A
PROJECT REPORT
ON
"CONTROL AND ESTIMATION OF VOICE SIGNAL USING ADAPTIVE FILTER"

Submitted in partial fulfillment of the Requirements for the award of the degree of

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In

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(2017-2021)

Submitted By:

ABHISHEK KUMAR SIMRA	182308351233
ADITYA AMAN	182308351234
SUDHANSU GUPTA	182308351250

UNDER THE GUIDANCE OF

Prof(Dr.) SHALINI KUMARI

(Associate Professor of ECE Dept.)

DEPARTMENT OF ELECTRONICS & COMMUNICATION ENGINEERING

RVS COLLEGE OF ENGINEERING AND TECHNOLOGY

EDALBERA, BHILAIPAHARI, JAMSHEDPUR, 831012 (INDIA)

(Approved by AICTE & affiliated to Kolhan University,Chaibasa)

RVS COLLEGE OF ENGINEERING AND TECHNOLOGY

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2017-2021

PROJECT EXAMINE & APPROVED

BY

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INTERNAL EXAMINER **EXTERNAL EXAMINER**

CERTIFICATE

I hereby certify that the work which is being presented in the B.Tech Project Report entitled "**Control And Estimation Of Voice Signal Using Adaptive Filter**", in partial fulfillment of the requirement for the award of the **Bachelor of Technology in Electronics and Communication Engineering** and submitted to the Department of Electronics & Communication Engineering of RVS College of Engineering & Technology, Jamshedpur (India) is an authentic record of my own work under the supervision of **Prof(Dr.) SHALINI KUMARI Asst. Prof. of ECE Department.**

The matter presented in this thesis has not been submitted by me for the award of any other degree elsewhere.

Name		Signature of Candidate
ABHISHEK KUMAR SIMRA	182308351233	…………………………...
ADITYA AMAN	182308351234	…………………………...
SUDHANSU GUPTA	182308351250	…………………………...

This is to certify that the above statement made by the candidate is correct to the best of my knowledge.

Date:

Signature of Head Of Department
Prof.(Dr.)RAKESH KUMAR
H.O.D

Signature of Guide
Prof(Dr.) SHALINI KUMARI
Asst. Prof. of ECE

Department of Electronics & Communication Engineering
RVS College of Engineering & Technology, Jamshedpur

INTERNAL **EXTERNAL**

DECLARATION

We declare that this written submission represents our ideas in our words and where other ideas or words have been included. We have adequately cited and referenced the original sources. We also declare that we have adhered to all principles of academic honesty and integrity and have not misrepresented or fabricated or falsified any idea/data/fact/source in our submission. We understand that any violation of the above will cause for disciplinary action by the Institute and can also evoke penal action from the sources which have thus not been properly cited or from whom proper permission has not been properly cited or from whom proper permission has not been taken when needed.

Name		Signature of Candidate
ABHISHEK KUMAR SIMRA	182308351233	…………………………...
ADITYA AMAN	182308351234	…………………………...
SUDHANSU GUPTA	182308351250	…………………………...

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Name		Signature of Candidate
ABHISHEK KUMAR SIMRA	182308351233	…………………………...
ADITYA AMAN	182308351234	…………………………...
SUDHANSU GUPTA	182308351250	…………………………...

ABSTRACT

An adaptive filter is a digital filter that can adjust its coefficients to give the best match to a given desired signal. When an adaptive filter operates in a changeable environment the filter coefficients can adapt in response to changes in the applied input signals. Adaptive filters depend on recursive algorithms to update their coefficients and train them to near the optimum solution. An everyday example of adaptive filters is in the telephone system where impedance mismatches causing echoes of a signal are a significant source of annoyance to the users of the system. The adaptive signal process is here to estimate and generate the echo path and compensate for it. To do this the echo path is viewed as an unknown system with some impulse response and the adaptive filter must mimic this response.

The effect of uncorrelated noises in primary and reference inputs, and presence of signal components in the reference input on the ANC performance is investigated. It is shown that in the absence of uncorrelated noises and when the reference is free of signal, noise in the primary input can be essentially eliminated without signal distortion. A configuration of the adaptive noise canceller that does not require a reference input and is very useful for many applications is also presented.

In this project, the adaptive algorithm using MATLAB & SIMULINK is implemented. The audio signal is taken from a source and noise is mixed in it, then the mixture of this is used as an input to the adaptive filter and a reference noice was also given in the adaptive filter, which was used to filter the audio signal. The adaptive filter step size was set to minimum to get the best result possible. The adaptive filter auto adjusts according to the step size set and filters the audio signal with reference to the noise signal provided.

Key words:

Adaptive noise cancellation (ANC), Least Mean square (LMS) Algorithm, Adaptive filtering and Normalized Least Mean Square (NLMS).

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LIST OF ABBREVIATIONS

ANC	**:**	**Adaptive Noise Cancellation**
LMS	**:**	**Least Mean Square**
NLMS	**:**	**Normalized Least Mean Square**
FXLMS	**:**	**Filtered-X Least Mean Square**
RLS	**:**	**Recursive Least Square**
FIR	**:**	**Finite Impulse Response**
IIR	**:**	**Infinite Impulse Response**
DSP	**:**	**Digital Signal Processing**

MOTIVATION

Noise has long been an enemy of human beings. It can disrupt communications, impair concentration, and even damage the auditory system if it is sufficiently loud. The traditional noise cancellation idea involves energy absorption: by strategically placing damping material close to the noise source, much of the sound energy can be converted to heat, therefore reducing the volume of the sound. The soft, porous, multi-layer material covering dance room and studio room walls can damp most of the energy of noise.

These methods are referred to as “passive noise cancellation”, since they only passively quarantine, or absorb, noise. The result can be ideal, since most foam can reduce the loudness by up to 35 dB. The weakness of this type of noise cancellation, however, is its scope. All sounds in the absorptive frequency range are reduced; if useful sound information is present, this information is filtered out as well. Passive noise cancellation also has a higher cost and requires more complicated instrument installation.

To deal with this problem, and to better cancel noise based on its characteristics (as opposed to general cancellation), people invented the idea of active noise control (ANC). Unlike passive noise cancellation, ANC involves playing “anti-noise”. Bose promotes this idea to the public, thus making ANC one of the hottest, most popular topics about “sound” these days

TO OUR READER

We are glad to have had an opportunity to share our knowledge with interested enthusiasts. In this book we have attempted to provide a brief compilation of our experiences in audio frequency & noise control in audio signal using MATLAB & SIMULINK.

Do not expect this book to be a panacea for all audio signal processing problems, rather you will have to sit and work for hours to get a functioning idea. Transform each failure into a stepping stone instead of stumbling over it. We appreciate the beauty of diamonds but little do we wonder how it becomes so bright? Its perseverance extending thousands of years transformed it into a present sparking state.

We plunge further into the field of vehicles with dedicated perseverance, make your own mistakes and gain valuable experience from them.

CHAPTER 1
INTRODUCTION

1. INTRODUCTION

An adaptive filter is a system with a linear filter that has a transfer function controlled by variable parameters and a means to adjust those parameters according to an optimization algorithm. Because of the complexity of the optimization algorithms, almost all adaptive filters are digital filters. Adaptive filters are required for some applications because some parameters of the desired processing operation (for instance, the locations of reflective surfaces in a reverberant space) are not known in advance or are changing. The closed loop adaptive filter uses feedback in the form of an error signal to refine its transfer function.

Adaptive noise control (ANC), also known as noise cancellation (NC), or active noise reduction (ANR), is a method for reducing unwanted sound by the addition of a second sound specifically designed to cancel the first. The concept was first developed in the late 1930s; later developmental work that began in the 1950s eventually resulted in commercial airline headsets with the technology becoming available in the late 1980s. The technology is now also used in road vehicles and in mobile telephones to suppress the noise from the surroundings.

The basic idea of an adaptive noise cancellation algorithm is to pass the corrupted signal through a filter that tends to suppress the noise while leaving the signal unchanged. This is an adaptive process, which means it does not require a priori knowledge of signal or noise characteristics. Adaptive noise cancellation (ANC) efficiently attenuates low frequency noise for which passive methods are ineffective. Although both FIR and IIR filters can be used for adaptive filtering, the FIR filter is by far the most practical and widely used. The reason being that FIR has adjustable zeros, and hence it is free of stability problems associated with adaptive IIR filters that have adjustable poles as well as zeros.

Adaptive Noise Cancellation (ANC) uses a noise-cancelling system to reduce unwanted background noise. The system is based on microphones that “listen” to the sounds outside and inside of the earphone, an ANC chipset inverting the soundwaves and a speaker inside the earphone cancelling the outside sound by the neutralising soundwaves. A bit like taking +2 outside and adding -2 inside to make zero.

Adaptive noise cancellation can be processed through the ANC chipset using either:

1) A feed-forward ANC system has a microphone which is placed on the outside of the earphone.

2) A feed-back ANC system has a microphone which is placed on the inside of the earphone.

3) A hybrid ANC system is a combination of a feed-forward and a feed-back ANC system.

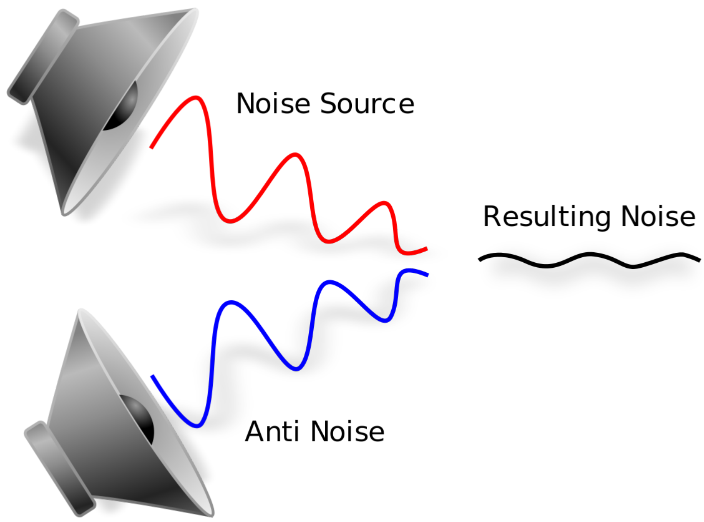

Figure 1.1 : Introduction of Noise

1.1 What is noise?

Audio noise reduction system is that kind of system which is helpful to remove the unwanted noise from speech signals. Audio noise reduction can be classified into two kinds. Complementary type and Non complementary type. Complementary type involves the compression of audio signal and proper way before recording. Non Complementary Type (single ended type) is an efficient technique to reduce the noise level which is present in source material already. Both analogue and digital devices have particular qualities that make them prone to noise. There is an active noise control (ANC) which is also called noise cancellation or active noise reduction (ANR) is a technique for reducing the unnecessary sound and that sound which is not processed, by addition of a second sound, specifically designed to cancel the existing one. sound is an analog signal that works on frequency, which comprises compression phase and rarefaction phase.

It's important to understand the distinction between noise and sound. Noise is a type of sound and is defined as unwanted, annoying, unpleasant or loud. Our ears are excellent at telling us what noise is. Most commonly, noise is an annoying tone that causes mild to major discomfort or irritation. These tones pierce through the background noise that accompanies our lives. When it comes to measuring the different types of noise, we want to replicate how the human ear interprets noise in order to get an accurate representation of its impact.

That's why we use something called the A-weighted frequency, which is much more sensitive between the 500 Hz and 6 kHz range. When noise has been measured in this way, you'll see dB(A). There's no single definition of audio noise, but in general, it's background sounds such as fans, people talking, cars or trucks driving by, buzz from faulty audio wires, or other ambient noises that shouldn't be in your video.

In this project, noise is defined as any kind of undesirable signal, whether it is borne by electrical, acoustic, vibration or any other kind of media. In this project, adaptive algorithms are applied to different kinds of noise.

1.2 The Four types of noise

1.2.1 Continuous noise

Continuous noise is exactly what it says on the tin: it's noise that is produced continuously, for example, by machinery that keeps running without interruption. This could come from factory equipment, engine noise, or heating and ventilation systems.

You can measure continuous noise for just a few minutes with a sound level meter to get a sufficient representation of the noise level. If you want to analyse the noise further, you need to look for a sound level meter with octave band analysis. Octave bands allow you to break the noise down into its separate frequencies. This information will tell you exactly what frequency is causing the noise. You may even want to investigate the noise with 1:3 octave bands, which can provide even more detail about the frequency content of the noise you're measuring.

1.2.2 Intermittent noise

Intermittent noise is a noise level that increases and decreases rapidly. This might be caused by a train passing by, factory equipment that operates in cycles, or aircraft flying above your house.

Intermittent noise, noise that stops and starts, is considered to be more annoying than continuous noise while the presence of audible tones (one frequency being heard above other frequencies, e.g., a high-pitched whine) also increases annoyance.

We measure intermittent noise in a similar way to continuous noise, with a sound level meter. However, you also need to know the duration of each occurrence and the time between each one. To gain a more reliable estimate of the noise level, you should measure over multiple occurrences to calculate an average. If you're using an integrating-averaging sound level meter, this will make the calculation for you and present this in terms of an LAeq.

1.2.3 Impulsive Noise

Impulsive noise is most commonly associated with the construction and demolition industry. These sudden bursts of noise can startle you by their fast and surprising nature. Impulsive noises are commonly created by explosions or construction equipment, such as pile drivers, or your next door neighbour doing some DIY on a Sunday morning.

To measure impulsive noise, you will need a sound level meter or a personal noise dosimeter that can calculate Peak values.

Don't forget that even in an environment that is usually quiet, a single very loud noise can cause hearing damage, which is why it's important to measure Peak levels alongside the average or Leq value. In most applications, Peak will be measured using the C-weighting, so you should make sure that your sound level meter provides this.

1.2.4 Low-frequency Noise

Low-frequency noise makes up part of the fabric of our daily soundscape. Whether it's the low background hum of a nearby power station or the roaring of large diesel engines, we're exposed to low-frequency noise constantly. It also happens to be the hardest type of noise to reduce at source, so it can easily spread for miles around.

For low-frequency noise, you should be using a sound level meter with third octave band analysis, so you can analyse the low frequencies that make up the noise. You may also need to look at the C-weighted measurements and compare this to the A-weighted measurements, as this can show how much low-frequency noise is present. If you're not sure what the different frequency weightings are, you can read more about them here.

If monitoring is taking place outside over a longer period, you may want to consider an environmental noise monitoring kit.

1.3 Need Of Clear Audio

"Can you hear me?", "What did you say?", are just some of the most common things you'll hear during virtual conference calls. As employees get used to spending a large chunk of their working hours remotely, there's a growing need for more virtual calls. The single biggest thing affecting most of these employees is the lack of good quality audio.

The justification for great audio is actually biological in nature. We have to work so much harder to understand someone when the sound quality is poor or choppy; and that work takes up brain power that needs to be devoted to understanding and absorbing the message, not just discerning the words. This unnatural, unnecessary work causes the listener to become fatigued during calls, and ultimately, less mentally alert during and after the call.

To understand the importance of good audio experience for businesses, EPOS conducted a survey to find out how employees feel audio impacts their day-to-day life. EPOS is a pioneer in offering the most advanced audio and collaboration technologies that empower companies to communicate in a highly efficient manner. The report highlights the current state of audio across different working environments across the globe.

1.4 Noise Cancellation types and settings

Your headphones can cancel noise in more ways than one. Pick the setting, mode or noise cancellation type that suits your commute or enhances your relaxation time.

- Passive Noise Cancellation uses well designed ear cups to seal out unwanted noise. This is used for both over-ear headphones and in-ear earphones where the earbud itself will keep surrounding noise out.
- Active Noise Cancellation uses microphones and speakers to reduce background and surrounding noises. This is the most known type and has mostly been used in over-ear headphones. Technology has become so small and battery efficient now that it can be used in true wireless in-ear earphones.
- Adaptive Active Noise Cancellation uses microphones and speakers to automatically adjust to your surroundings. This is the more sophisticated type of ANC where the level of noise cancelling digitally adapts to the surroundings.
- Adjustable Active Noise Cancellation lets you change how much background noise you hear by manually adjusting noise cancellation levels. This is useful when you want to have full control.
- Transparency Mode lets you easily tune back into the world around you, without switching off your music or taking your earphones out of your ears.
- Adjustable Transparency Mode lets you change how much of the outside world you want to pass through, without switching off your music.

1.5 Audio Processing / Noise Control

Audio Signal processing is a method where intensive algorithms, techniques are applied to audio signals. Audio signals are the representation of sound, which is in the form of digital and analog signals. Their frequencies range between 20 to 20,000 Hz, and this is the lower and upper limit of our ears. Analog signals occur in electrical signals, while digital signals occur in binary representations. This process encompasses removing unwanted noise and balancing the time-frequency ranges by converting digital and analog signals. It focuses on computational methods for altering the sounds. It removes or minimizes the overmodulation, echo, unwanted noise by applying various techniques into it.

The best way to fix noisy audio is to not have noisy audio to begin with. That means recording in an environment that's as quiet as possible. You don't need a professional recording studio to get great results, but you do want to pick the quietest room or area you can find. Then, you should get familiar with the typical ambient sounds in that area.

Noise reduction is the process of removing noise from a signal. Noise reduction techniques exist for audio and images. Noise reduction algorithms may distort the signal to some degree. All signal processing devices, both analog and digital, have traits that make them susceptible to noise.

Can you hear large trucks or other traffic from outside? What about the heating or air conditioner system? Can you hear the fan turning on and off? Can you hear colleagues or others talking in other rooms? Is there a buzz from the fluorescent lights?

Those are just a few of the kinds of noises that can show up on your voice over when you record.

Next, do a test recording of your room. You don't need to speak, but use the microphone you will use for your voice over recording. Record 10-20 seconds of the natural noise in the room.This is called recording your room tone.

Then, listen to your room tone recording in headphones. What can you hear that you can immediately eliminate?

For example, if you can hear the fan from your heating/cooling system, you could turn it off while you record. If you hear people talking in the background, you could (politely) ask them to move their conversation to a different area. You can turn off any buzzing lights if possible.

Your room tone recording will also help you reduce audio noise after you've recorded.

Your room tone recording can be a baseline for your audio software to remove noise.

1.6 A Brief Introduction to Adaptive filter

An *adaptive filter* is a digital filter that has self-adjusting characteristics. It is capable of adjusting its filter coefficients automatically to adapt the input signal via an adaptive algorithm. Adaptive filters play an important role in modern digital signal processing (DSP) products in areas such as telephone echo cancellation, noise cancellation, equalization of communications channels, biomedical signal enhancement, active noise control (ANC), and adaptive control systems. Adaptive filters work generally for the adaptation of signal-changing environments, spectral overlap between noise and signal, and unknown or time-varying noise. For example, when the interference noise is strong and its spectrum overlaps that of the desired signal, removing the interference using a traditional filter such as a notch filter with the fixed filter coefficients will fail to preserve the desired signal spectrum,

However, an adaptive filter will do the job. Note that adaptive filtering, with its applications, has existed more than two decades in the research community and is still active. This chapter introduces some fundamentals of the subject, adaptive finite impulse response (FIR) filters with a simple and popular least mean square (LMS) algorithm and recursive least squares (RLS) algorithm. Further exploration into adaptive infinite impulse response (IIR) filters, adaptive lattice filters, their associated algorithms and applications, and so on.To understand the concept of adaptive filtering, we will first look at an illustrative example of the simplest noise canceller to see how it works before diving into detail. The block diagram for such a noise canceller.

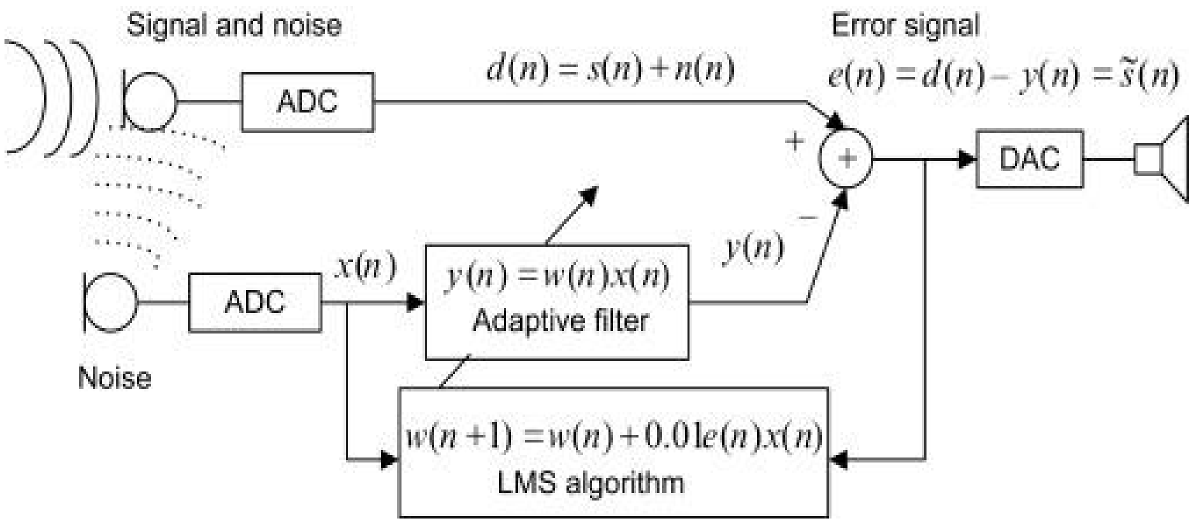

Figure 1.2 : Block Diagram of a Noise Canceller using Adaptive Filtering

An adaptive filter is defined by four aspects:

1. The signals being processed by the filter
2. The structure that defines how the output signal of the filter is computed from its input signal.
3. The parameters within this structure can be iteratively changed to alter the filter's input-output relationship.
4. The adaptive algorithm that describes how the parameters are adjusted from one time instant to the next.

Various applications of the ANC are studied including an in depth quantitative analysis of its use in canceling sinusoidal interferences as a notch filter, for bias or low-frequency drift removal and as Adaptive line enhancer. Other applications dealt qualitatively are use of ANC without a reference input for canceling periodic interference, adaptive self-tuning filter, antenna sidelobe interference canceling, cancellation of noise in speech signals, etc. Computer simulations for all cases are carried out using Matlab & Simulink software and experimental results are presented that illustrate the usefulness of Adaptive Noise Canceling Technique. By choosing a particular adaptive filter structure, one specifies the number and type of parameters that can be adjusted. The adaptive algorithm used to update the parameter values of the system can take on a myriad of forms and is often derived as a form of optimization procedure that minimizes an error criterion that is useful for the task at hand.

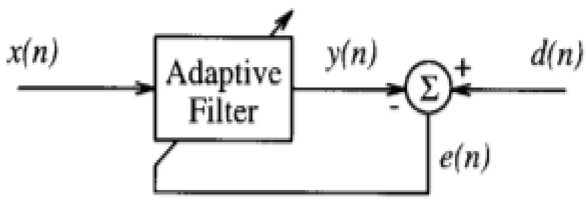

Figure 1.3 : Adaptive Filter Block Diagram

1.7 The Adaptive Filtering Problem

Figure shows a block diagram in which a sample from a digital input signal x(n) is fed into a device, called an adaptive filter, that computes a corresponding output signal sample y(n) at time n. For the moment, the structure of the adaptive filter is not important, except for the fact that it contains adjustable parameters whose values affect how y(n) is computed. The output signal is compared to a second signal d(n), called the desired response signal, by subtracting the two samples at time n. This difference signal, given by

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

is known as the error signal. The error signal is fed into a procedure which alters or adapts the parameters of the filter from time n to time (n + 1) in a well-defined manner. This process of adaptation is represented by the oblique arrow that pierces the adaptive filter block in the figure. As the time index n is incremented, it is hoped that the output of the adaptive filter becomes a better and better match to the desired response signal through this adaptation process, such that the magnitude of e(n) decreases over time. In this context, what is meant by “better” is specified by the form of the adaptive algorithm used to adjust the parameters of the adaptive filter. In the adaptive filtering task, adaptation refers to the method by which the parameters of the system are changed from time index n to time index (n + 1). The number and types of parameters within this system depend on the computational structure chosen for the system. We now discuss different filter structures that have been proven useful for adaptive filtering tasks.

1.8 Adaptive Noise Removal Approaches

In the present work, using the Audio signal mixed with noise and passing it through the filtering system and filtered output has been analyzed for different algorithms. There are so many algorithms used for noise removal techniques. In this thesis four different techniques have been used for the suppression process. These are LMS, NLMS, WIENER FILTER and RLS filter.

1.8.1 Introduction to LMS Algorithm Approach

The LMS algorithm was derived by Wisdrow and Hopf in 1959 in their study of a pattern recognition scheme known as adaptive linear element. This algorithm is amember of the stochastic gradient algorithms, [Poulankas (2006)]. There are many iterative search algorithms derived for minimizing the underlying cost function with the true statistics replaced by their estimate obtained in some manner, Gradient-based iterative methods.

(i) Method of Steepest Descent

This technique first developed by Riemann (1892) and is extremely useful for handling integrals of the form:

$$I(\lambda) = \int_C e^{\lambda p(z)} q(z)\, dz$$

where C is a contour in the complex plane and p(z),q(z) are analytic functions, and λ is taken to be real.(If λ is complex ie $\lambda = |\lambda|\, e^{i\alpha}$ we can absorb the exponential factor into p(z)). We require the behaviour of $I(\lambda)$ as $\lambda \to \infty$.

The basic idea of the method of steepest descent (or sometimes referred to as the saddle-point method), is that we apply Cauchy's theorem to deform the contour C to contours coinciding with the path of steepest descent. Usually these contours pass through points $z=z_0$ where $p'(z_0)=0$. As we will see on the steepest descent contours, $\Im(p(z))$ is constant and so we are left with integrals of the type which can be handled using Watson's lemma.

(ii) Newton's Method

The LMS algorithm is a linear adaptive altering algorithm, which, in general,consists of two basic processes: The filtering process,which involves computing the output of the adaptive filter in response to the vector input signal comparing this output with the desired response adaptive filtering algorithm, it generally consist two processes:

(i)A filtering process and

(ii)An adaptive process,

The combination of these two processes working together constitutes a feedback In the basic real form of the LMS algorithm, the tap weight update by mean of equation :

$$y(n)=\sum_{i=0}^{M-1} \hat{w}_i(n)u(n-1) \quad \ldots\ldots\ldots\ldots\ldots (1.1)$$

$$e(n)= d(n)-y(n) \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (1.2)$$

$$\hat{w}_i(n+1) = \hat{w}_i(n) + \mu u(n-1)e(n) \ldots\ldots (1.3)$$

e(n) is the error

d(n) is the desired output

y(n) is the filter output

$\hat{w}_i(n)$ is the tap weight

M is traversal tilter length and u is the step-size parameter. After a certain iteration the error signal becomes the actual signal required.

1.8.2 Normalized Least Mean Square algorithm approach

In structural terms the normalized LMS filter is exactly the same as the standard LMS filter. NLMS filter differ from LMS in the way in which the weight controller is mechanized.

Three kinds of tap weight iteration approach is taken in this algorithm

$$\hat{w}(n+1) = \hat{w}(n) + \frac{1}{\|u(n)\|^2} u(n)e^*(n) \quad \text{..........} \quad (1.4)$$

$$\hat{w}(n+1) = \hat{w}(n) + \frac{\hat{\mu}}{\|u(n)\|^2} u(n)e^*(n) \quad \text{.............} \quad (1.5)$$

$$\hat{w}(n+1) = \hat{w}(n) + \frac{\hat{\mu}}{a+\|u(n)\|^2} u(n)e^*(n) \text{........} \quad (1.6)$$

The rest approach is same as the LMS approach the fundamental equation is

$$\text{y(n)} = \sum_{i=0}^{M-1} \hat{w}_i(n) u(n-1) \text{ ....} (1.7)$$

$$\text{e(n)= d(n)-y(n) ....} (1.8)$$

Where e(n), y(n) and d(n) represents the same variables as in LMS algorithm that is,

e(n) is the error

d(n) is the desired output

y(n) is the filter output

ŵ(n) is the tap weight

1.8.3 Recursive Least Square Algorithm

In this algorithm, the cost function to be minimized as ε(n)

$$\varepsilon(\text{n}) = \sum_{i=1}^{n} \beta(\text{n, i}) |e(i)|^2 \text{ ....} (2.2)$$

where e(i) is the difference between desired response d(i) and the output y(i) produced by a traversal Filter whose lap Inputs equal:

$$u(i) = [u(i), u(i-1), \ldots\ldots\ldots, u(i-M+1)]^r$$

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

$$e(i) = d(i) - w^H(n)\, u(i) \text{...................................} (2.3)$$

The fundamental difference between RLS and LMS is that the step size parameter in the LMS algorithm is replaced by a matrix that is inverse of the correlation matrix of input vector u(n).

CHAPTER 2
Literature Review

2. LITERATURE REVIEW

In this chapter , a brief review of literature on speech signal characteristics , function of human ear and cochlea , cochlear implant , discrete wavelet transform , adaptive signal processing algorithms like LMS , NLMS , RLS and comparison for different adaptive algorithms for various values and voice activity detection algorithms are covered.

- Kuo S M and Morgan D.R (1999) in his review the Acoustic Noise Control traditionally involves passive methods such as enclosures, barriers and silencers to attenuate noise. These techniques use either the concept of impedance change or the energy loss due to sound absorbing materials. These methods are however not effective for low frequency noise. A technique to overcome this problem is Active Noise Cancellation (ANC), which is sound field modification by electracoustic means. ANC is an electro acoustic system that cancels the primary unwanted noise by introducing a canceling "antinoise" of equal amplitude but opposite phase, thus resulting in an attenuated residual noise signal as shown in Figure.

The design of ANC systems was first conceived in the 1930's by Lueg. In the ensuing years, ANC has been the focus of a lot of research. An overview can be found in the tutorial paper by Kuo and Morgan and also in the book by the same authors. ANC systems are based either on feedforward control where a coherent reference noise input is sensed or feedback control where the controller does not have the benefit of a reference signal. Further, ANC systems are classified based on the type of noise they attempt to cancel as either broadband or narrowband. A brief

overview of the various approaches to ANC follows next.

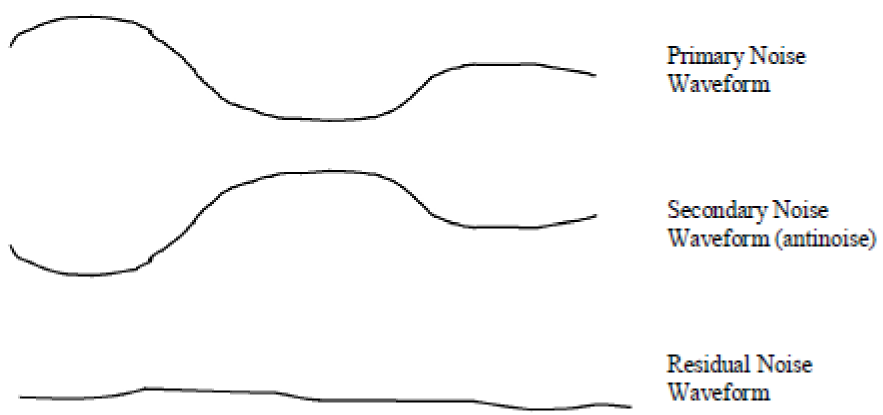

Figure 2.1 : Physical concept of Active Noise Control

2.1 Broadband feed-forward Active Noise Control

- Diniz P.S.R. (2002) in his book, the systems that have a single secondary source, a single reference sensor and a single error sensor. The single channel duct acoustic ANC system shown in Figure 2.2 is an example of such a system

This basic broadband ANC system can be described as an adaptive system identification framework as shown in Figure 2.3. Essentially, an adaptive filter W (z) is used to estimate an unknown plant P(z) which consists of the acoustic response from the reference sensor to the error sensor. The objective of the adaptive filter W (z) is to minimize the residual error signal e(n).

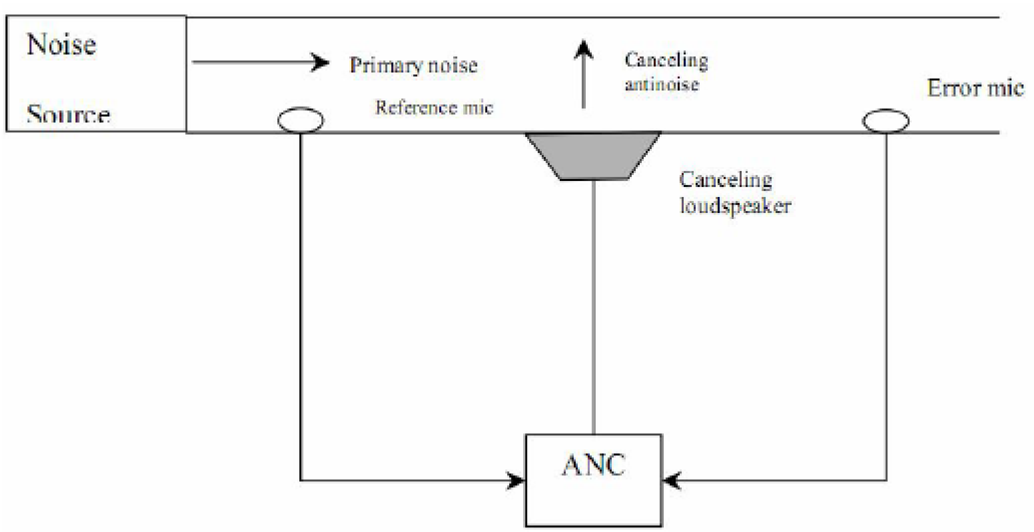

Figure 2.2 : Single channel broadband feedforward Active Noise Control.

However, the main difference from the traditional system identification scheme is the use of an acoustic summing junction instead of the subtraction of electrical signals. Therefore it is necessary to compensate for the secondary path transfer function S(z) from the output of the adaptive filter till the point where the error signal gets recorded.

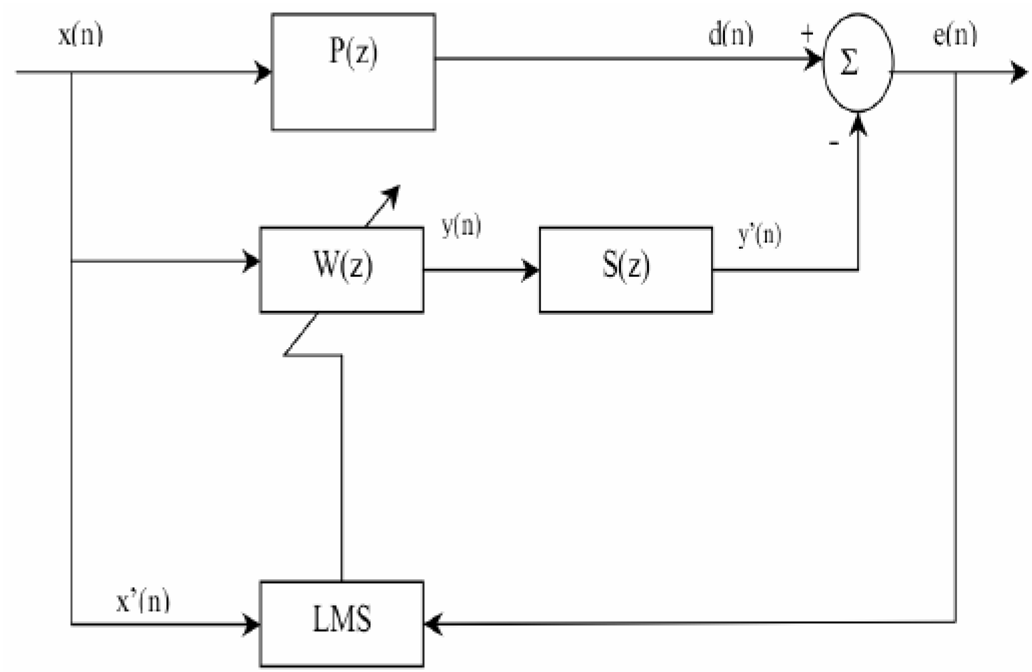

Figure 2.3 : System identification view of ANC

From Figure 2.3, we see that the z transform of the error signal is given by

$$E(z) = X(z)[P(z)-S(z)W(z)] \qquad 2.1$$

Assuming that after convergence of the adaptive filter, the error signal is zero, W(z) is required to realize the optimal transfer function

$$W(z) = P(z) / S(z) \qquad 2.2$$

The introduction of the secondary path transfer function in a system using the standard LMS algorithm leads to instability. This is because it is impossible to compensate for the inherent delay due to S(z) if the primary path P(z) does not contain a delay of equal length. Also, a very large FIR filter would be required to effectively model 1/S(z). This can be solved by placing an identical filter in the reference signal path to the weight update of the LMS equation. This is known as the filtered-X LMS algorithm. The block diagram of an ANC system using the FXLMS algorithm is shown in Figure 2.4.

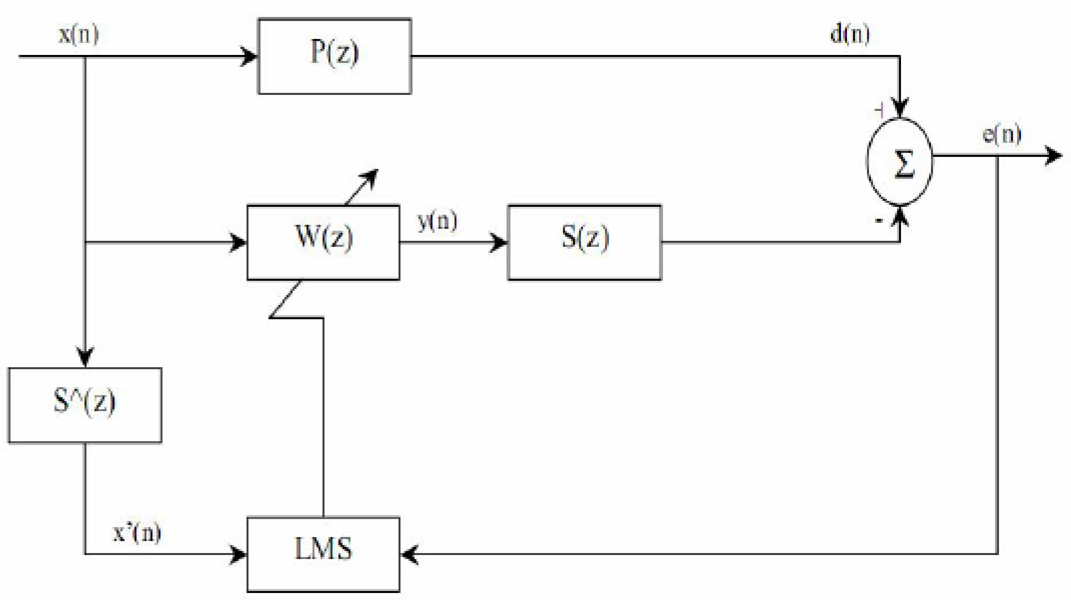

Figure 2.4 : ANC system using the FXLMS algorithm

A rudimentary explanation of the FXLMS algorithm is presented below. In figure 2.4, the residual error signal can be expressed as

$$E(n) = d(n) - s(n)*[\mathbf{w}^T(n)\mathbf{x}(n)] \qquad 2.3$$

Where s(n) is the impulse response of the secondary path S(z) at time n. Assuming a mean square cost function $\xi(n) = E[e^2(n)]$, the adaptive filter minimizes the instantaneous square error $\hat{\xi}(n) = e^2(n)$ according to

$$\mathbf{w}(n+1) = \mathbf{w}(n) - \frac{\mu}{2}\nabla\hat{\xi}(n) \qquad 2.4$$

Since

$$\nabla\hat{\xi}(n) = -2\mathbf{x}'(n)e(n) \qquad 2.5$$

The weight update equation reduces to

$$W(n+1) = W(n) + \mu X'(n)e(n) \tag{2.6}$$

In practical applications, the secondary path transfer function S(z) is unknown and must be estimated by an additional filter $\hat{S}(z)$. Therefore, x'(n) = $\hat{S}(z)$ * x(n), where $\hat{S}(z)$ is the impulse response of $\hat{S}(z)$. As shown by Morgan, the FXLMS algorithm seems to be remarkably tolerant to errors in the estimation of S(z) by the filter S(z) and within the limit of slow adaptation, the algorithm will converge with nearly 90% of phase error between S(z) and S(z). Therefore, offline modeling techniques can be used to model S(z). Nelson and Elliot showed that the maximum

step size that can be used with the FXLMS algorithm is given by

$$\mu_{\max} = \frac{1}{P_x'(L+\Delta)} \tag{2.7}$$

Where Px' = E[x'2(n)] is the power of the filtered reference signal and Δ is the number of samples corresponding to the overall delay in the secondary path. However, errors in estimating the secondary path transfer function will alter the stability bounds on ∞. A detailed analysis of the stability criterion is available in the literature.

In the feed-forward ANC system shown in Figure 2.3, the anti-noise output of the speaker also radiates upstream to the reference microphone resulting in acoustic feedback and hence a corrupted reference signal x(n). Instability will occur if the open loop phase lag reaches 180 and the gain is greater than unity. This can be solved by using a separate offline adaptive feedback cancellation filter within the ANC system. Feedback can also be solved by using an adaptive IIR filter in place of the FIR filter in the ANC system. However, IIR filters are not unconditionally stable, as adaptation may converge to a local minimum and can have relatively slow convergence rates. A detailed analysis of adaptive IIR filters is available in the literature.

2.2 Narrowband Feed-forward ANC

- Boucher C, Elliott S J and Nelson P A, (1990), proceeding article discussed, many noise sources are periodic in nature such as engines, compressors, motors, fans, etc. In such cases, direct observation of the mechanical motion using an appropriate sensor is used to provide an electrical reference signal which consists of the primary frequency and all the harmonics of the generated noise. The basic block diagram is as shown in Figure 2.5.

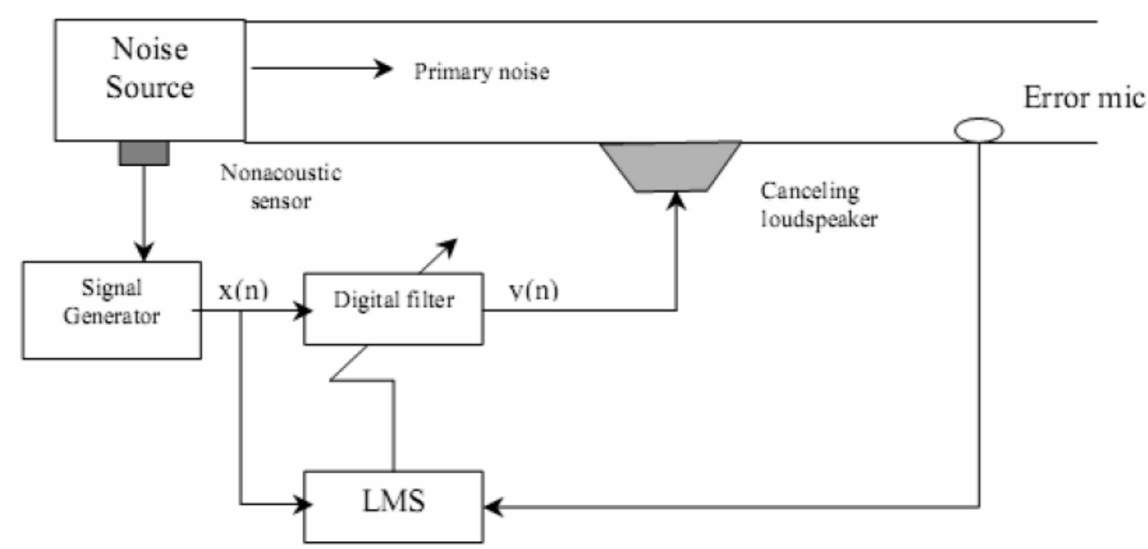

Figure 2.5 : Narrowband feedforward ANC system.

This technique avoids the undesired acoustic feedback to the reference sensor, as well as nonlinearities and aging problems with acoustic microphones. The periodicity of the noise removes the causality constraint, as each harmonic can be controlled independently and a much shorter FIR filter can be used to model the secondary path.

2.3 Feedback Active Noise Control

- Vijayan D (1994) in his research thesis discussed, the Feed forward ANC systems (broadband and narrowband) use a reference sensor to measure the primary noise signal, a feed forward adaptive filter and an error sensor to measure the residual error signal. However, in some applications, it is not feasible to have a sensor to measure or internally generate the error signal. This section describes a class of algorithms known as feedback ANC in which the reference signal is generated from the output of the error sensor. This is used in applications that combat spatially incoherent noise generated from turbulence, noise generated from many sources and propagation path induced resonance where no coherent reference signal is available.

- The technical article on ‘A Comparison of Noise Reduction Techniques for Speech Recognition in Telecommunications Environments’ shows how human speech carries different two types of sounds like voiced sound and unvoiced sound. The production and characteristics of the acoustic speech signal upon which recognition systems operate is well understood and can be modeled quite accurately. Paper also shows the physiology of the human vocal tract imposes articulatory constraints on the range of sounds which may be generated. The sounds may be classified according to their excitation .

- The research article on ‘A novel approach for single microphone active noise cancellation’ presents a novel approach for subband feedback Active Noise Control . This paper presents a time domain algorithm for single sensor subband feedback ANC using relatively short fixed FIR filters to do the subband processing. The adaptive coefficients in the system are updated using a weight constrained NLMS algorithm for feedback ANC. The proposed subband algorithm had a significant performance advantage over the traditional single band ANC algorithm in terms of the rate of convergence and the noise attenuation that could be obtained .

- The research paper on ‘On the convergence behavior of the LMS and the normalized LMS algorithms’ shows how it’s happened that for the designing of filter very less knowledge of input is available , normalized LMS algorithm is potentially faster converging algorithm compared to LMS algorithm. Paper also describes the response of the NLMS can be speeded up by using time varying step size. By white noise arbitrary input here prior information of the signal can be also predicted

- The technical article on ’ Principles Of Adaptive Noise Canceling ‘ shows the basic concept of the LMS (Least-Mean-Square) algorithm to develop an adaptive filter that can be used in ANC (Adaptive Noise Cancellation) applications. The method uses a noisy signal as primary input and a reference input that consists of noise correlated in some unknown way with the primary noise. By adaptively filtering and subtracting the reference input from the primary input, the output of the adaptive filter will be the error signal, which acts as a feedback to the adaptive filter. With this setup, the adaptive filter will be able to cancel the noise and obtain a less noisy signal estimate

- The research article on ‘Real time background noise cancellation in end user devices suggests that intolerable noise has always been undesirable in end user communication devices. This is evident for instance during a cricket commentary by the noise of the crowd, or while conversing on a cell phone if the speaker at the other end is on a busy road or any such environment. Proposed paper provides a real time noise cancellation in end user devices using correlation between first primary noisy speech and reference speech in the LMS background

CHAPTER 3

Hardware And Software

3. HARDWARE AND SOFTWARE

3.1 System/Hardware Requirements - Release 2020a - Windows

Operating Systems

• Windows 10 (version 1709 or higher)

• Windows 7 Service Pack 1

• Windows Server 2019

• Windows Server 2016

Processors

Minimum: Any Intel or AMD x86-64 processor

Recommended: Any Intel or AMD x86-64 processor with four logical cores and AVX2 instruction set support

Disk

Minimum: 30 GB of HDD space for MATLAB

Recommended: An SSD is recommended of 500 GB or a 1TB HDD

A full installation of all MathWorks products may take up to 31 GB of disk space

RAM

Minimum: 4 GB

Recommended: 8 GB For Polyspace, 4 GB per core is recommended

Graphics

No specific graphics card is required.

Hardware accelerated graphics card supporting OpenGL 3.3 with 1GB GPU memory is recommended. GPU acceleration using the Parallel Computing Toolbox requires a GPU that supports CUDA 3 or newer.

3.2 Software Requirements

Simulink Product Description

Simulation and Model-Based Design

Simulink® is a block diagram environment for multi domain simulation and Model-Based Design. It supports system-level design, simulation, automatic code generation, and continuous test and verification of embedded systems. Simulink provides a graphical editor, customizable block libraries, and solvers for modeling and simulating dynamic systems. It is integrated with MATLAB®, enabling you to incorporate MATLAB algorithms into models and export simulation results to MATLAB for further analysis.

Key Features

- Graphical editor for building and managing hierarchical block diagrams
- Libraries of predefined blocks for modeling continuous-time and discrete-time systems
- Simulation engine with fixed-step and variable-step ODE solvers
- Scopes and data displays for viewing simulation results
- Project and data management tools for managing model files and data
- Model analysis tools for refining model architecture and increasing simulation speed
- MATLAB Function block for importing MATLAB algorithms into models
- Legacy Code Tool for importing C and C++ code into models

Simulink is a simulation and model-based design environment for dynamic and embedded systems, integrated with MATLAB. Simulink, also developed by MathWorks, is a data flow graphical programming language tool for modelling, simulating and analyzing multi-domain dynamic systems. It is basically a graphical block diagramming tool with a customizable set of block libraries.

It allows you to incorporate MATLAB algorithms into models as well as export the simulation results into MATLAB for further analysis.

Simulink supports −

- System-level design
- Simulation
- Automatic code generation
- Testing and verification of embedded systems

There are several other add-on products provided by MathWorks and third-party hardware and software products that are available for use with Simulink.

CHAPTER 4
Project Approach

4. PROJECT APPROACH

The usual method of estimating a signal corrupted by additive noise is to pass it through a filter that tends to suppress the noise while leaving the signal relatively unchanged i.e. direct filtering.

Figure 4.1 : General Filter Block Diagram

The design of such filters is the domain of optimal filtering, which originated with the pioneering work of Wiener and was extended and enhanced by Kalman, Bucy and others.

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

1. Fixed filters - The design of fixed filters requires a priori knowledge of both the signal and the noise, i.e. if we know the signal and noise beforehand, we can design a filter that passes frequencies contained in the signal and rejects the frequency band occupied by the noise.

2. Adaptive filters - Adaptive filters, on the other hand, have the ability to adjust their impulse response to filter out the correlated signal in the input. They require little or no a priori knowledge of the signal and noise characteristics. (If the signal is narrowband and noise broadband, which is usually the case, or vice versa, no a priori information is needed; otherwise they require a signal (desired response) that is correlated in some sense to the signal to be estimated.) Moreover adaptive filters have the capability of adaptively tracking the signal under non-stationary conditions.

Noise Cancellation is a variation of optimal filtering that involves producing an estimate of the noise by filtering the reference input and then subtracting this noise estimate from the primary input containing both signal and noise.

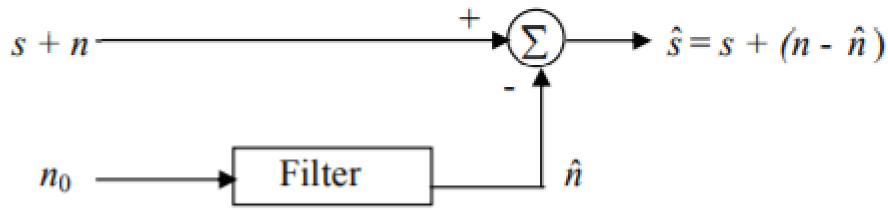

Figure 4.2 : Noise Cancelling Filter Block Diagram

It makes use of an auxiliary or reference input which contains a correlated estimate of the noise to be cancelled. The reference can be obtained by placing one or more sensors in the noise field where the signal is absent or its strength is weak enough.

Subtracting noise from a received signal involves the risk of distorting the signal and if done improperly, it may lead to an increase in the noise level. This requires that the noise estimate ˆn should be an exact replica of n. If it were possible to know the relationship between n and nˆ , or the characteristics of the channels transmitting noise from the noise source to the primary and reference inputs are known, it would be possible to make nˆ a close estimate of n by designing a fixed filter. However, since the characteristics of the transmission paths are not known and are unpredictable, filtering and subtraction are controlled by an adaptive process. Hence an adaptive filter is used that is capable of adjusting its impulse response to minimize an error signal, which is dependent on the filter output. The adjustment of the filter weights, and hence the impulse response, is governed by an adaptive algorithm. With adaptive control, noise reduction can be accomplished with little risk of distorting the signal. Infact, Adaptive Noise Canceling makes possible the attainment of noise rejection levels that are difficult or impossible to achieve by direct filtering.

The error signal to be used depends on the application. The criteria to be used may be the minimization of the mean square error, the temporal average of the least squares error etc. Different algorithms are used for each of the minimization criteria e.g. the Least Mean Squares (LMS) algorithm, the Recursive Least Squares (RLS) algorithm etc. To understand the concept of adaptive noise cancellation, we use the minimum mean-square error criterion. The steady-state performance of adaptive filters based on the mmse criterion closely approximates that of fixed Wiener filters. Hence, Wiener filter theory (App.I) provides a convenient method of mathematically analyzing statistical noise canceling problems. From now on, throughout the discussion (unless otherwise stated), we study the adaptive filter performance after it has converged to the optimal solution in terms of unconstrained Wiener filters and use the LMS adaptive algorithm (App.IV) which is based on the Weiner approach.

4.1 Adaptive Noise Cancellation – Principles

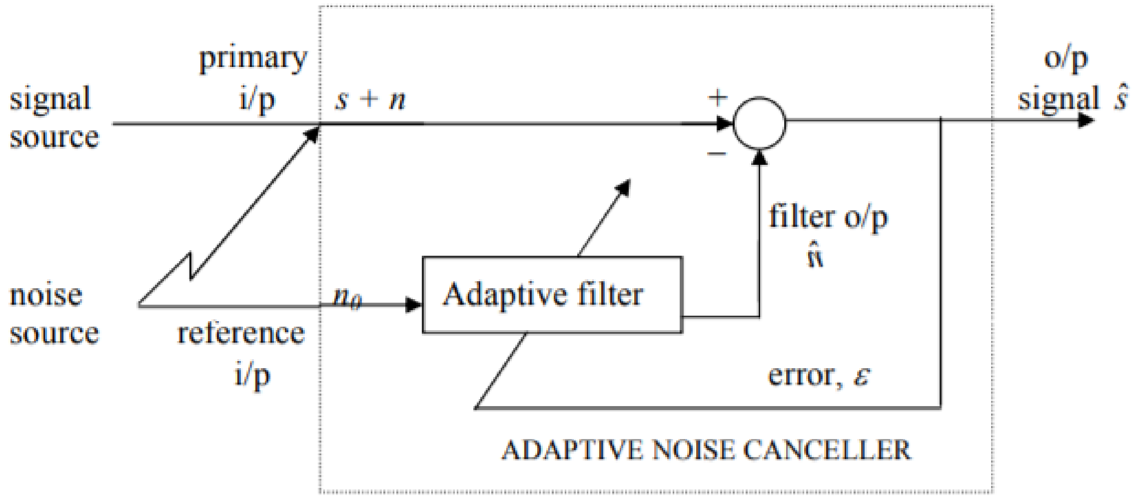

Figure 4.3 : Adaptive Noise Canceller

As shown in the figure, an Adaptive Noise Canceller (ANC) has two inputs – primary and reference. The primary input receives a signal s from the signal source that is corrupted by the presence of noise n0 uncorrelated with the signal. The reference input receives a noise n0 uncorrelated with the signal but correlated in some way with the noise n. The noise no passes through a filter to produce an output ˆn that is a close estimate of primary input noise. This noise estimate is subtracted from the corrupted signal to produce an estimate of the signal at sˆ , the ANC system output.

In noise canceling systems a practical objective is to produce a system output sˆ = s + n – nˆ that is a best fit in the least squares sense to the signal s. This objective is accomplished by feeding the system output back to the adaptive filter and adjusting the filter through an LMS adaptive algorithm to minimize total system output power. In other words the system output serves as the error signal for the adaptive process.

Assume that s, n0, n1 and y are statistically stationary and have zero means. The signal s is uncorrelated with n0 and n1, and n1 is correlated with n0.

$$s\hat{} = s + n - n\hat{}$$

$$\Rightarrow s\hat{}\ 2 = s\ 2 + (n - n\hat{}\ )\ 2 + 2s(n - n\hat{}\ )$$

Taking expectation of both sides and realizing that s is uncorrelated with n_0 and $\hat{n}$,

$$E[\hat{s}^2] = E[s^2] + E[(n - \hat{n})^2] + 2E[s(n - \hat{n})]$$

$$= E[s^2] + E[(n - \hat{n})^2]$$

The signal power $E[s^2]$ will be unaffected as the filter is adjusted to minimize $E[\hat{s}^2]$.

$$\Rightarrow \min E[\hat{s}^2] = E[s^2] + \min E[(n - \hat{n})^2]$$

Thus, when the filter is adjusted to minimize the output noise power $E[\hat{s}^2]$, the output noise power $E[(n - \hat{n})^2]$ is also minimized. Since the signal in the output remains constant, therefore minimizing the total output power maximizes the output signal-to-noise ratio.

Since

$$(\hat{s} - s) = (n - \hat{n})$$

This is equivalent to causing the output $\hat{s}$ to be a best least squares estimate of the signal s.

4.2 The Least-Mean-Square (LMS) Algorithm

The least-mean-square (LMS) algorithm as an application of the method of stochastic gradient descent that was presented in the preceding chapter. Specifically, we will expand on why the LMS algorithm is of fundamental importance in linear adaptive filtering in theory as well as application.

We begin the chapter with a signal-flow graph representation of the LMS algorithm, which clearly exhibits the fact that the LMS algorithm is basically a nonlinear feedback control system. With feedback known to be a "double-edged sword," it can work for us or against us. It is not surprising, therefore, to find that with the control mechanism being directly dependent on how the step-size parameter, m, is chosen. This parameter plays a critical role in assuring convergence of the algorithm (i.e., its stability when viewed as a feedback control system) or in failing to do so.

The study of convergence is carried out under the umbrella of statistical learning theory of the LMS algorithm, which occupies a good part of the chapter. Although, indeed, the LMS algorithm is simple to formulate, its mathematical analysis is very difficult to carry out. Nevertheless, ideas related to efficiency of the algorithm that are derived from this theory are supported through the use of Monte Carlo simulations.

For convenience of presentation, we reproduce the LMS algorithm summarized in

$$y(n) = \hat{\mathbf{w}}^{\mathrm{H}}(n)\mathbf{u}(n),$$
$$e(n) = d(n) - y(n),$$

$$\hat{\mathbf{w}}(n+1) = \hat{\mathbf{w}}(n) + \mu\mathbf{u}(n)e^{*}(n),$$

where,

u(n) is the input vector (regressor),

d(n) is the corresponding desired response, and

ŵ(n) is an estimate of the unknown tap-weight vector, w(n), of the linear multiple regression model used to represent the environment from which u(n) and d(n) are jointly picked.

The superscript H denotes Hermitian transposition (i.e., transposition combined with complex conjugation), and the asterisk denotes complex conjugation.

$$\begin{pmatrix}\text{updated}\\\text{tap-weight}\\\text{vector}\end{pmatrix} = \begin{pmatrix}\text{old}\\\text{tap-weight}\\\text{vector}\end{pmatrix} + \begin{pmatrix}\text{learning-}\\\text{rate}\\\text{parameter}\end{pmatrix} \times \begin{pmatrix}\text{tap-}\\\text{input}\\\text{vector}\end{pmatrix} \times \begin{pmatrix}\text{error}\\\text{signal}\end{pmatrix}.$$

$$w(n+1)=w(n)+\mu * x(n) * e(n)$$

Where ,

w(n+1)= Updated tap-weight vector

μ= Learning rate parameter (step size)

x(n)= Tap- input vector (filter input)

e(n)= Error signal

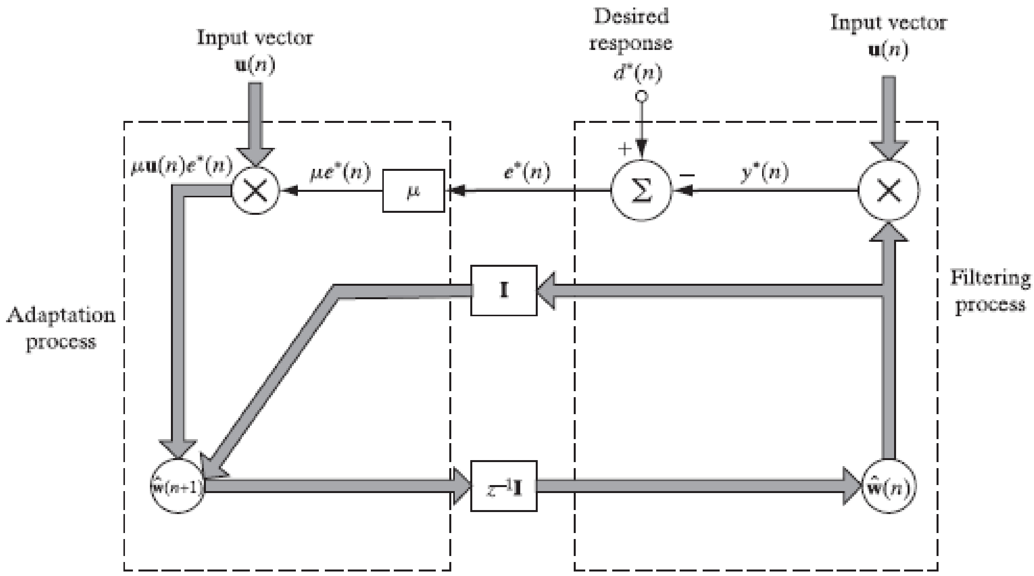

Figure 4.4 : Signal-Flow graph representation of the LMS algorithm, where I is the identity matrix and z^{-1} is the unit-time delay operator

Given this set of equations, we may construct a signal-flow graph of the LMS algorithm as shown in Fig . Based on this diagram, we see that the LMS algorithm embodies two basic processes that continually build on each other:

4.2.1 Filtering process

This first process involves two operations:

- One computing the output, y*(n), of the finite-duration impulse response (FIR) filter within the algorithm, in response to the input signal u(n), and
- The other one generating the estimation error, e*(n), by subtracting y*(n) from d*(n).

4.2.2 Adaptation process

This second process involves updating the present value of the estimated weight vector ŵ(n) by an "incremental" amount equal to the product term μu(n)e*(n) to produce ŵ (n + 1), where the incrementality is assured by choosing a small value for the step-size parameter, m.

These two processes are identified on the right- and left-hand sides of Fig, respectively.
1 Henceforth, each complete cycle of the LMS algorithm is referred to as an adaptation cycle.

From Fig. , we readily find that: Computational complexity of the LMS algorithm scales linearly with dimensionality of the estimate ŵ(n).

4.3 Normalized Least-Mean-Square (NLMS) Algorithm

In the traditional form of a least-mean-square (LMS) algorithm the adjustment applied to the tap-weight vector of the filter at adaptation cycle n + 1 consists of the product of three terms:

• The step-size parameter μ, which is under the designer's control.

• The tap-input vector u(n), which is supplied by a source of information.

• The estimation error e(n) for real-valued data, or its complex conjugate e*(n) for complex-valued data, which is calculated at adaptation cycle n.

The adjustment is directly proportional to the tap-input vector u(n). Therefore, when u(n) is large, the LMS algorithm suffers from a gradient noise amplification problem. To overcome this difficulty, we may use the normalized LMS algorithm.1 In particular, the adjustment applied to the tap-weight vector at adaptation cycle n + 1 is "normalized" with respect to the squared Euclidean norm of the tap-input vector u(n) at adaptation cycle n—hence the term "normalized."

In structural terms, the normalized LMS algorithm is exactly the same as the traditional LMS algorithm, as shown in the block diagram of Fig . Both adaptive filtering algorithms are built around a finite-duration impulse response (FIR) filter, but differ only in the way in which the weight controller is mechanized. The M-by-1 tap-input vector u(n) produces an output y(n) that is subtracted from the desired response d(n) to produce the estimation error, or error signal, e(n). In response to the combined action of the input vector u(n) and error signal e(n), the weight controller applies a weight adjustment to the FIR filter. This sequence of events is repeated for a number of adaptation cycles until the filter reaches a steady state.

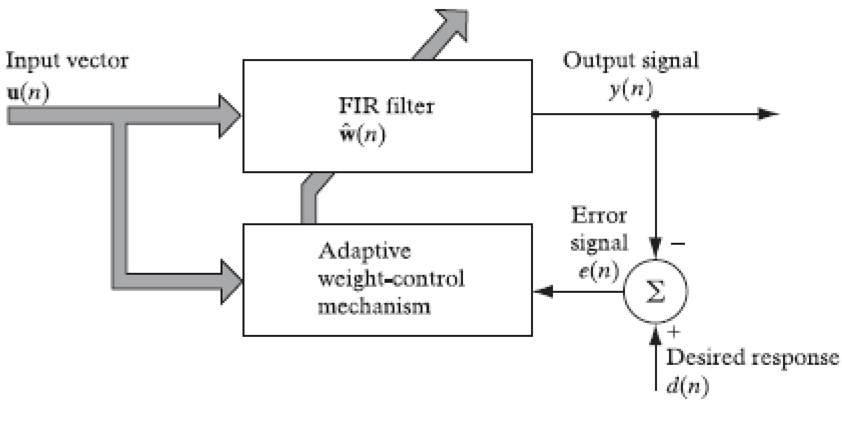

Figure 4.5 : Block diagram of adaptive FIR filter

The normalized LMS algorithm is a manifestation of the principle of minimal disturbance, which may be stated as follows:

From one adaptation cycle to the next, the weight vector of an adaptive filter should be changed in a minimal manner, subject to a constraint imposed on the updated filter's output.

To cast this principle in mathematical terms, let $\hat{w}(n)$ denote the old weight vector of the filter at adaptation cycle n and $\hat{w}(n + 1)$ denote its updated weight vector at adaptation cycle n + 1. We may then formulate the criterion for designing the normalized LMS algorithm as that of constrained optimization: Given the tap-input vector u(n) and desired response d(n), determine the updated tap-weight vector $\hat{w}(n + 1)$ so as to minimize the squared Euclidean norm of the change,

$$\delta\hat{\mathbf{w}}(n+1) = \hat{\mathbf{w}}(n+1) - \hat{\mathbf{w}}(n),$$

subject to the constraint

$$\hat{\mathbf{w}}^{\mathrm{H}}(n+1)\mathbf{u}(n) = d(n),$$

where the superscript H denotes Hermitian transposition (i.e., the operation of transposition combined with complex conjugation).

A general form of the adaptive filter is illustrated in Fig . where d(n) is a desired response (or primary input signal), y(n) is the actual output of a programmable digital filter driven by a reference input signal x(n), and the error e(n) is the difference between d(n) and y(n). The function of the adaptive algorithm is to adjust the digital filter coefficients to minimize the mean-square value of e(n). A technique to adjust the convergence speed is the Normalized LMS (NLMS) algorithm. The NLMS is shown as follows:

$$w(n + 1) = w(n) + \mu(n)x(n)e(n)$$

$\mu(n)$ is the adaptive step size which is calculated from the power and the step size of the filter.

CHAPTER 5
Experimental Results

5. EXPERIMENTAL RESULTS

Performance Analysis of the LMS and NLMS Algorithm

5.1 Simulation using LMS filter Approach

Simulation block for LMS shown in the figure 5.1, the input signal is actual audio signal and a actual noise from the surrounding is inserted and is passed through a digital filter and both the signal are mixed together. The noised mixed audio signal is inserted in the input port of the LMS filter and the filtered noise signal is given to the desired port of the filter.

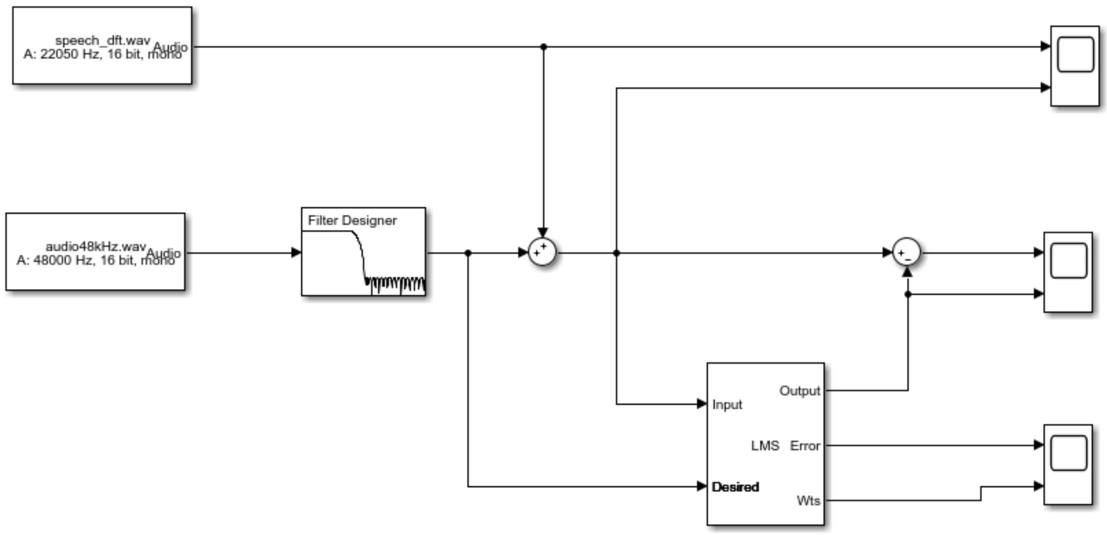

Figure 5.1 : LMS Simulation Block

Filter length:10

Step Size :0.1

Respective results using LMS filter are:

Fig. 5.2 Shows the original audio signal which is used for the project , the original audio signal is free from all kind of noise and is fully understandable.

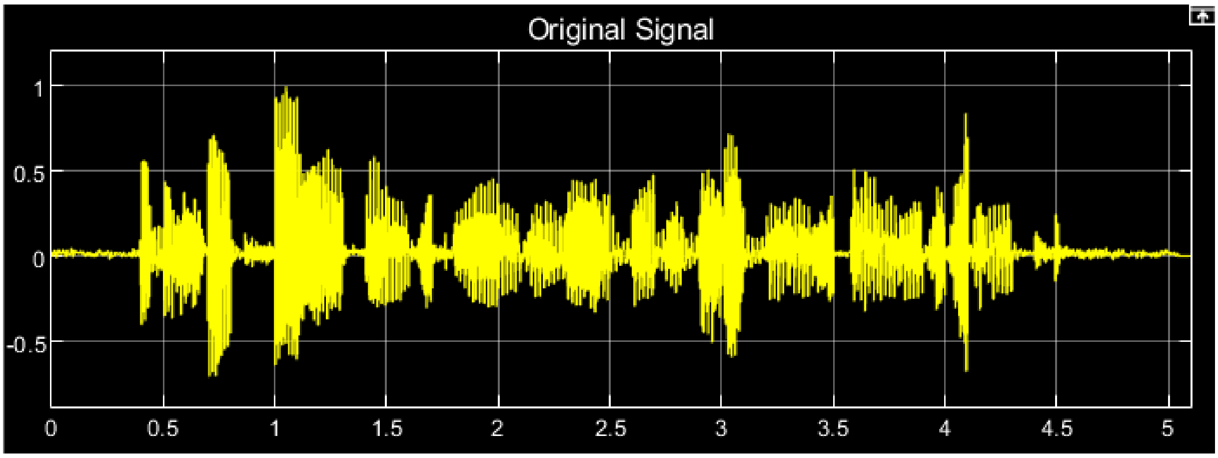

Figure5.2 : LMS Simulation Original audio signal

Fig. 5.3 Shows the audio signal in which the noise was mixed and the audio signal was corrupted and was made unclear to understand and makes it diffucult to understand.

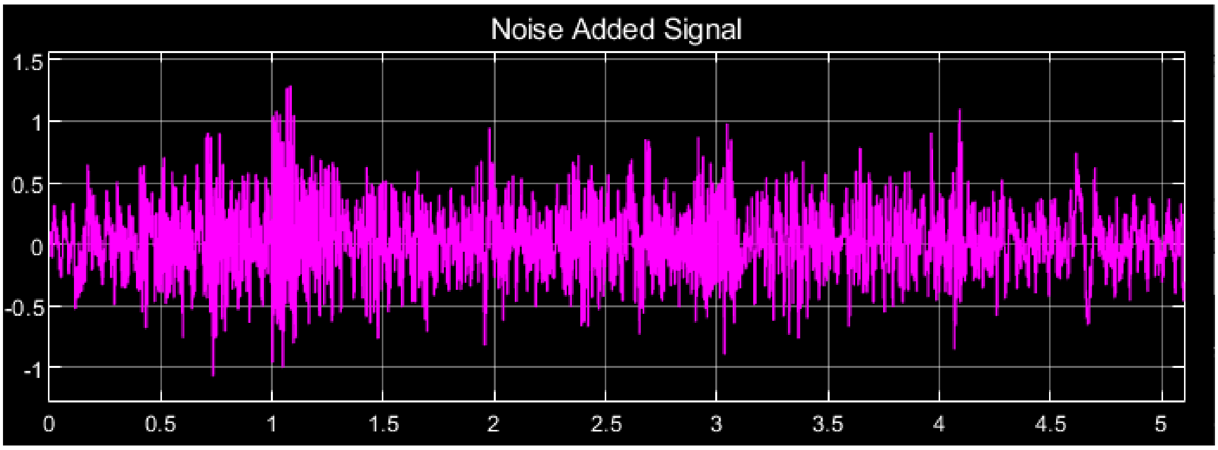

Figure5.3 : LMS Simulation Noise Added signal

Fig. 5.4 Shows the recovered audio signal filtered from the lms filter , the signal is filtered and noise is removed.

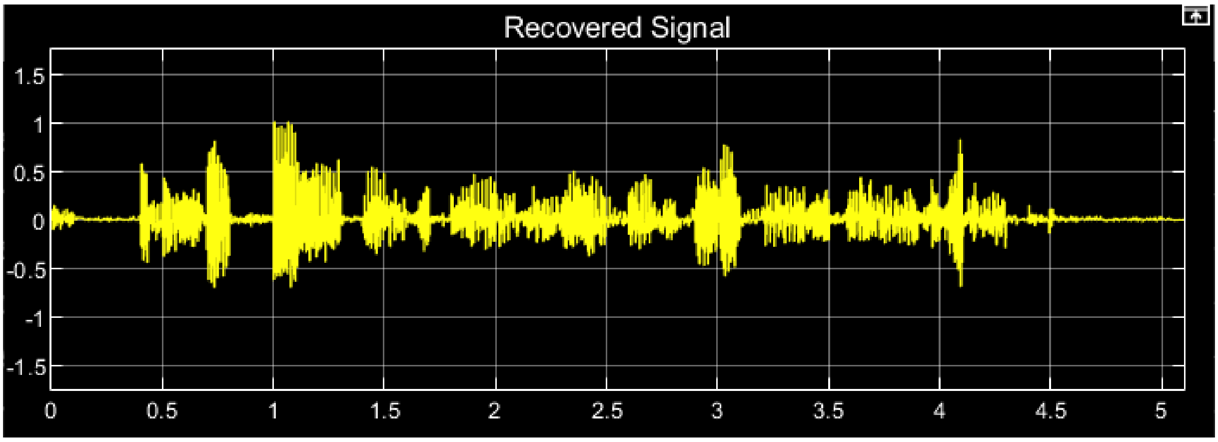

Figure5.4 : LMS Simulation Recovered signal

Fig. 5.5 Shows the separated noise signal filtered from the lms filter , it is the noise signal which was added to the audio signal to make it unclear to hear.

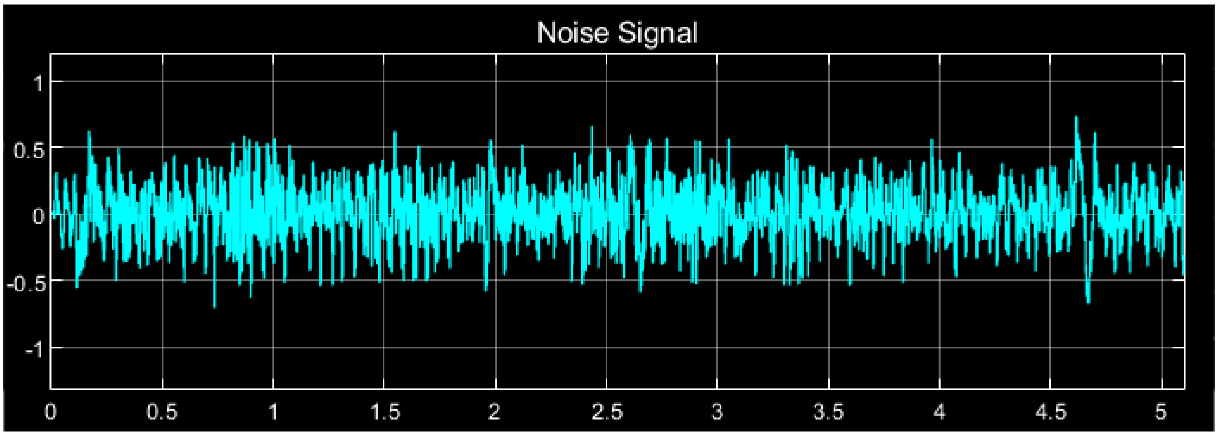

Figure5.5 : LMS Simulation Noise signal

Fig. 5.6 Shows the Error signal filtered from the lms filter .

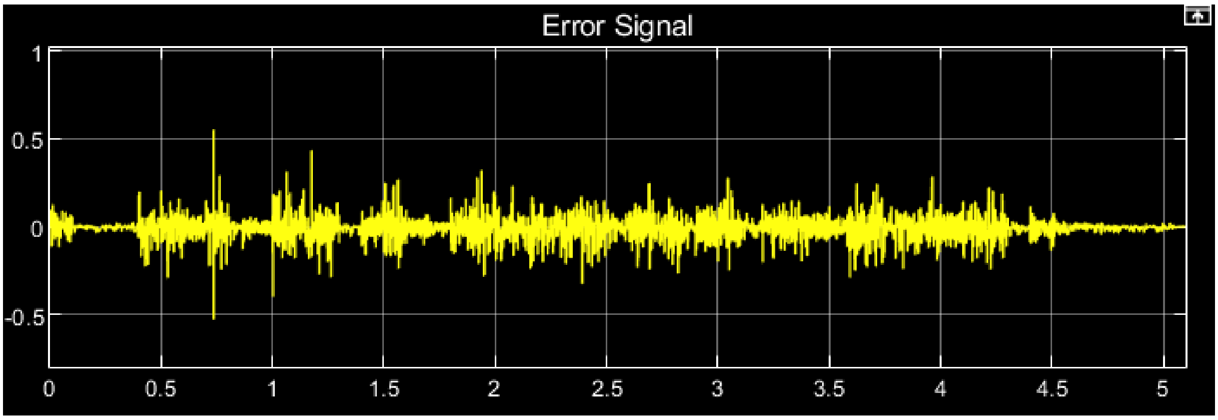

Figure5.6 : LMS Simulation Error signal

Fig. 5.7 Shows the weights of the lms filter .

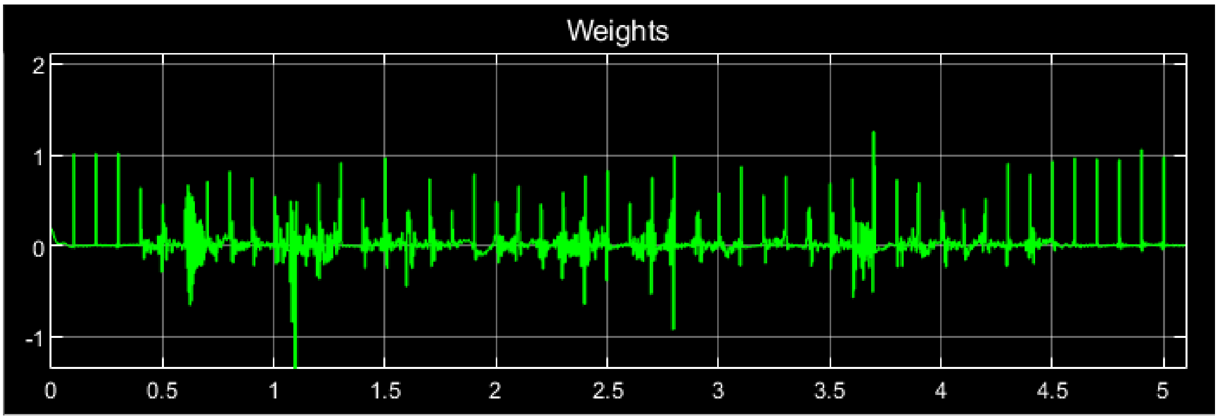

Figure5.7 : LMS Simulation Weights

5.2 Simulation using NLMS filter Approach

Simulation block for NLMS shown in the figure the input signal is actual audio signal and a actual noise from the surrounding and both the signals are mixed together and finally goes to the desired input and the noise goes in the input as shown in the simulink model below.

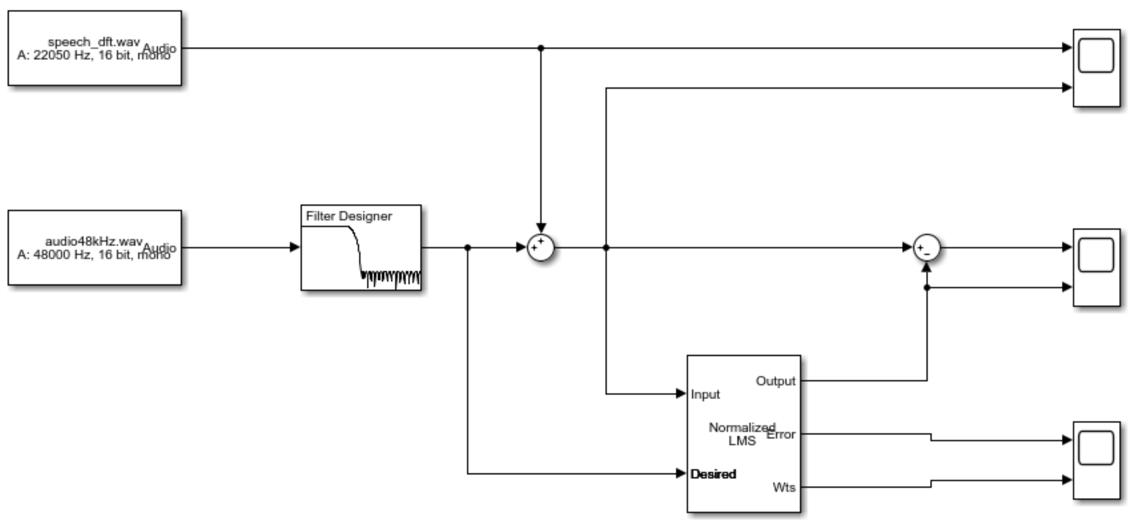

Figure5.8 : NLMS Simulation Block

Filter length:10

Step Size : 0.1

Respective results using NLMS filter are

Fig. 5.9 shows the original audio signal which is used for the project , the original audio signal is free from all kind of noise and is fully understandable.

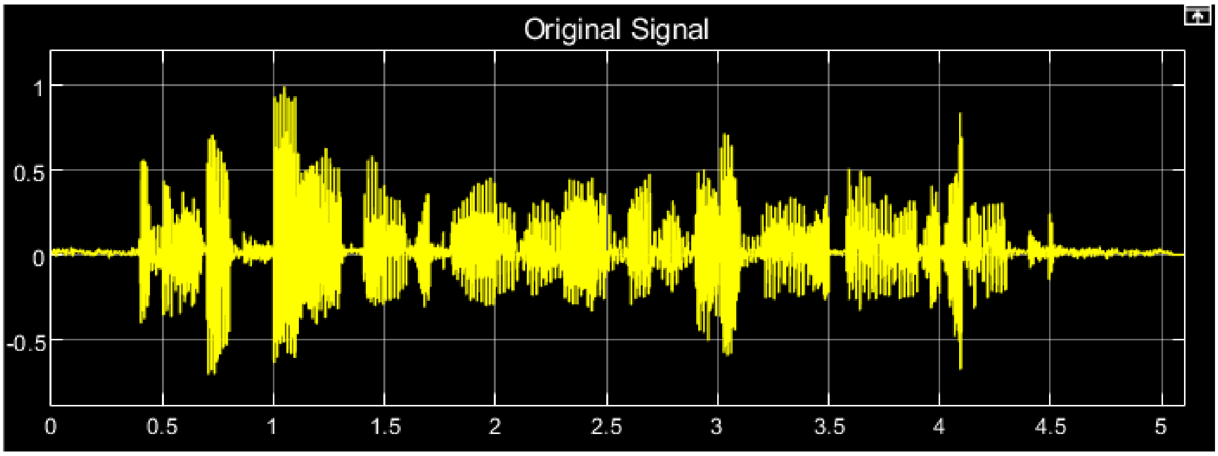

Figure5.9 : NLMS Simulation Original audio signal

Fig. 5.10 shows the audio signal in which the noise was mixed and the audio signal was corrupted and was made unclear to understand and makes it diffucult to understand.

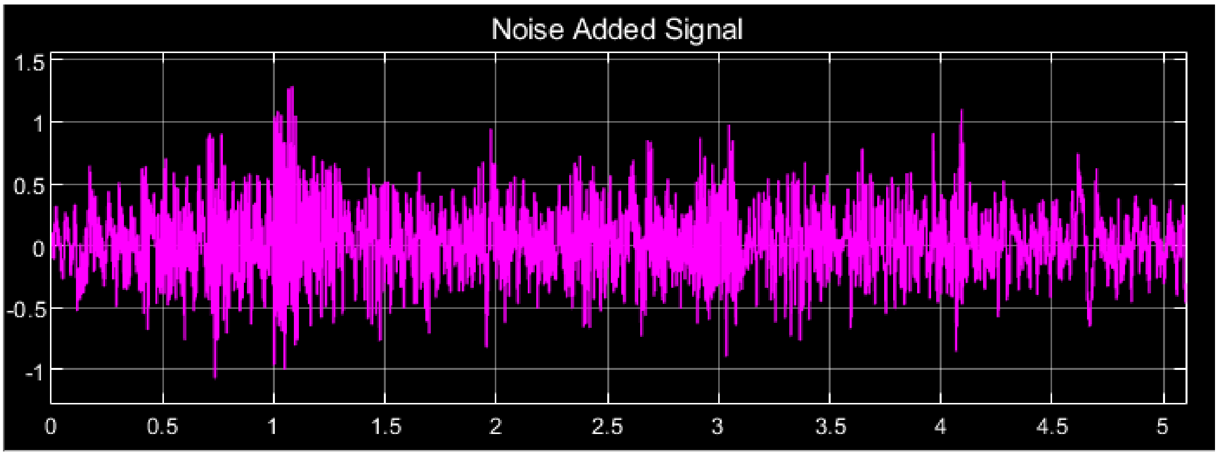

Figure5.10 : NLMS Simulation Noise Added Audio Signal

Fig. 5.11 shows the recovered audio signal after passing from the NLMS filter and almost the same audio signal with almost same frequency was recovered

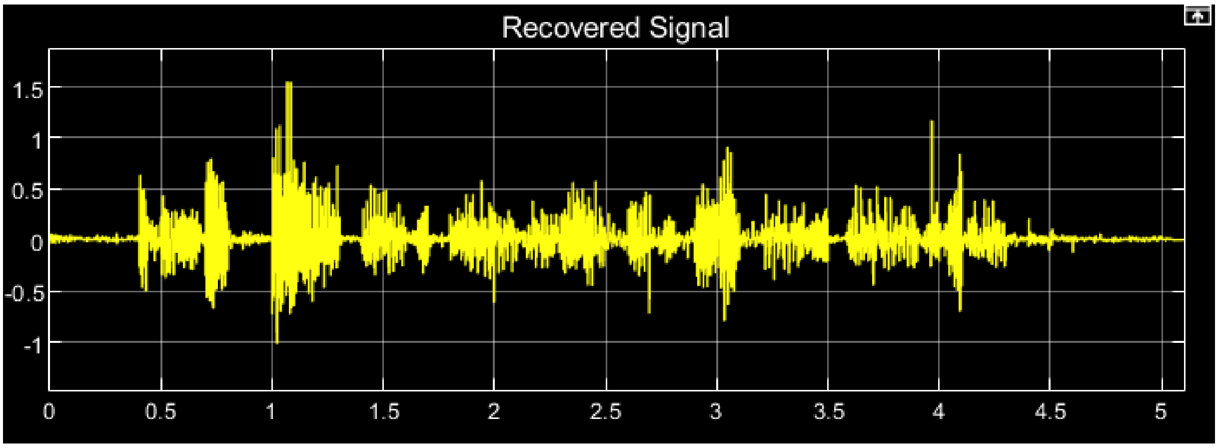

Figure5.11 : NLMS Simulation Recovered Audio Signal

Fig. 5.12 shows the separated noise signal filtered from the nlms filter and almost the same noise was separated.

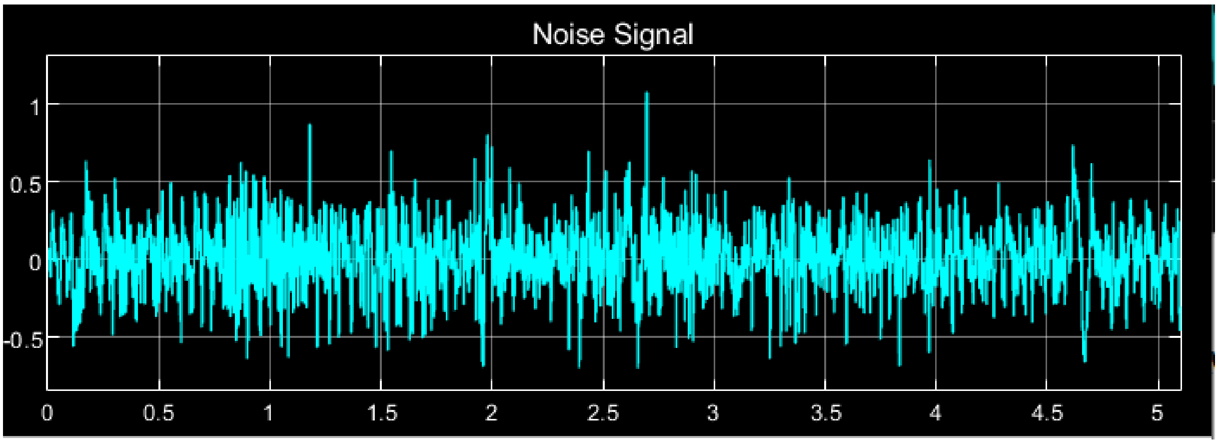

Figure5.12 : NLMS Simulation Noise Signal

Fig. 5.13 shows the Error signal filtered from the nlms filter , and we can see the maximum error was seen at the point where the frequency of audio signal and noise where high , at that point the error was seen max.

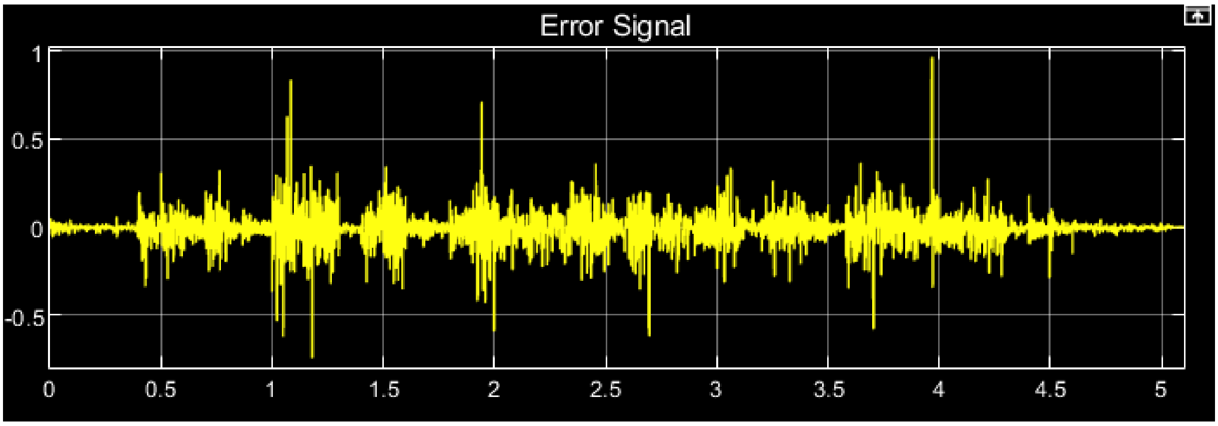

Figure5.13 : NLMS Simulation Error signal

Fig. 5.14 shows the weights of the nlms filter , and we can observe that the weight was adjusted at each point and filtering of audio was done in smooth way.

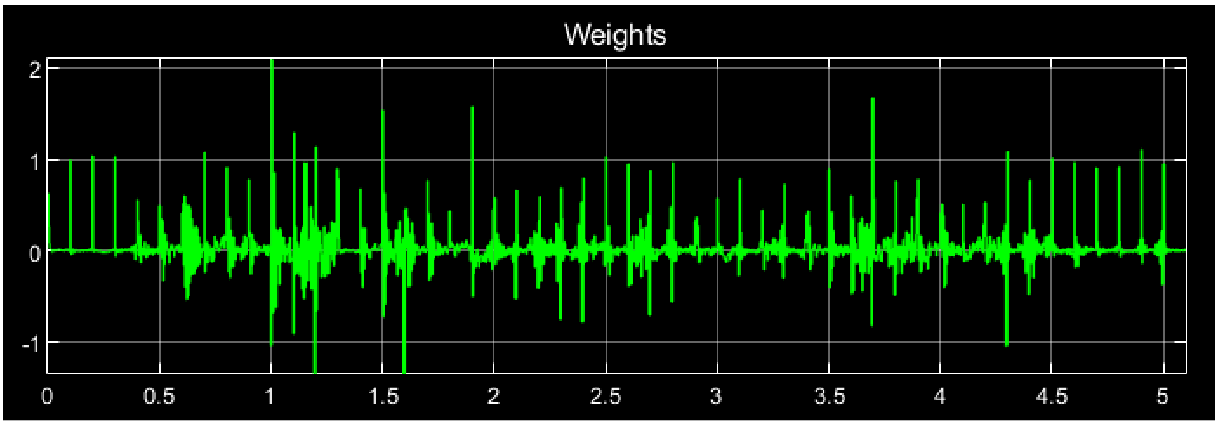

Figure 5.14 : NLMS Simulation Weights

CHAPTER 6
Discussion of Results

For different types of adaptive filter algorithms the minimum square error for LMS and NLMS systems. The minimum square error for the processes for the noise is shown in Table 1.

Sl. No.	Algorithm	Signal Power in dB	Estimated Signal Power in dB	Noise Power in dB	Estimated Noise Power in dB
01.	LMS	43.4312	41.8416	46.8142	48.1364
02.	NLMS	43.4312	46.6241	46.8142	41.6828

Table 1 : Minimum square error for different types of adaptive filter algorithm LMS and NLMS system.

By using the formula for signal to noise ratio we got a set of results for the different types of adaptive algorithms for noise. We observed that the input signal to ratio means the original voice signal and the noise is 0.6515dB SNR = 10log $d^2(k)/n^2(K)$, the improvement in SNR shown in Table 2.

Added Noise (Power Line Interface)	LMS (dB)	NLMS (dB)
Noise for input SNR	0.6515	0.6515
Noise for output SNR (After Filtering)	1.2173	0.9730

Table 2 : Improved SNR

The computation time for different filter algorithms is shown in Table 3.

Filter Length	LMS Filter (Time in sec)	NLMS Filter (Time in sec)
5	5.2641	6.0242
10	9.6132	10.7751
15	13.6806	15.4769
20	17.9328	23.7694

Table 3 : Comparison table for the computation time of LMS and NLMS filters.

CHAPTER 7
Conclusion

7.1 CONCLUSION

Adaptive Noise Cancellation is an alternative way of canceling noise present in a corrupted signal. The principal advantages of the method are its adaptive capability, its low output noise, and its low signal distortion. The adaptive capability allows the processing of inputs whose properties are unknown and in some cases non-stationary. Output noise and signal distortion are generally lower than can be achieved with conventional optimal filter configurations. This Project indicates the wide range of applications in which Adaptive Noise Canceling can be used. The simulation results verify the advantages of adaptive noise cancellation. In each instance canceling was accomplished with little signal distortion even though the frequencies of the signal and interference overlapped. Thus it establishes the usefulness of adaptive noise cancellation techniques and its diverse applications

In this project , the fundamental algorithm of noise cancellation, Least Mean Square (LMS) algorithm and Normalised LMS algorithm is studied and enhanced with adaptive filter. The simulation of the noise cancellation using LMS adaptive filter algorithm and Normalised LMS algorithm is developed. The noise corrupted speech signal and the noise signal are used as inputs for LMS adaptive filter algorithm and Normalised LMS algorithm. The filtered signal is compared to the original noise-free speech signal in order to highlight the level of attenuation of the noise signal. The result shows that the noise signal is successfully canceled by the developed adaptive filter.

This study has revealed the useful properties of the LMS and the NLMS algorithms in case of adaptive noise cancellation. It has been found that the LMS algorithm generally performs better irrespective of the nature of the signal and noise used in the performance of the project. The LMS takes less time to compute, especially when the filter length is large. But change in filter length doesn’t have too much effect on the convergence behavior of the LMS. For the NMLS, this increase is quite substantial. In the end, it can be stated that the LMS algorithm should be preferred over the NLMS for adaptive noise cancellation of voice signals if the computation time is of great concern, also the SNR ratio of LMS is better in comparison to the SNR ratio of NLMS filter. More tests will be conducted to further investigate its performance in the future.

7.2 Scope of Present Work

In practical application, the statistical characteristics of signal and noise are usually unknown or, cannot have been learned so that we hardly design fix coefficients of filter. To overcome this problem, the theory of adaptive filter and adaptive noise cancellation are researched deeply. The scope of this paper is noise cancellation which is concerned with removal of noise superposed on speech signal. Noise cancelling makes use of an auxiliary or reference input derived from one or more sensors located in a noise field where the signal is undetectable. This input is filtered from primary input containing both signal and interference. Adaptive filtering which are able to lock- in on the frequency of interference and to tracks its changes is required. In order to achieve this, a reference signal should be available which is strongly correlated with the interference only. To this purpose RLS algorithm implementation is considered. The Recursive least square (RLS) adaptive filter is an algorithm which recursively finds the filter coefficients that minimize a weighted linear least squares cost function relating to input signals. This is in contrast to other algorithms such as least mean square (LMS) that aim to reduce mean square error. Compared to most of its competitors the RLS exhibits extremely fast convergence.

7.3 Scope of Future Work

In this project, the Least-Mean-Squares Algorithm and Normalised LMS Algorithm , has been used. Other adaptive algorithms can be studied and their suitability for application to Adaptive Noise Cancellation compared. Other algorithms that can be used include Recursive Least Squares, Variable Step-size algorithm etc.

The future of active noise control in industry is dependent on a number of issues associated with hardware configuration and cost, user friendly software, generalisation of system design, development of low-cost, rugged actuators and sensors together with an acceptance of what is possible and what is not. Novel approaches to achieving the control objective of reduced noise levels at the ears of industrial employees, which sidestep limitations imposed by the physical properties of sound and vibration fields, are also required to enable practical application of the technology in many cases. One such novel approach, which involves virtual sensing combined with very local control and beam steering that tracks a person's ear is discussed.

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