filter at various selected times.

The MSE values of each filter are taken from the results by tracing the amplitude on each sample at each selected time. The amplitude of the error signal for each filter has different values which in turn shows their performance on removal of the pink noise from a corrupted speech signal. The smaller the MSE value means the better the performance of the adaptive filter and vice versa.

Table 5.2: Numerical simulation result summery of Kalman, LMS, RLS and Wiener filters

SNR	Iteration	Time in seconds	Mean Square Error			
			Kalman	Wiener	LMS	RLS
5dB	10	0.25	0.00366	0.0045	0.0049	0.0215
		0.5	0.0056	0.006	0.0096	0.026
		0.75	0.0096	0.0099	0.0123	0.0165
		1	0.00061	0.005	0.0065	0.0125
		1.25	0.0027	0.00285	0.00287	0.0104
		1.5	0.00055	0.0031	0.0037	0.0075
		1.75	0.0063	0.00677	0.0125	0.0213
		2	0.0055	0.00787	0.01087	0.03
	15	0.25	0.00026	0.0038	0.0045	0.02
		0.5	0.00042	0.003	0.0062	0.012
		0.75	0.0086	0.0043	0.0114	0.0138
		1	0.0002	0.0044	0.0053	0.0099
		1.25	0.00025	0.0025	0.0026	0.0051
		1.5	0.000403	0.00165	0.00356	0.004
		1.75	0.00616	0.0064	0.0102	0.01437
		2	0.0035	0.004	0.0046	0.025
10dB	10	0.25	0.00023	0.0005	0.0034	0.015
		0.5	0.0004	0.0015	0.00298	0.0105
		0.75	0.0004	0.00275	0.0014	0.01185
		1	0.00018	0.00026	0.0015	0.007
		1.25	0.0002	0.00063	0.00158	0.00427
		1.5	0.000039	0.00132	0.00135	0.0035
		1.75	0.000525	0.001148	0.00301	0.00895
		2	0.000609	0.00057	0.002337	0.013
	15	0.25	0.000078	0.00029	0.0033	0.003
		0.5	0.000156	0.0014	0.0029	0.0034
		0.75	0.000097	0.001095	0.0012	0.00135
		1	0.000063	0.000161	0.00147	0.0035
		1.25	0.000107	0.00049	0.00149	0.0012
		1.5	0.000025	0.00013	0.00134	0.0032
		1.75	0.00014	0.000762	0.0029	0.00108
		2	0.000076	0.00042	0.0022	0.0026

As we can see the results on the table, there is a visible difference on the performance of filters depending on their MSE values. As the number of iterations or filter length and SNR values are increased the performance of the algorithms improved for the same noisy input speech signal. Using the mean square error numerical values from the above table, we can express the performance of adaptive filters graphically as follows.

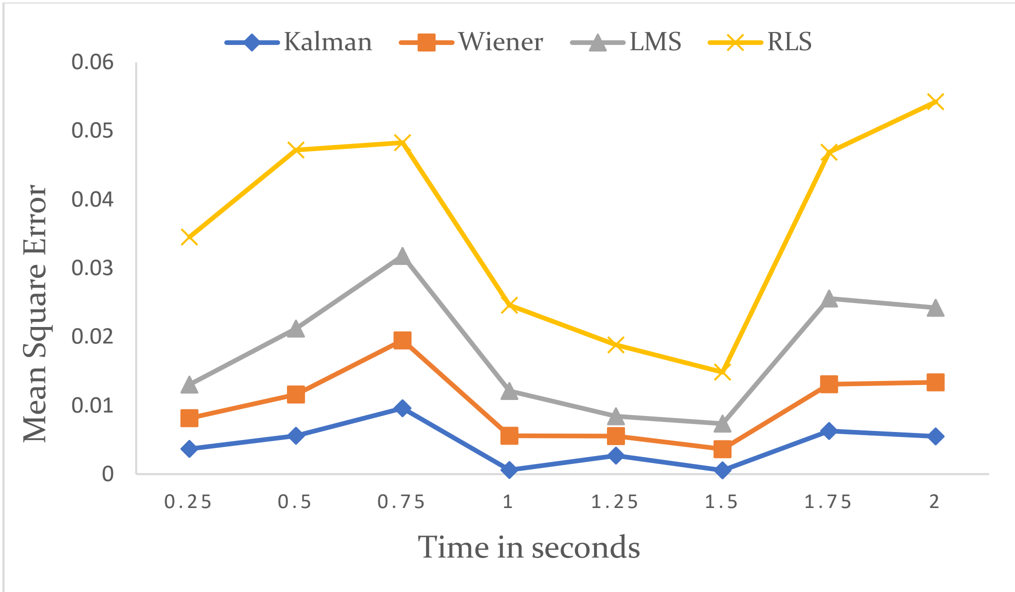

Figure 5.17: Comparison of adaptive filters using MSE values on a noisy speech signal of 5dB SNR value and 10 number of iterations

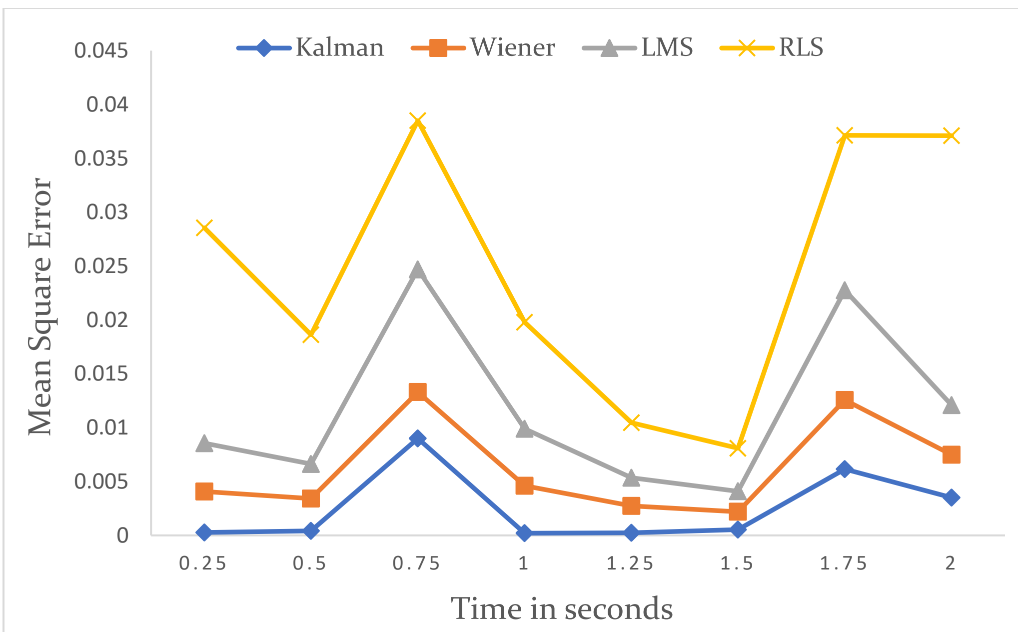

Figure 5.18: Comparison of adaptive filters using MSE values on a noisy speech signal of SNR value 5dB and iterations of 15

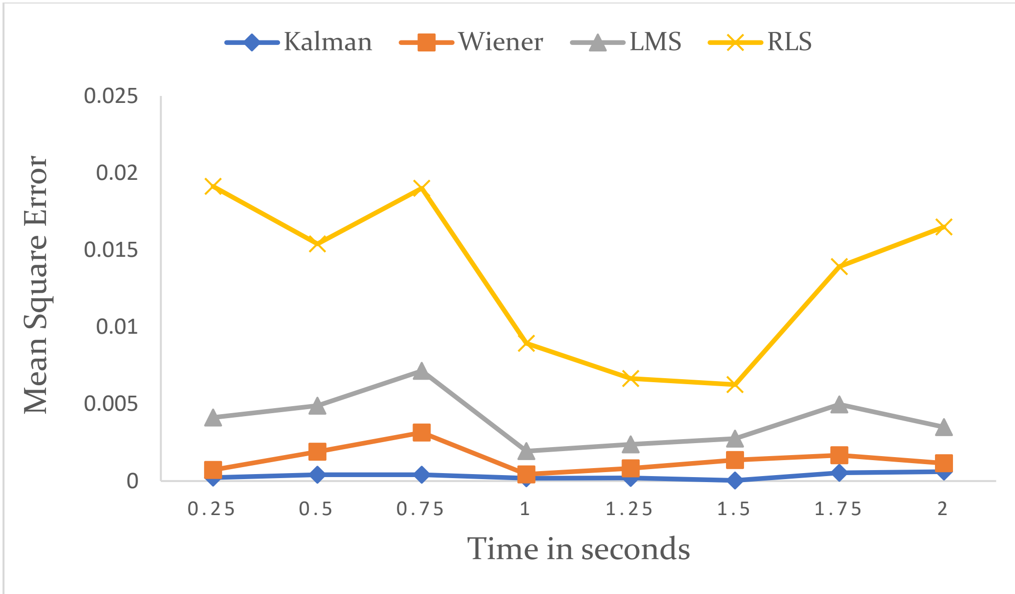

Figure 5.19: Comparison of adaptive filters using MSE values on a noisy audio signal of SNR value 10dB and 10 iterations

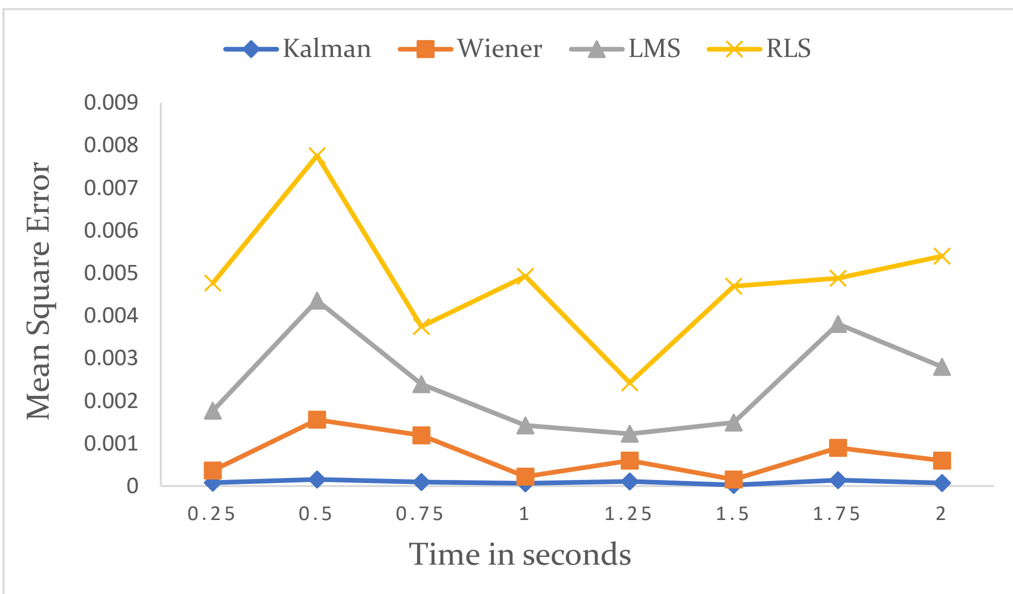

Figure 5.20: Comparison of adaptive filters using MSE on a noisy audio signal of SNR value 10dB and 15 iterations

5.2 Comparison in terms of Computational complexity, Stability and Convergence speed

The performance of adaptive filters can also be measured using computational complexity, stability and convergence speed metrics. Each of these metrics are basically dependent on the mathematical models and simulation results.

Computational complexity

In this work, computational complexity is expressed in terms of arithmetic operations using two fundamental mathematical operators (addition and multiplication) as shown on the below table.

Table 5.3: Computational complexity of adaptive filters (Kalman, Wiener, LMS, RLS)

Arithmetic operations	**Type of filter**			
	LMS	**RLS**	**Weiner**	**Kalman**
Number of complex additions	N	2N	N-1	13N
Number of complex multiplications	3N	7N	N^2+4N	6N
Total Operations	4N	9N	N^2+5N -1	19N

Where N indicates filter length and as we can see on the table, each filter has different computational complexities calculated based on their mathematical models. Arithmetic operations (addition and multiplication) are considered to find complexity. When iterations are increased the algorithms go through numbers of operations and in turn it affects its performance in time, space and other complexity measures.

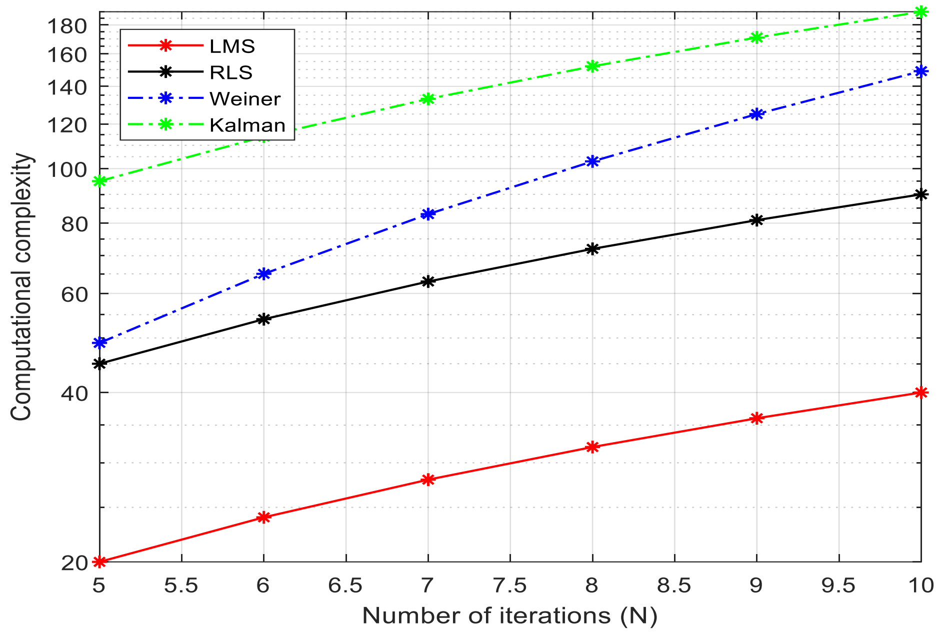

Figure 5.21: Comparison interms of computational complexity

As we can see on the above figure (Figure 5.21) adaptive filters are compared using their computational complexity metrics and Kalman filter is found to be more complex than others.

Stability

In this thesis work, the stability of adaptive filters (Kalman, LMS, RLS and Wiener) is compared with the help of simulation results (Table 5.2). This is accomplished by taking the difference between MSE output values of each filter for the input noisy speech signal taken at different SNR values and number of iterations. The MSE values of filters at iteration 10 and SNR of 5dB and 10dB is subtracted from MSE value of iteration 15 and SNR of 5dB and 10dB on all of the samples. In doing this, the adaptive filter with small value at each iteration is selected to be more stable than others. In this case, LMS is more stable than RLS, Kalman, and Weiner filters.

Convergence speed

In speech signal de-noising, convergence speed indicates the process in reducing mean square error of the noisy signal. Adaptive filters attempt to minimize the mean square error signal by iteratively adjusting the filter coefficients and their convergence speed is evaluated by displaying the error signals or learning curves. The convergence of the adaptive filter is faster when the adaptive filter takes a short time to calculate the appropriate filter coefficients that minimize the MSE of the signal. The step size and filter length of an adaptive filter affects the convergence speed.

As shown on the simulation results above Figures (5.17, 5.18, 5.19 and 5.20) all the adaptive filters have significant difference on their MSE performance and the convergence speed measurement is explained using learning curves. Hence, depending on the arrangement of reduced MSE learning curves, Kalman filter has faster rate of convergence followed by Wiener, LMS and RLS algorithms respectively.

CHAPTER SIX

6. CONCLUSION AND RECOMENDATION

6.1 Conclusion

This thesis work evaluates the performance comparison of adaptive filters LMS, RLS, kalman and wiener on a speech signal corrupted by pink noise having different signal to noise ratio values. Comparison is done using SNR, MSE, Filter length, computational complexity, stability and convergence speed metrices.

Depending on the simulation results, the performnce of kalman filter is most efficient in reducing pink noise from corrupted speech signal. It has better MSE performance at every iteration tested with the same input speech signal on every samples taken. When SNR and filter lengths are increased, performance of all the filters show a significant improvement on their MSE values, But, kalman is more effecitve in denoising the distorted signal followed by wiener, LMS and RLS algorithms respectively. In terms of computational complexity, stability and convergence speed metrices Kalman filter is found computationally more complex and have faster rate of convergence, but LMS is more stable. Therefore, we concluded that in removal of pink noise from a corrupted speech signal, Kalman filter has better MSE and rate of convergence performance compared to wiener, LMS and RLS filters with a cost of high computational complexity.

6.2 Recommendation for future work

The result discussed above on this work can be used for future to have a clear insight on speech signal communication effects and helps to come up with a common solution on all the background noises affecting audio signals. For the development of speech signal communication system, removal of background noise is the primary task. There are some limitations in this work that we need to recommend for the future in order to accomplish the expected performance of speech communication system. Hence, there can be a lot of possible thesis ideas related to this topic for the future:

- ✓ One possible thesis idea will be comparative analysis of adaptive filters on a speech signal corrupted by all the colored noises including white noise, it will be more inclusive to see the performance of the adaptive filters on all kinds background noises occurred naturally.
- ✓ Additionally, the probable idea for future work related to this thesis is to make a frequency domain analysis of a pink noise corrupted speech signal, since this work is mainly concerned on time domain analysis.
- ✓ Making a comparative analysis of adaptive filters (Kalman, Wiener, LMS and RLS) at low SNR (below -10dB) using the metrices listed in this thesis and others by considering beamforming concepts may be additional possible idea for another work.

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