YAŞAR UNIVERSITY

GRADUATE SCHOOL OF NATURAL AND APPLIED SCIENCES

DESIGN AND IMPLEMENTATION OF AN ACTIVE NOISE CANCELLATION SYSTEM

Erdem UĞUR

Thesis Advisor: Asst. Prof. Dr. Mustafa SEÇMEN

Department of Electrical and Electronics Engineering

Bornova – İZMİR

July 2012

This study titled “DESIGN AND IMPLEMENTATION OF AN ACTIVE NOISE CANCELLATION SYSTEM” and presented as MSc Thesis by Erdem UĞUR has been evaluated in compliance with the relevant provisions of Y.U Graduate Education and Training Regulation and Y.U Institute of Science Education and Training Direction and jury members written below have decided for the defence of this thesis and it has been declared by consensus / majority of votes that the candidate has succeeded in thesis defence examination dated……………………..

Jury Members:	**Signature:**
Head : ………………	………………...
Rapporteur Member: ……………….	…………………
Member : ……………….	…………………

ÖZET

BİR AKTİF GÜRÜLTÜ BASTIRMA SİSTEMİNİN TASARIMI VE GERÇEKLEŞTİRİMİ

UĞUR, Erdem

Yüksek Lisans, Elektrik ve Elektronik Mühendisliği Bölümü

Tez Danışmanı: Yard. Doç. Dr. Mustafa SEÇMEN

Temmuz 2012, 72 sayfa

Bu tezde, araç sürücüsüne ulaşan motor gürültüsünü yok etmek için bir aktif gürültü bastırma sistemi önerilmektedir. En küçük ortalama kare (LMS) algoritması, basitliği ve gürbüz yapısı nedeniyle bu sistemde uyarlanır süzgeç olarak tercih edilmiştir. Ortalama kare hatasını (MSE) ve yaklaşım hızını etkileyen adım sayısı ve süzgeç boyutu, yaklaşım hızını artırmak ve kalıcı durum hatasını azaltmak amacıyla incelenmiştir. Literatür araştırmasından sonra, değişken adım sayısı ve değişken süzgeç boyutu algoritmaları gerçek zamanlı uygulamalar için en iyi gerçekleştirimler olarak seçilmişlerdir. Bu algoritmalar bilgisayar simülasyonları ile gerçekleştirilmiş ve sonuçları klasik LMS ile karşılaştırılmıştır. LMS algoritmasının çeşitlerinden olan normalize LMS (NLMS) ve sign-sign yapıları da sistemin hızını artırmak ve işlem karmaşıklığını azaltmak için kullanılmıştır. Algoritmaların sayısal işaret işlemci uygulamaları için uygunluğunu doğrulamak amacıyla farklı motor sesleri ve sinüs sinyalleri ile çok sayıda test yapılmıştır. Bu çalışmada değişken adım sayısı ve değişken filtre boyutlu algoritmalarının klasik LMS algoritmasına göre daha iyi performansa sahip olduğu ve diğer karmaşık algoritmalara göre de daha hızlı çalıştığı görülmüştür.

Anahtar Sözcükler: Aktif gürültü bastırma, en küçük ortalama kare algoritması, normalize en küçük ortalama kare algoritması, değişken adım boylu en küçük ortalama kare algoritması, motor gürültüsü

ABSTRACT

DESIGN AND IMPLEMENTATION OF AN ACTIVE NOISE CANCELLATION SYSTEM

UĞUR, Erdem

MSc, Department of Electrical and Electronics Engineering

Supervisor: Asst. Prof. Dr. Mustafa SEÇMEN

July 2012, 72 pages

This thesis presents an active noise cancellation system to annihilate motor noise of a car belonging to driver. Least Mean Square (LMS) is used as an adaptive filter in this system due to its simplicity and robust characteristics. Step size and filter length, which affect mean-square error (MSE) and convergence rate, are investigated to increase speed of convergence and decrease steady state error. After the literature search, a variable step size algorithm and a variable tap length algorithm are selected as the best implementations for real time applications. These algorithms are realized with computer simulations and the corresponding results are compared with classical LMS algorithm. As being different types of LMS, normalized LMS (NLMS) and sign-sign structure are also used to increase speed of the system and decrease the computational complexity. Several tests are done with different motor sounds and sinusoidal signals to verify the availability of the algorithms for DSP implementations. In this study, it is shown that variable step size and variable tap length algorithms have better performance than classical LMS and process time is shorter than other complex algorithms.

Keywords: Active noise cancellation, least mean square algorithm, normalized least mean square algorithm, variable step size least mean square algorithm, motor noise

ACKNOWLEDGEMENTS

I would like to thank my supervisor Asst. Prof. Dr. Mustafa Seçmen for his guidance and patience during this study.

I would also like to thank Asst. Prof. Dr. Nalan Özkurt for her comments and advices.

TEXT OF OATH

I declare and honestly confirm that my study titled "DESIGN AND IMPLEMENTATION OF AN ACTIVE NOISE CANCELLATION SYSTEM", and presented as Master's Thesis has been written without applying to any assistance inconsistent with scientific ethics and traditions and all sources I have benefited from are listed in bibliography and I have benefited from these sources by means of making references.

19/07/2012

Erdem UĞUR

TABLE OF CONTENTS

TABLE OF CONTENTS (continue)

Page

TABLE OF CONTENTS (continue)

Page

INDEX OF FIGURE

INDEX OF FIGURE (continue)

INDEX OF FIGURE (continue)

INDEX OF FIGURE (continue)

INDEX OF TABLE

CHAPTER 1: INTRODUCTION

There are two types of acoustic noise in the environment. First type is caused by turbulence and it is generally random. This noise is called as broadband noise due to distributing its energy across the frequency bands. Low frequency noise of a jet plane and impulse noise of an explosion can be considered as broadband noise examples. On the contrary to broadband noise, the second type of acoustic noise concentrates its energy at specific frequencies, which is called as narrowband noise. Most of the cases of this type are periodic since, this type of noise is related to repetitive machines. Noise of engines, compressors and vacuum pumps are the examples of narrowband noise (Kuo et al., 1996).

With the increase in the usage of industrial equipments (engines, blowers, fans, transformers), acoustic noise become an important problem (Kuo, 1999). There are two main methods to reduce this noise. These are passive noise cancellation and active noise cancellation. Because, it is often cheap and simple to implement. Passive noise control is the mostly used one among all practical control methods. There are two commonly used techniques for passive noise control (Synder, 2000). First one uses acoustic insulation to muffle sound. The aim of this technique is to absorb the sound energy and this absorbed energy turns to heat energy. Second one reduces the volume velocity of noise source. This method is implemented by attenuating the vibration of the noise source frequently. Using rubber isolators under the motor of cars is one of the most common examples of this technique. Although the passive silencers are effective to attenuate the noise over a broad frequency range, these techniques are ineffective, bulky and expensive at low frequencies (Elliott and Nelson, 1993). Since, the wavelength of low frequency sound is large. For example, wavelength of a 100 Hz sound wave is 3.4 meters in air. Thus, the thickness of the absorber in acoustic wavelengths becomes larger than a typical acoustic absorber. On the other side, the intervening barrier must be very heavy to attenuate the low frequency signal. As the result of all these reasons, it is difficult to solve acoustic noise by passive methods at low frequencies.

Active noise cancellation or equivalently active noise control (ANC) system contains an electroacoustic device to cancel the unwanted noise (Hansen, 2003). This electroacoustic device generates antinoise signal having an equal amplitude and opposite phase with the noise signal. Acoustic noise cancellation based on superposition principle works provided that the acoustic environment is linear, which is the validity rule of superposition principle. The noise and the generated antinoise are summed up and noise will be cancelled. The physical concept of active noise cancellation is shown in Figure 1.1.

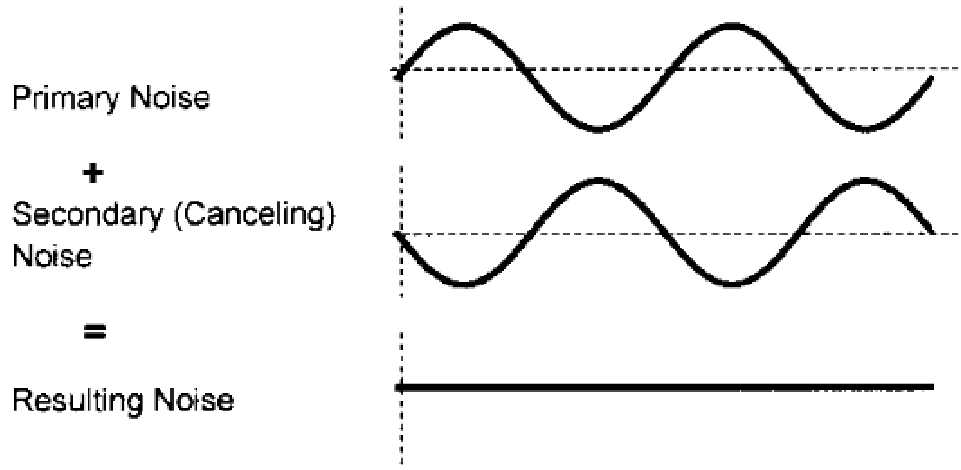


Figure 1.1: Physical Concept of Active Noise Cancellation (Kestell and Hansen, 1999)

Although active noise cancellation and the passive noise cancellation seem to be the alternative of each other, they are complementary (Cuesta et al., 2000). Since the performance of these two techniques are related to frequency of noise. This relationship can be seen in Figure 1.2. If the environment, which includes active noise control, is stationary and the frequency of noise signal is low (especially below 200 Hz), there is no need to use an additional passive filter. Similarly it is not required using active control methods with passive filters when frequency of noise signal is high (especially above 500 Hz).

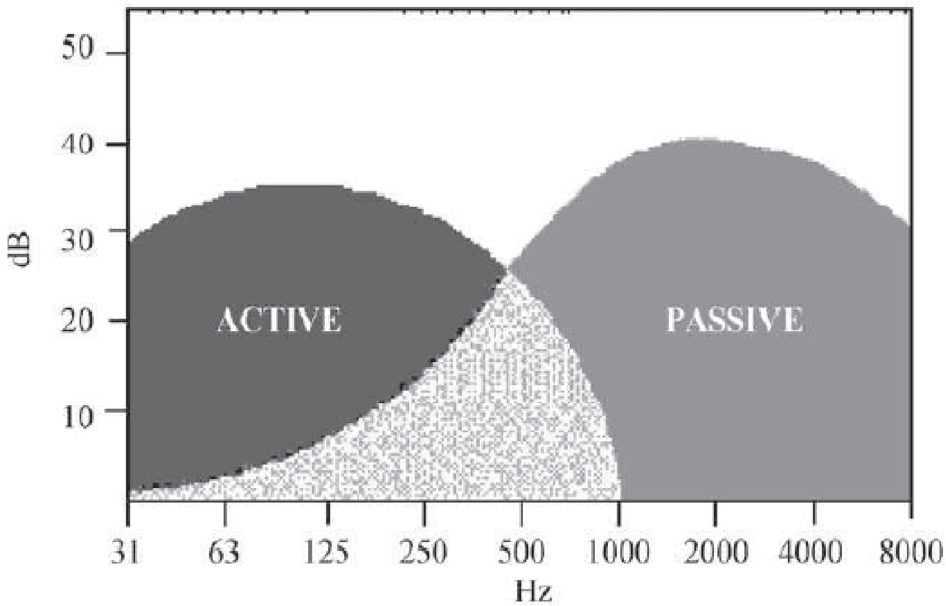


Figure 1.2: Active and Passive Control Attenuation (Mingues et al., 1999)

By regarding to active noise control, there are two types of active noise control. First type is local cancellation. Here, antinoise signal is generated electronically and loudspeaker converts this electronic signal to sound. If cancellation only occurs at near the controller, noise level might be reduced at this region. However, total energy of antinoise signal and noise signal is conserved. The noise level will increase at other regions. Active headset is an example for the application of local cancellation. At active headsets, noise is cancelled near the ear while noise level is increased outer region. The second type of active noise control absorbs sound by the antinoise signal at a space such as a duct. For example, assume that there is a loudspeaker in a free space and other one is in front of it. If the first loudspeaker starts to radiate sound wave, the other loudspeaker will generate an antinoise by tuning amplitude and phase itself. Then, the sound wave, which is radiated from first loudspeaker, is cancelled. As a result, sound pressure is not radiated to far field while local sound field also exists in the near field of these two loudspeakers.

Engine noise of a car changes approximately from 90 Hz to 150 Hz due to engine’s angular speed varying from 2700 rpm to 4500 rpm mostly (Wan et al., 2008). Hence, the use of ANC is required for these low frequencies. If passive methods are preferred, it will be expensive and bulky for a car.

To make ANC applicable in real system, an adaptive filter is required. Thus, these systems are also called as Adaptive ANC. LMS is one of the most popular adaptive filtering algorithms because of its robust characteristics and simple form with respect to other adaptive algorithms.

Step size and tap length are two important parameters, which affect performance of LMS adaptive filter. These parameters change converge speed and steady state error performance of the filter. However, choosing constant values for these parameters cause degradation in convergence speed and steady state error performances. Therefore, variable step size and variable tap length algorithms are used to overcome this drawback.

Types of LMS such as normalized LMS and sign-sign LMS are also used widely in DSP applications especially to get better performance or decrease computational complexity. Normalized LMS changes the step size with input signal and it improves error performance of the system with higher convergence speed. On the other hand, sign-sign LMS algorithm only uses sign value of both error and input signal to find new tap weights of the adaptive filter. So, it provides huge improvement to computational complexity due to the elimination of the multiplications.

1.1 Scope of the Thesis

The aim of this study is to explore suitable LMS filtering algorithms to implement active noise cancellation of a motor noise with respect to the usage of classical LMS algorithm. Variable tap length and variable step size are aimed to increase efficiency of the method by changing these values by time. It is also aimed to show that algorithms are suitable for real time implementation with digital signal processors (DSP).

1.2 Outline

The outline of this thesis is as follows. The definition of ANC and historical development are given in Chapter 2. Types, advantages and disadvantages of ANC are also given in this chapter.

In Chapter 3, it is introduced the adaptive filtering with Wiener filter. Then, the theory of Steepest Descent and LMS are given. The types of LMS are explained and using variable step size and variable tap length to overcome some conflicts are included in this chapter.

The system of ANC for motor noise is shown in Chapter 4, which is also based for all algorithms and simulations in this thesis. Methods and the algorithms for variable step size LMS and variable tap length LMS are also shown.

Chapter 5 includes results of computer simulations which are done as a consequence of Chapter 4. In this chapter, simulation results are compared with classical LMS and other types of LMS. The effects of different step size values and different tap length values on system performance are also examined.

CHAPTER 2: ACTIVE NOISE CANCELLATION

In this chapter, historical development of acoustic noise control and different types of active noise control methods are investigated.

2.1 Development of Active Techniques for Acoustic Noise Control

Basic idea of using active noise cancellations was firstly described and patented by German physicist Paul Lueg in 1936. The described system is shown in Figure 2.1 (Elliott and Nelson, 1993).

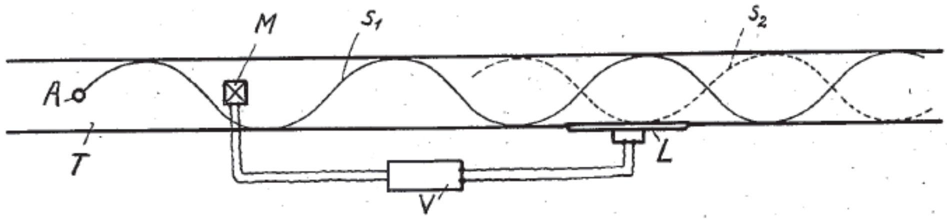


Figure 2.1: Lueg's Patent Application (Lueg, 1936)

This prepared system is also defining the active noise control. The noise source A emits its sound waves in all directions because, it is placed in open space. Then, microphone M and loudspeaker L which are interconnected by amplifier V, are located. The microphone M measures the noise signal s_1 and amplifier V generates an antinoise signal s_2. Afterwards, the antinoise signal drives the loudspeaker L. Finally, the noise sound s_1, which is produced by A, is cancelled by opposite phase sound s_2 produced by loudspeaker L (Lueg, 1936). On the other hand, this system did not have applications practically due to some problems related the environment. Phase, velocity and amplitude of the sound and environment are nonstationary and therefore, it is needed to active noise controlling to overcome these problems (Kuo et al., 1996).

There was no important research about Active Noise Cancelling after Lueg until 1950s. Then, realization of active noise control in room, duct, headset and earmuff were investigated by Olson in 1950s. But, his system provided very limited attenuation levels. He got his results for a very narrow frequency range. He suffered from instability, which is caused by high frequency noise (Hansen, 2003).

W. Conover also made experiments nearly at the same years as Olson about active noise cancelling for noise of transformer. Radiated noise sound by these transformers includes even harmonics of line frequency. Therefore, there is no need to use microphone to detect noise signal because of the periodicity of sound. Then loudspeaker is driven by electronic controller (Elliott and Nelson, 1993). But, this prepared system was not practical too. Indeed, the controller was adjusted manually due to the changes in environmental conditions and it had to be adjusted periodically to eliminate effects of changing wind and temperature. The other restriction of this experiment was the reduction of the noise over only a very narrow angle subtended from the loudspeaker and microphone (Hansen, 2003). The Conover's prepared system is shown in Figure 2.2. As shown in the figure, amplitude and phase of the antinoise signal are adjusted manually by observing the sound analyzer. So, it cannot be used for commercial purpose.

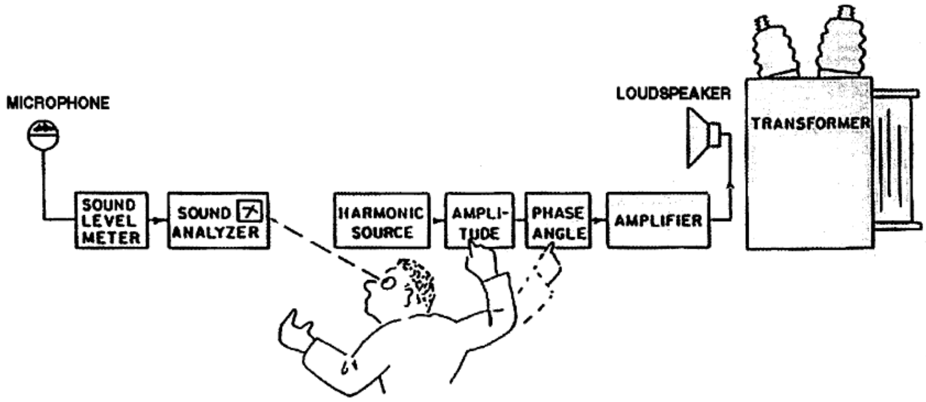


Figure 2.2: Conover's Manually Adaptive Feedforward Active Noise Control System (Elliott and Nelson, 1993)

After Conover and Olson's experiments, application on active noise control was not popular by the scientists until 1970s. After the invent of Least Mean Square (LMS) algorithm in 1960, rapid progress of high speed and low cost electronic controllers such as digital signal processor (DSP) provide applicable ANC system widely (Zhou et al., 2004). Hence, ANC is used in many areas of life such as automotive, industrial and transportation nowadays.

2.2 Active Noise Control

Active noise control gets attention in long wavelength sound whose frequency is low. Principle of active noise control is based on superposition. Noise sound called as primary source and other electroacoustic devices called as secondary source are summed up. As the result of this process, primary source is suppressed and output of these secondary sources is controlled by a microcontroller. (Elliott and Nelson, 1993).

An active noise cancellation system needs

• Reference and error signals. Microphone is mostly used sensor to get reference signal and measure error.

• Electronic controller system: It is needed to process adaptive algorithms at an active noise control system. Therefore, microcontrollers and especially Digital Signal Processors (DSP) are widely used in applications of ANC.

• A loudspeaker. Generated antinoise signal is converted from electrical signal to sound wave whose output changes with time (Hansen, 2003).

Selection of these sensors, controllers, loudspeakers and other components quite depend on type of noise source and physical environment (Kestell and Hansen, 1999). If noise travels through the air, microphones and loudspeakers can be chosen commonly. Although, microphone and loudspeaker are also valid, other sensors and actuators are also used especially at structure born noise. Strain gauges, tachometers and accelerometers are some examples of these sensors (Mingues et al., 1999).

On the other hand, the location of microphone is very important for the efficiency of the ANC system since standing waves are generated by producing different frequencies and different sound levels (Kestell and Hansen, 1999). If location of the microphone is not selected properly, the certain frequency may be shifted or it might be seen as blind. Thus, location of the microphones must be arranged precisely and it must be also closely spaced with respect to wavelength of the sound signal.

Antinoise signal is generated by microcontroller whose input is taken from the sensors. Steady state can be provided by supplying ideal environment. But, acoustic environment and the noise sound are variable in practice. For this purpose, controller must also have self tuning property to work at unideal environment efficiently (Kestell and Hansen, 1999).

2.3 Types of Active Noise Control System

The developed active noise techniques are very effective at narrowband noise cancellation. Narrowband noise is caused by periodic, rotational machines generally. Therefore, other sensors such as tachometer can be also used instead of input microphone. Because repetitive noises are occurred at the harmonics of the machine's rotational frequency, the controller can generate antinoise signal at these frequencies. This type of control system is mostly used in vehicle cabin because it is not affected from speech and other signals. Control of this type cancellation system depends on speed of the engine rotation only (Kuo et al., 1996).

Although higher frequency active noise control systems exist, these are more suitable for low frequencies which are below 500 Hz. This is because technical difficulties such as more complex vibration and required higher sampling rates limit the efficiency of higher frequency applications (Hansen, 2003).

Feedforward ANC and feedback ANC are the two common methods of active noise cancellation.

2.3.1 Adaptive Feedforward Control

A simple feedforward control system in enclosed environment is shown in Figure 2.3. Reference signal (noise signal) is sensed by an input microphone, which is called as reference microphone, and this signal is filtered by microcontroller. Then, the filtered electronic signal is converted to sound by loudspeaker. The effectiveness of the control system is controlled by the error microphone and it is used to adjust of algorithm (Kuo et al., 1996). Processing time of the noise cancellation algorithm must be fast as it can be possible. But, required amount of time depend on the application. The processing time of a broadband noise controller must be less than the propagation time of noise signal from the source to the controller. On the other hand, the permitted processing time can be larger at narrowband noise controlling. This flexibility occurs due to narrowband noises, which are composed of repetitive signals (Hansen, 2003).

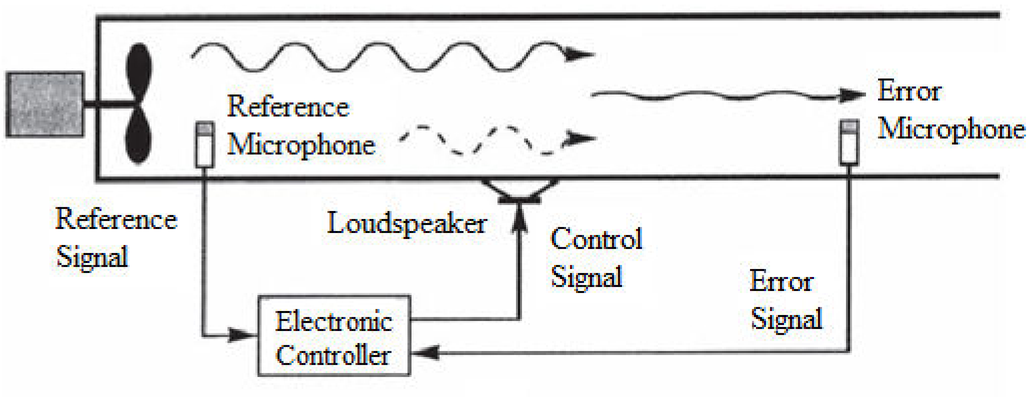


Figure 2.3: Feedforward Active Noise Control System in a Duct (Hansen, 2003)

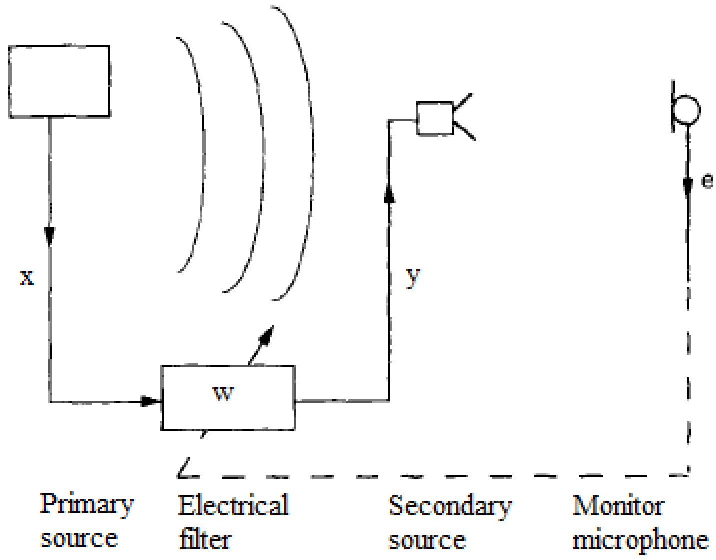


Figure 2.4: Feedforward Active Noise Control System in a Space (Elliott and Nelson, 1993)

A sample of a feedforward control system in space is shown in Figure 2.4. It can be easily seen that the principle of this system is same as the one in Figure 2.3. But, application of this system is more complicated than system in a duct due to physical structure of sound in space.

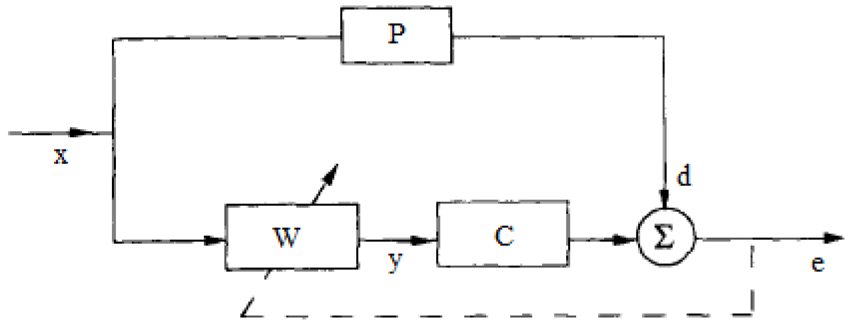


Figure 2.5: Block Diagram of Feedforward Control (Elliott and Nelson, 1993)

Equivalent block diagram of feedforward system is also shown in Figure 2.5. In this figure, primary path from noise source to error microphone is represented with block P, while controller is represented with block W and secondary path from loudspeaker to error microphone is represented with block C. Transfer function of this block diagram is given by

$$\frac{E(s)}{D(s)} = 1 + \frac{W(s)C(s)}{P(s)} \tag{2.1}$$

This system gives complete cancellation of error spectrum because the spectrum of error signal is related with the response of electrical controller linearly. So, it can be adjusted at each frequency and by inverting secondary path, complete cancellation is occurred principally (Elliott and Nelson, 1993).

The usage of a microphone as a reference signal in Figure 2.3, is not only choice for the sensor. Variable types of sensors can be used such as tachometer. A feedforward control system using nonacoustical sensor is shown in Figure 2.6.

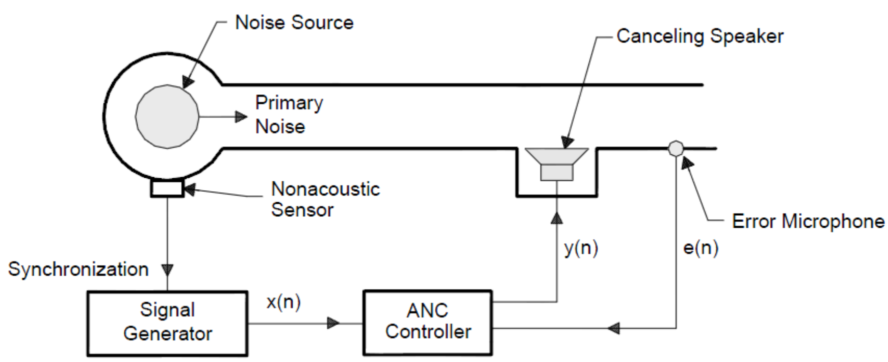


Figure 2.6: Feedforward Active Noise Control System with Nonacoustical Sensor (Kuo et al., 1996).

There are some advantages of using nonacoustical sensors to get noise signal. The first advantage is the avoiding of undesired acoustic feedback from the cancelling speaker. The other one is the flexibility of positioning the loudspeaker since noise waveform is constant. Required adjustment is only at magnitude and frequency of the noise. Toleration of longer delays is the other advantage of this application (Kuo et al., 1996).

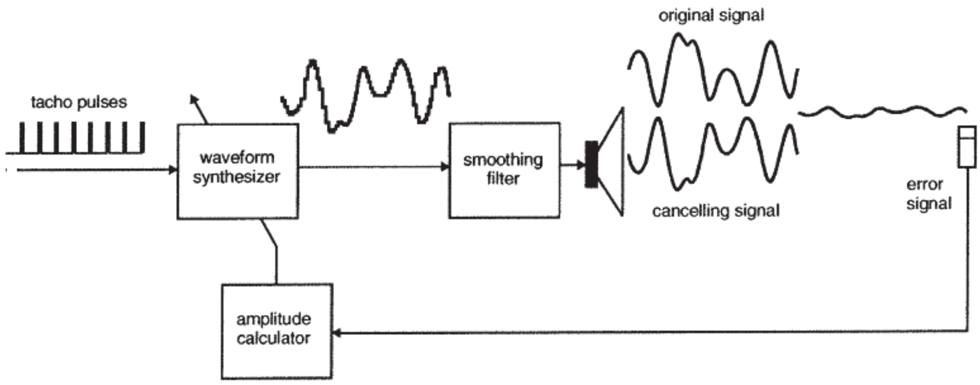


Figure 2.7: Waveform Synthesis Control System (Hansen, 2003).

A sample of tachometer used in a feedforward system is shown in Figure 2.7, which is also called as waveform synthesis controller. In this system, a gear wheel is used to generate pulse signals from the tachometer. Then, coming pulses are converted to corresponding output amplitudes. After that, error signal is detected synchronously by the microphone at each incoming pulse to update generating signal.

Accuracy of the output waveform shape depends on the number of pulses at a period. So, required number of pulses will increase if required noise reduction increases and vice versa (Hansen, 2003).

Although this method is successful to attenuate the noise at the fundamental frequency and its harmonics, it cannot cancel the noise whose frequencies are along the harmonics (Hansen, 2003).

2.3.2 Adaptive Feedback Control

The reference signal is not used in the feedback active noise cancellation. There is only an error microphone and antinoise sound is generated by processing of error signal. Characteristics of feedback control system are selected to unperturbed state quickly. Although feedforward controllers perform better than feedback controllers, feedback controllers are faster. Thus, this type of controller is selected where feedforward controllers can not response early enough (Hansen, 2003).

There is only a microphone at this type of controller. This microphone is used to get undesired noise signal as an error microphone. The detected error signal is returned through to controller and the antinoise signal is generated as shown in Figure 2.8 (Kuo et al., 1996).

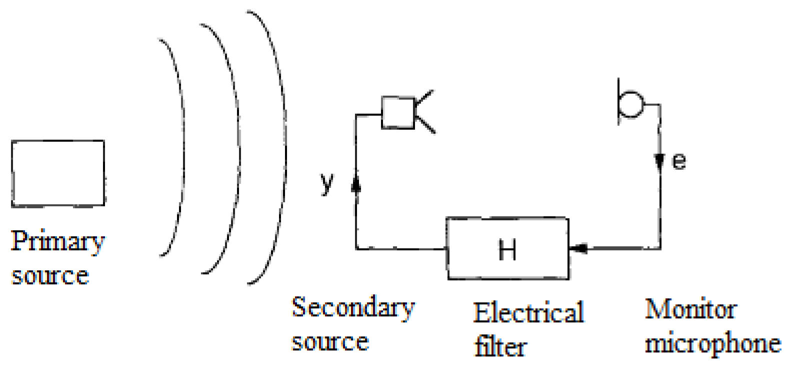


Figure 2.8: Feedback Active Noise Control System in a Space (Elliott and Nelson, 1993)

In this figure, *e* represents signal taken from microphone, which is combination of noise source *d* (can be also described as primary disturbance) and output of the feedback loop (Elliott and Nelson, 1993). The feedback loop acts as an attenuation force to reduce *e* as small as possible as compared to *d*. In this way, acoustic pressure can be cancelled at the microphone.

Equivalent block diagram of the feedback system is also shown in Figure 2.9. Block H represents the gain of the feedback loop, block C represents the transfer function from loudspeaker to microphone, which is called as error path. The transfer function of the control block can be expressed as

$$\frac{E(s)}{D(s)} = \frac{1}{1 + C(s)H(s)} \tag{2.2}$$

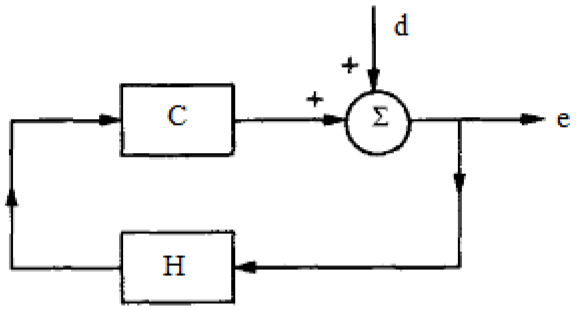


Figure 2.9: Block Diagram of Feedback Control (Elliott and Nelson, 1993)

Location of the microphone and loudspeaker should be close to each other to decrease acoustic delay and improve performance and stability of control system. However, the sound pressure may not be reduced at large distances because of near field effect. Nevertheless, it is not a problem for most of the feedback applications such as ear muffs. If the distance between microphone and loudspeaker is too close, far field performance will decrease due to near field effects. But, noise will be cancelled within a very small area around the microphone (Hansen, 2003).

Adaptive feedback control method can be only implemented by using a digital filter. But, this implementation causes a delay to process algorithm on microcontroller such as digital signal processors. This type controller is preferred to feedforward control only when it is not possible to get any reference signal (Hansen, 2003).

2.3.3 Multiple Channel Active Noise Control

Single channel active noise control systems use a microphone and a loudspeaker to cancel the noise. But, quiet zone is only produced around the microphone. So, single channel controller can not attenuate noise wave at far distances (Kuo et al., 1996). Indeed, as complexity geometry of the sound field increases, it is not adequate to use single error microphone and single loudspeaker. The multichannel active noise control system includes an array of sensors and actuators as shown in Figure 2.10 (Elliott and Nelson, 1993).

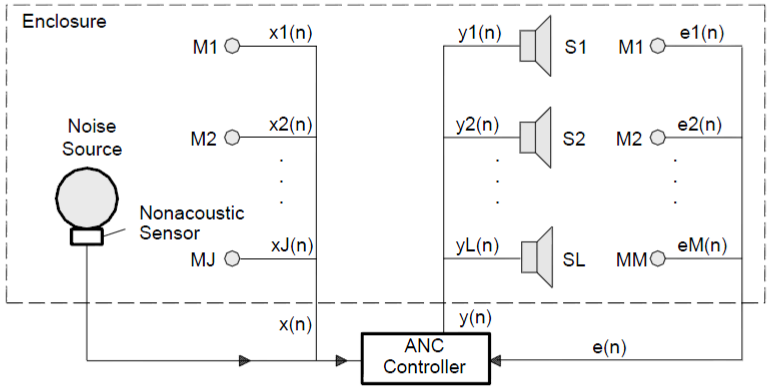


Figure 2.10: Multichannel Active Noise Control System (Design of Active Noise Control Systems with the TMS320 Family)

The usage of a few error sensors are ususally needed to obtain higher cancellation of total noise energy. In order to get best attenuation level from this error microphones, microphone locations must be correct. These locations highly depend on the shape of enclosure. For example, they can be placed at each corner of the enclosure to have maximum sound pressure if the shape of enclosure is rectangular and the location of loudspeakers must be directly couple to the noise source (Kuo, 1999).

CHAPTER 3: ADAPTIVE FILTER

Adaptive processing is a system which can change its process behavior to maximize performance of filter where the mean square error is mostly used as a performance criterion (Stranneby et al., 2004). Adaptive filtering is also a time varying process since its coefficients are changing with input signal, output signal or system parameters to meet required performance (Vijaykumar et al., 2007).

3.1 Wiener Filter

Wiener Filters are known as the linear optimum discrete time filters (Tan, 2008). The Wiener filter adjusts its tap weights to produce optimum filter output. Optimum filter output can be provided when output signal is as close as possible to desired signal and this optimum function is called as cost function (Poularikas and Ramadan, 2006).

As shown in Figure 3.1, the input of the filter consists of time samples (u(0), u(1), u(2),…) and filter generates tap weights, which are characterized by itself ($w_0, w_1, w_2, \ldots$). Then, the filter produces an output, which is denoted by y(n). The aim of producing this output is to estimate the desired signal which is denoted by d(n). The estimation error in this figure, e(n), is the difference between the output and the desired response, and so, the filter tries to minimize this error as small as possible (Haykin, 1996).

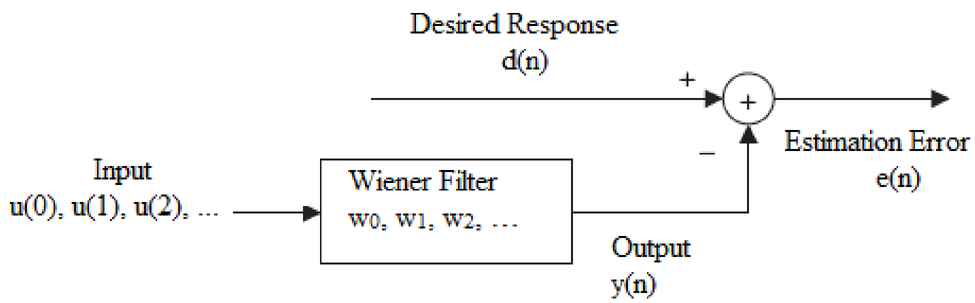


Figure 3.1: Block Diagram of Wiener Filtering (Haykin, 1996)

This filter has also two important advantages. First of all, it is linear, therefore, it is easy to analyze mathematically. Secondly, it is a discrete time filter. For that reason, it can be implemented on digital hardware devices (Haykin, 1996).

From Figure 3.1, the output signal for a single-weight case can be written as

$$y(n) = wu(n) \tag{3.1}$$

and error signal is given by

$$e(n) = d(n) - wu(n) \tag{3.2}$$

To find best tap-weight, the square of the error is taken as

$$e^2 = (d(n) - wu(n))^2 \tag{3.3}$$

$$e^2 = d(n)^2 - 2d(n)wu(n) + w^2u^2 \tag{3.4}$$

The expected value of Equation 3.4 is found as

$$E\{e^2\} = E\{d^2\} - 2wE\{d(n)u(n)\} + w^2E\{u^2(n)\} \tag{3.5}$$

where E is expected operator. Finally, cost function is written from (3.5) as

$$J = \sigma^2 - 2wP + w^2R \tag{3.6}$$

where,

$$J = E\{e^2(n)\} = MSE(Mean\ Square\ Error)$$

$$\sigma^2 = E\{d^2(n)\} = Power\ of\ Corrupted\ Signal$$

$$P = E\{d(n)u(n)\} = Cross - Correlation\ between\ d(n) and\ u(n)$$

$$R = E\{u^2(n)\} = Autocorrelation$$

Since σ^2, P and R are constants, the cost function (J) may be plotted as in Figure 3.2.

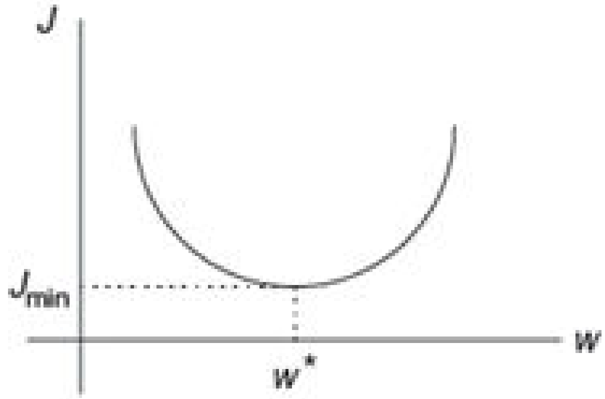


Figure 3.2: Mean Square Error Quadratic Function (Tan, 2008)

According to this figure, optimum tap-weight is at minimum mean square error. To find optimum tap-weight, the derivative of cost function is equated to zero.

$$\frac{dJ}{dw} = 0 \tag{3.7}$$

$$\frac{dJ}{dw} = -2P + 2wR \tag{3.8}$$

Then, the best tap-weight can be finally written as (Tan, 2008)

$$w = R^{-1}P \tag{3.9}$$

3.2 Steepest Descent

In order to solve the Wiener equation, which is shown in (3.9), several computations are required. Widrow and Stearns have described a method by using steepest descent algorithm. The purpose of this algorithm is to minimize the mean square error (MSE) by changing the filter coefficients in each sample (Tan, 2008).

Steepest descent algorithm helps to find minimum mean square error, J_{min}, value. The steps of steepest descent algorithm can be summarized as follows (Poularikas and Ramadan, 2006).

Step-I: Algorithm starts with the initial value assignment *w(0)*, which is usually equal to null vector.

Step-II: Gradient vector $\nabla J(w(0))$ is computed.

Step-III: To obtain *w(1)*, $-\mu\nabla J(w(0))$ is calculated and added to *w(0)*.

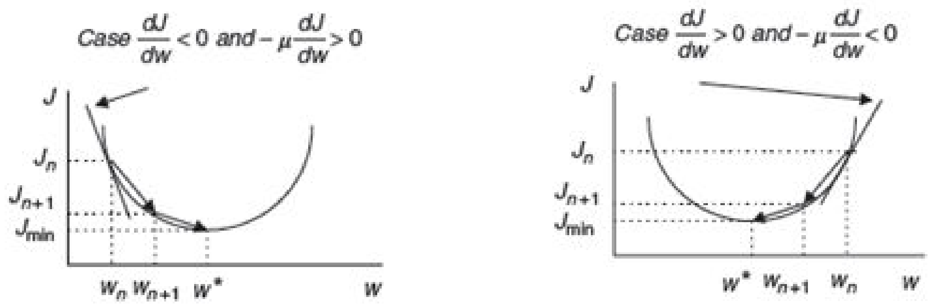
Step-IV: After that go to Step-II and continue the process to find optimum coefficients (until $\nabla J(w(0))$ is equal to zero)

The updated tap-weight vector can be written from the steepest descent algorithm as (Haykin, 1996),

$$w_{n+1} = w_n - \frac{1}{2}\mu\frac{dJ}{dw} \tag{3.10}$$

where μ is a real constant which is known as step size parameter at this equation. Here, the aim of using the factor $\frac{1}{2}$ is to cancel the factor of 2 at the equation (3.8).

The calculation of optimal tap-length value w^* of the steepest descent algorithm is shown in Figure 3.3.



a) b)

Figure 3.3: Illustration of the Steepest Descent Algorithm (Tan, 2008) (a) Case where $\frac{dJ}{dw}$ is negative (b) Case where $\frac{dJ}{dw}$ is positive.

Two different situations are shown in Figure 3.3. The first situation is the case, where $\frac{dJ}{dw}$ is smaller than zero (Figure 3.3(a)). If $\frac{dJ}{dw}$ is negative, it is easy to understand from (3.10) that $-\frac{1}{2}\mu\frac{dJ}{dw}$ will positive and updated tap length coefficient w_{n+1} will be increased. On the contrary, If $\frac{dJ}{dw}$ is positive (Figure 3.3(b)), it is understood from (3.10) that $-\frac{1}{2}\mu\frac{dJ}{dw}$ will negative and new tap length coefficient w_{n+1} will be decreased.

If (3.8) is substituted into (3.10), the updated tap weight can be computed by using the simple recursive relation such as in (3.11).

$$w_{n+1} = w_n + \mu[P - Rw_n] \tag{3.11}$$

3.3 Least Mean Square

The Least Mean Square (LMS) algorithm was invented by Widrow and Hoff in 1960, which is a kind of stochastic gradient algorithm (Poularikas and Ramadan, 2006).

A least mean square (LMS) algorithm consists of two basic processes (Haykin, 1996). First one is the filtering process that output of the filter is computed and estimation error is found by the difference between output and desired signal. The other is adaptive process. It provides automatic adjustment of the tap weights according to estimation error.

A feedback loop built with combination of these two processes, which are fundamental components of LMS algorithm and this feedback loop, is shown in Figure 3.4.

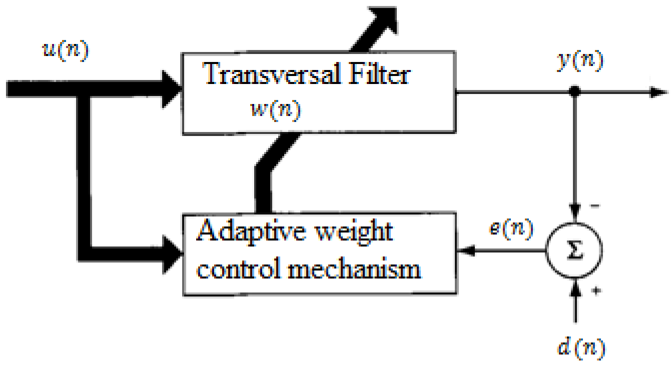


Figure 3.4: Block Diagram of Adaptive Transversal Filter (Haykin, 1996)

According to the Figure 3.5, tap inputs, *u(n)*, are processed by transversal filter and the result will be *y(n)*. Output of the transversal filter, *y(n)*, is also called as estimation of desired response. The estimation error, *e(n)*, can be found by difference between desired response, *d(n)*, and filter output. Then, adaptive control mechanism adjust coefficient of the filter tap lengths according to estimation error values (Haykin, 1996).

Some of the most important properties of LMS algorithm are (Poularikas and Ramadan, 2006)

- Autocorrelation and inverse matrices are not required in LMS algorithm. Thus, it decreases the computational complexity.
- It has a simple structure for implementations. This property is one of the most important reasons why LMS algorithm is preferred in applications.
- It has a step size parameter which controls stability and convergence rate of the algorithm
- LMS algorithm is stable and robust for different conditions and it is the other important reason for the popularly usage of LMS algorithm.

Based on sample values of tap input and desired response, autocorrelation, *R(n)*, and the cross-correlation are given by

$$R(n) = u(n)u^H(n) \tag{3.12}$$

$$P(n) = u(n)d(n) \tag{3.13}$$

If (3.8) is rewritten by using (3.12) and (3.13), instantaneous estimate of gradient vector is

$$\nabla J(n) = -2u(n)d(n) + 2u(n)u^H(n)w(n) \tag{3.14}$$

A new recursive relation to update the tap weight can be written by substituting (3.14) into (3.10), which is calculated as

$$w(n+1) = w(n) + \mu u(n)[d(n) - u^H(n)w(n)] \tag{3.15}$$

According to Figure 3.5, the output of filter is

$$y(n) = w^H(n)u(n) \tag{3.16}$$

and estimated error is

$$e(n) = d(n) - y(n) \tag{3.17}$$

A new form of (3.15) can be formed by substituting (3.16) and (3.17) into these equation that

$$w(n+1) = w(n) + \mu u(n)e(n) \tag{3.18}$$

3.4 Types of LMS

3.4.1 Normalized LMS

The correction $\mu u(n)e(n)$, which is added to tap weight $w(n)$ at iteration n+1, is directly proportional to input $u(n)$. Hence, gradient noise amplification problem will occur if tap input vector $u(n)$ is large. So, normalized least mean square (NLMS) algorithm can be used to solve this problem (Haykin, 1996). The normalized least mean square error (NLMS) algorithm is given (Haykin, 1996)

$$w(n+1) = w(n) + \frac{\tilde{\mu}}{\|u(n)\|^2} u(n)e(n) \tag{3.19}$$

where $\tilde{\mu}$ is the adaptation constant and new step size is

$$\mu = \frac{\tilde{\mu}}{\|u(n)\|^2} \tag{3.20}$$

The reason of using the normalized term can be seen from (3.20). Product of *u(n)* and *e(n)* is normalized by norm of the input *u(n)* (Haykin, 1996).

This algorithm has two advantages over classical LMS algorithm. First of all, it has potentially-faster convergence speed. The other one is independency of the stable behavior ($0 < \tilde{\mu} < 2$) from correlation statistics of input data (Douglas, 1994).

NLMS algorithm has also its own gradient noise amplification problem. The problem may occur if input vector *u(n)* is small due to division of squared norm of a small number $\|u(n)\|^2$. For that reason, a positive constant can be added to norm vector such as (Haykin, 1996)

$$w(n+1) = w(n) + \frac{\tilde{\mu}}{a + \|u(n)\|^2} u(n)e(n) \tag{3.21}$$

3.4.2 Sign Error

Multipliers are primary source of complexity at implementation of digital filters (Rath and Chakraborty, 2010). For that reason, in design stage, it is essential that low number of multipliers should be used to reduce complexity. If a multiplier is replaced by a single signed term, the complexity of the algorithm will reduce enormously. Thus, sign variation of LMS algorithm is very popular especially at hardware implementations. Since, it requires only addition and/or subtraction instead of multiplication. The basic types of sign LMS are

i) The Error Sign LMS

The signed error algorithm can be defined as

$$w(n+1) = w(n) + \mu\, sign\big(e(n)\big)u(n) \tag{3.22}$$

where

$$sign(n) = \begin{cases} 1 & n > 0 \\ 0 & n = 0 \\ -1 & n < 0 \end{cases} \tag{3.23}$$

is the signum function. The use of signum function provides simplification on hardware implementation. Thus, only shift and add/subtract operations can be enough for implementation.

ii) The Data Sign Algorithm

The signed data algorithm can be defined as

$$w(n+1) = w(n) + \mu\, sign\big(u(n)\big)e(n) \tag{3.24}$$

iii) The Sign Sign Algorithm

The sign sign algorithm can be defined as

$$w(n+1) = w(n) + \mu\, sign\big(e(n)\big)\, sign(u(n)) \tag{3.25}$$

3.4.3 Variable step-size algorithm

One of the most popular approaches is to use variable step size in the standard LMS algorithm (Aboulnasr et al., 1997).

Four important technical targets of adaptive filtering algorithm are (Yan et al., 2010)

- Convergence rate
- Tracking performance
- Static error
- Complexity

In this part, two important characteristics of an adaptive filter, convergence behavior and steady state mean square error (MSE), are investigated (Slock, 1993).

In original LMS algorithm step size is fixed. However, using fixed step size gives a drawback of conflict between mean square error and convergence speed. If step size is small, convergence time will be longer and square error will be lower (Kwong et al., 1992). On the contrary, convergence speed will be improved but square error will be higher if higher step size is selected.

Many algorithms are proposed to solve this conflict (Liu et al., 2009). Although all kinds of improved algorithms are seemed to be different than each other, all of them have same approach. At initial stages, the square error is high. So, step size is selected higher to increase speed of convergence. Then step size is adopted a lower level at convergence stable state to decrease stable static error.

The details about the formulation of this algorithm will be given in Chapter 4.

3.4.4 Variable tap-length algorithm

Tap length control is an effective way to improve LMS algorithm because the algorithm's performance is influenced by the tap length significantly (Gu et al., 2004), at fixed tap length LMS algorithms selection of suitable tap length reflects a tradeoff between steady state error and the speed convergence (Hui et al., 2010). For example, although selecting small tap length gives small steady state error, it increases the convergence time. On the other hand, selecting very long tap length causes increase in adaptation noise, but, also increase in process time of algorithm.

The advantages of the variable tap length algorithm on an adaptive filter mainly depend on the performance of the tap-length adaptation algorithm. If tap length is selected so large, the computational complexity will increase enormously. On the other hand, the tap-length algorithm should have fast convergence rate and good stability in order to be effective (Yu et al., 2008).

To find optimum result from these two contradictory situations, there is a commonly used method which is used mostly. Initially, the number of tap length is kept low to achieve fast convergence then, gradually increased to finally give the desired steady state performance (Pritzker and Feuer, 1991)

CHAPTER 4: ADAPTIVE FEEDFORWARD CONTROL SYSTEM

4.1 Adaptive Feedforward System Used in This Thesis

An adaptive feedforward system for the car environment is planned to use, which is shown in Figure 4.1 in this thesis. All simulations are done regarding to this control system. The reason of use of a feedforward system is the ability of taking reference signal from noise source, which is the main discrimination with a feedback system. Feedback system is generally used when it is not possible to get reference signal from the noise source as in headset application (Erkan, 2009). However, if it is able to acquire sample noise signal, which is usually possible in closed environment, feedforward systems should be preferred. Therefore, there are two microphones in the system as shown in Figure 4.1. First microphone is the reference microphone and sound of motor noise is collected by this microphone. Consequently, it must be placed near the motor. The other microphone is called as error microphone. The aim of this microphone is to sense difference between sound inside the cabin of the car and antinoise generated by the controller. Error microphone is used to update the coefficients of the adaptive filter via a digital signal processor. So, it directly changes effectiveness of the system. The error microphone and speakers are located near the driver in order to create a silence zone for driver.

In the given system, two speakers are used in order to cancel the motor noise at two ears of the driver. Correspondingly, two error microphones for two ears should be theoretically used. However, the maximum frequency to be considered in this application is about 150 Hz, which corresponds to the wavelength of 2.26 m for a sound wave in air. The distance between two ears of a people is about 25-30 cm. If one error microphone is placed between two ears, the distance between error microphone and speaker will be at most 15 cm, which belongs to 0.056 λ (20 degrees) at maximum frequency. Therefore, placing one microphone between speakers brings no significant magnitude and phase difference as compared to the case where two microphones are put adjacently to two speakers.

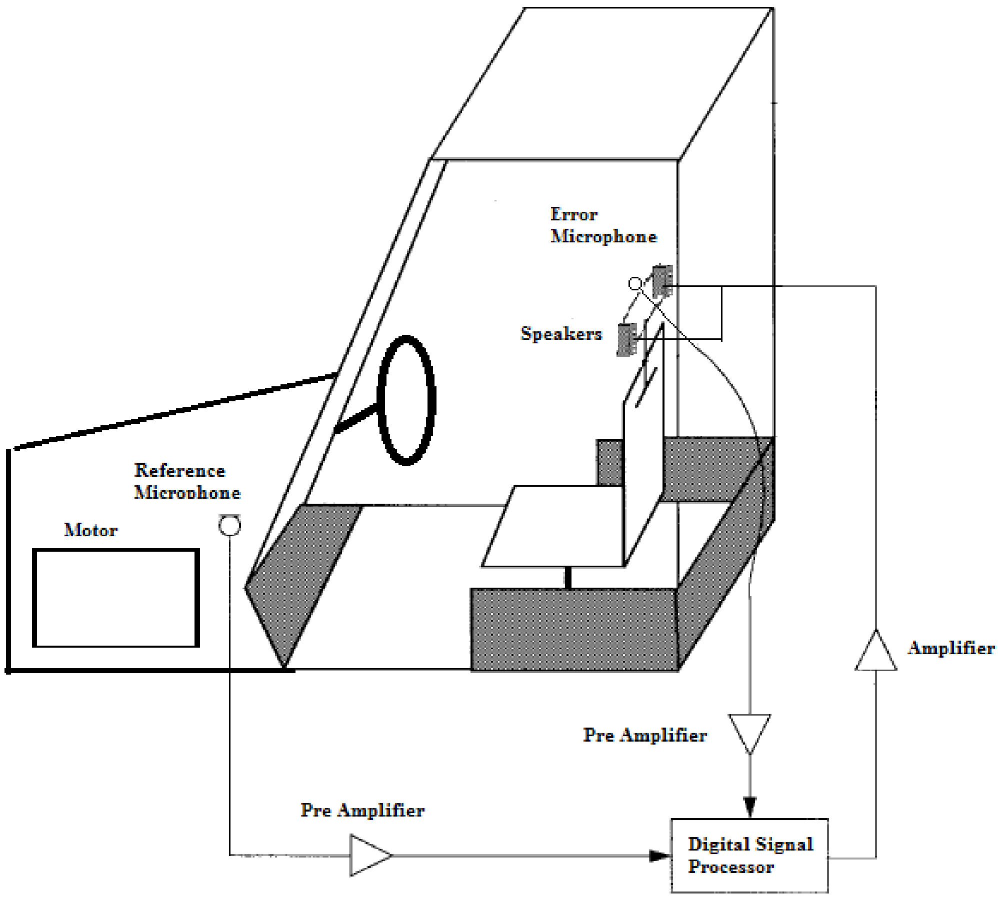


Figure 4.1: Proposed ANC System to Cancel Motor Noise for Driver (Kuo, 1999).

Tachometer can be also used to get information about motor sound. In this method, tachometer sends the data about revolution per minute to DSP. Honda is also used this system at their cars. There are two main differences in Honda's system as compared to the one this study. They are utilized from tachometer instead of reference microphone, and they cancel the motor noise at every location inside the cabin. For this purpose, as shown in Figure 4.2 they use two microphones inside the car as error microphones and multiple speakers to generate antinoise signal. The system has carried out about 10 dB reduction the noise for the frequencies below 100 Hz (Honda, 2012).

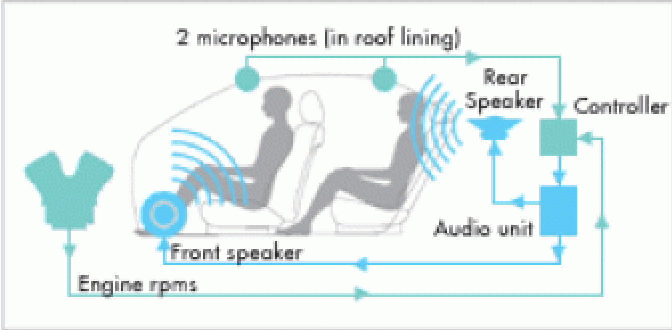


Figure 4.2: Honda's ANC System in the Cabin Area (Honda, 2012)

A similar project was also performed by (Minguez et al., 1999) using Filtered-X LMS algorithm. A tachometer is also used in this project to get engine signal. Block diagram of the system is shown in Figure 4.3.

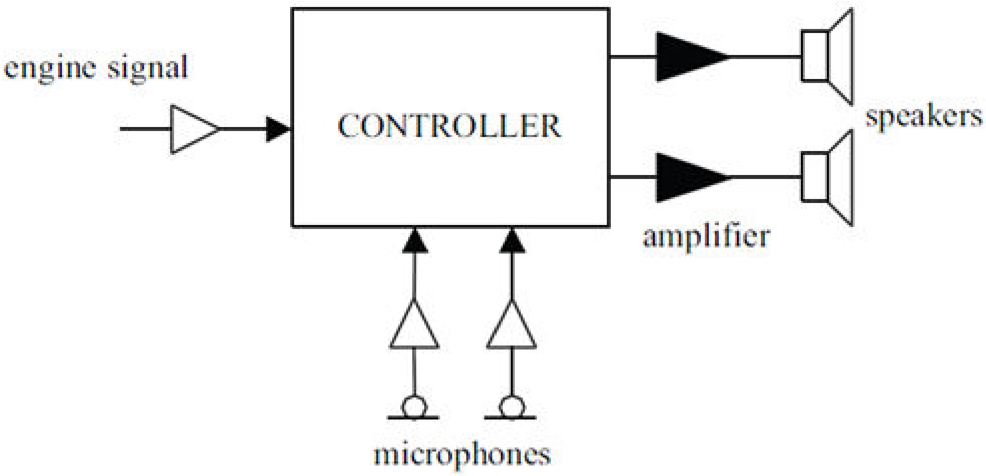


Figure 4.3: Block Diagram of the Active Noise Control System (Minguez et al., 1999).

4.2 Variable Length Least Mean Square Algorithm

Different types of Variable Length Least Mean Square (VLMS) algorithms are investigated in this part. But, it is paid attention in this investigation that algorithm must not include heavy calculations such as inverse matrix. These calculations cause important increase in the computational complexity and reduce real time performance of the system. Therefore, it is tried to search algorithms having computational complexity as low as possible.

4.2.1 Novel Stochastic Gradient Adaptive Algorithm with variable Length

A novel adaptive algorithm with variable tap length is proposed by (Rusu and Cowan, 2001). This study includes three different parts. These are adaptive filter length update, step size update and adaptive filter coefficient update.

In first part of the algorithm, the estimated error is calculated and as the result of this calculation, new filter length is defined.

Error estimator $\hat{e}$ is computed as (Rusu and Cowan, 2001)

$$\hat{e}(n) = \frac{L}{L+1}\hat{e}(n-1) + \frac{1}{L+1}|e(n)| \tag{4.1}$$

and new filter length is defined as

$$M(n+1) = \begin{cases} \frac{M(n)}{2}; if\ \hat{e}(n) > \frac{2}{M} \\ 2M(n); if\ \hat{e}(n) < \frac{4}{M} \\ M(n); otherwise \end{cases} \tag{4.2}$$

Updating step size is the second part of this algorithm. In this algorithm, $\mu(n)M(n)$ is always kept constant. So, step size changes as filter length changes.

The last part of the algorithm is the same as classical LMS equation.

In this thesis, this algorithm is used with some modifications except the second part. Because step size is changing with tap length, usage of second part causes some problems such as increase in computational complexity and the determination of constant value of $\mu(n)M(n)$.

In second part of the algorithm, the initial value of the step size must be entered manually. Therefore, selection of this value effects system performance directly and if it is not selected properly, the system will be unstable. Hence, step size must be controlled at each iteration to satisfy the stability condition of $0 < \mu < \frac{2}{\lambda_{max}}$. But, this situation increases the complexity enormously. On the other hand, error, which is caused by improper selected step size, may not be decreased very much. Besides, in this part, the filter lengths are selected as powers of two. Because the step size changes only with tap length, these changes are restricted only at discrete values most of the time.

Normalized LMS method is used instead of second part of the algorithm to overcome problems caused by improper selection of step size. Using Normalized LMS provides some advantages over constant $\mu(n)M(n)$ structure. One of these advantages is that it is not needed to define initial value of μ. Step size is calculated with the input signal. The other advantage is that since $\mu(n)$ is independent from tap length $M(n)$, we have more flexibility about step size change. So, values of step size have been in a larger interval in Normalized LMS. For these reasons, error by using NLMS may be decreased more than the case where second step of the algorithm is used.

Step size is updated as

$$\mu(n) = \frac{0.01}{1 + \sum_{k=1}^{M} u(k)^2} \tag{4.3}$$

4.2.2 Other Variable Tap Length LMS Algorithms

A variable tap length algorithm is suggested for LMS structure by (Won et al., 1994). This paper benefits from time constant concept to find new tap length. But, in order to find time constant, some complex operations such as calculation of correlation matrix are needed. Therefore, this algorithm is not used in this study.

The study given in (Alwan, 2006) uses a VLMS algorithm and it is tested in an echo canceller application. This algorithm includes some operations like factorial, and these calculations cause the increase of processing time. For these reasons this algorithm is not preferred.

The study in (Zhang et al., 2007) suggests a new VLMS algorithm. However, this algorithm uses logarithm operant at every iterations. So, it causes increasing in computational complexity. Therefore, this algorithm is also not considered in this study.

4.3 Variable Step Size Least Mean Square Algorithm

In this part, variable step size LMS algorithms are explained. Although there are many algorithms about step size, most of them cannot be used in this thesis due to their complexity.

4.3.1 Variable Step Size LMS Adaptive Filtering Algorithm

The variable step size algorithm used in this thesis is based on the study in (Li and Peng, 2009). In this study, the update equations for step size values are given by

$$\mu(n) = \beta(n)(1 - e^{-\alpha(n)|e(n)e(n-1)|}) \tag{4.4}$$

$$\beta(n) = \gamma\beta(n-1) + (1-\gamma)|e(n)e(n-1)| \tag{4.5}$$

$$\alpha(n) = a_1, a_2 \quad (a_2 > a_1) \tag{4.6}$$

where $\mu(n)$ is the step size, $\beta(n)$ is the parameter, which restricts step size, $\alpha(n)$ is defined as hop parameter and it is randomly selected as either a_1 and a_2 in each iteration. γ is a constant ,which is called as correlation factor. However, it can be easily concluded that this structure increases computational complexity significantly. So, another structure of the formula given in the same study is preferred (Li and Peng, 2009). According to this structure, step size equation is

$$\mu(n) = \beta\frac{1}{1+e^{-\alpha|e(n)|}} - 0.5 \tag{4.7}$$

where α and β are algorithm-specific constants and both are selected as 1 in the following simulations.

4.3.2 Other Variable Step Size LMS Algorithms

In a paper given by (Won et al., 1994), a variable step size algorithm for LMS is introduced. This algorithm uses time constant concept to find new step size. But, correlation matrix must be calculated to get time constant. For this reason, it is not suitable to the in this thesis.

A new variable step size algorithm is suggested at (Akhtar et al., 2006). This algorithm needs some pre-calculations to calculate new step size value and these pre-calculations cause increasing in the computational complexity. On the other hand, this algorithm can be considered as an alternative since pre-calculations consist in only simple operations.

(Hu et al., 2010) suggests a new and simple method to find VSLMS algorithm. However, the constant in the method is defined by eigenvalues at correlation matrix. Therefore, this algorithm is not suitable to real time applications.

CHAPTER 5: SIMULATIONS and RESULTS

This part includes tests and their results about subjects, which are informed in Chapter 3 and Chapter 4, respectively. MATLAB is used at these simulations. The prepared Graphical User Interface (GUI) is also given in Appendix A.

5.1 ANC Tests for Pure Sinusoidal

Tap length and step size are two parameters that affect performance of an adaptive filter and, therefore effect of these two parameters are tested in this part. A pure sinusoidal signal, which has the frequency of 150 Hz, is used as desired signal. A signal, which has sinusoidal frequency of 1000 Hz, and a random noise are added to contaminate the desired signal. Last 20% part of desired and noisy signal is shown in Figure 5.1 and Figure 5.3, respectively and Fourier transform of desired and overall noisy signals can be seen in Figure 5.2 and Figure 5.4, respectively.

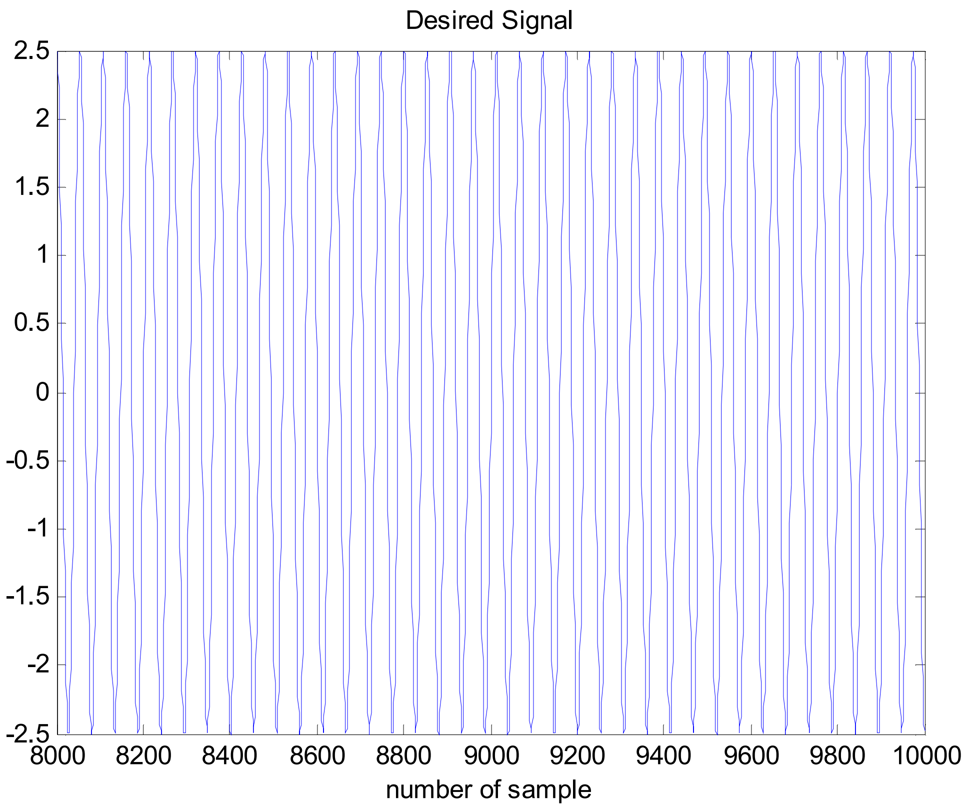


Figure 5.1: Last 20% Part of the Pure Sinusoidal Signal

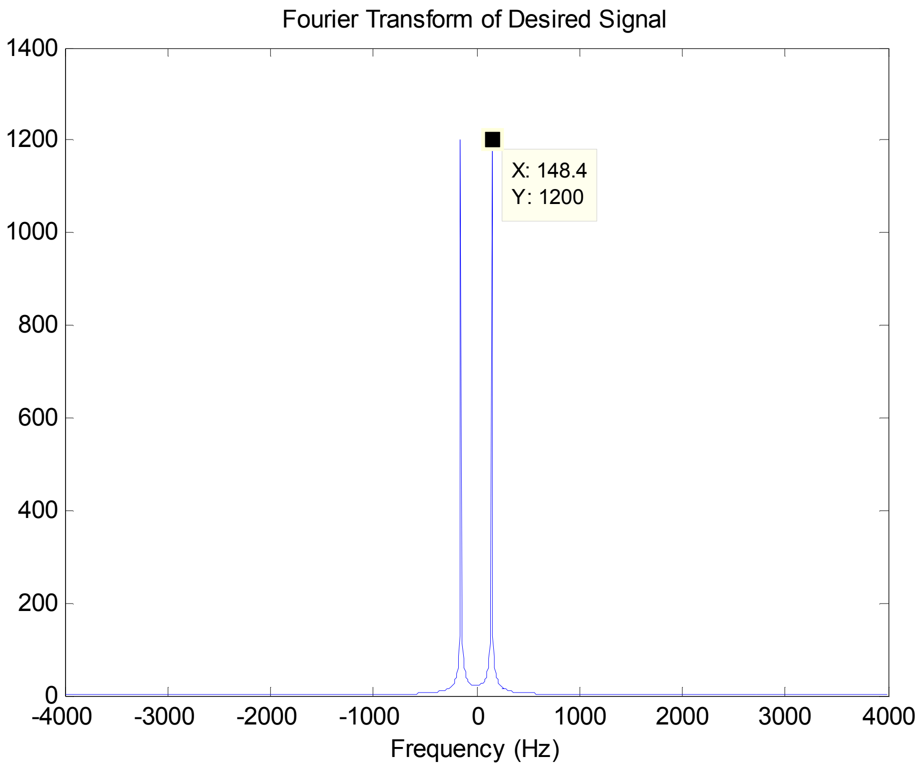


Figure 5.2: Fourier Transform of Desired Signal

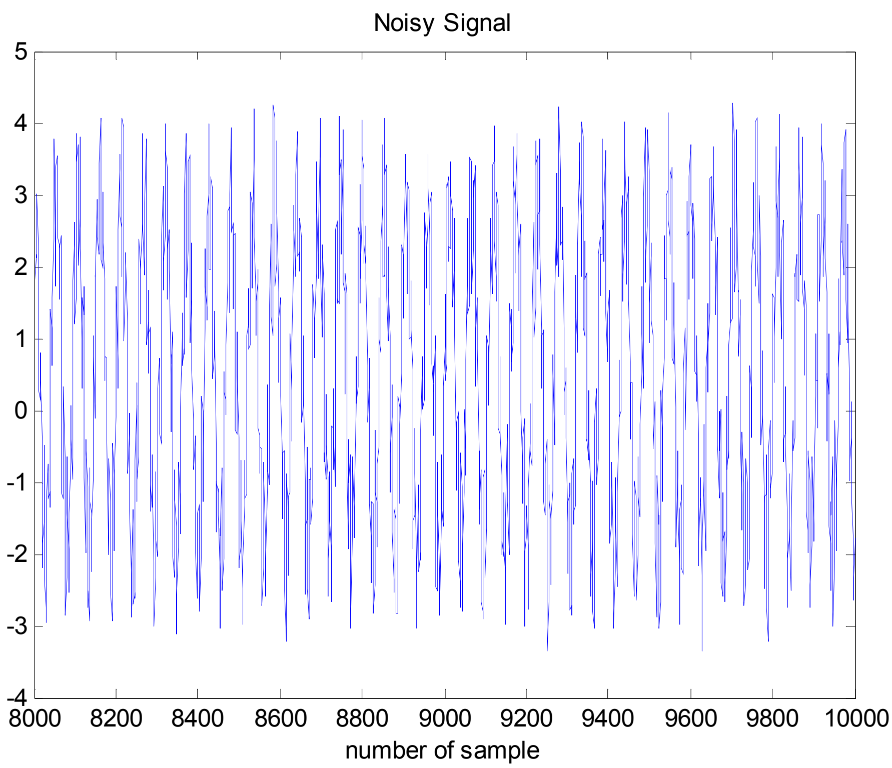


Figure 5.3: Last 20% Part of the Noisy Sinusoidal Signal

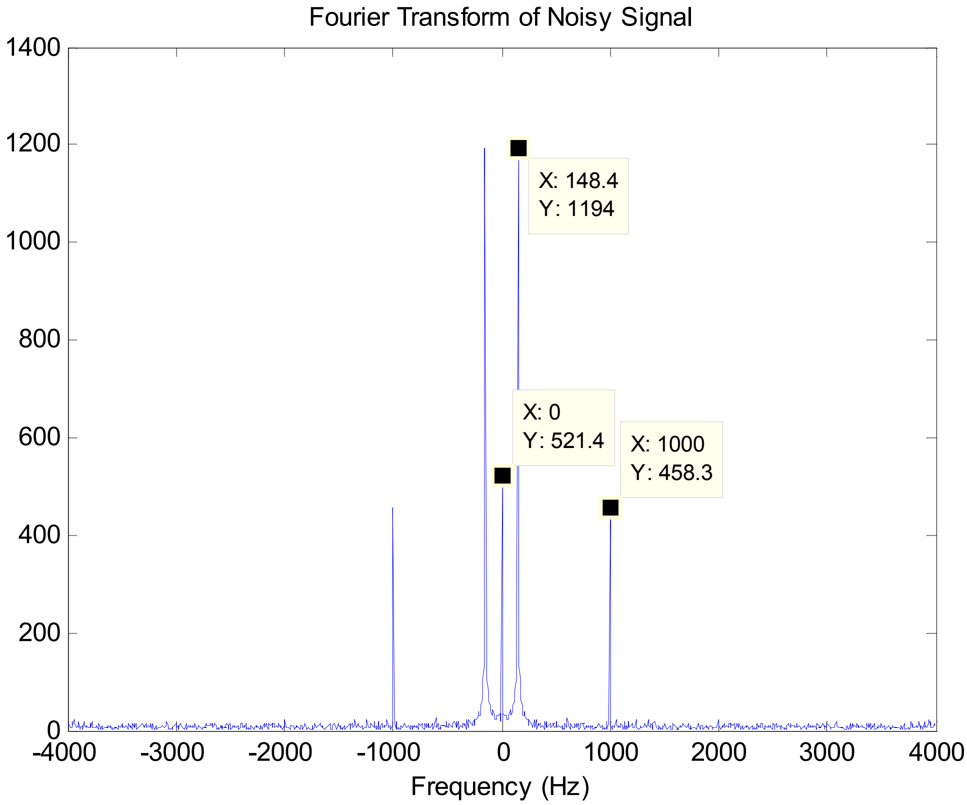


Figure 5.4: Fourier Transform of Noisy Signal

There is no DC component in the original signal and DC component is added as a noisy signal. This is achieved by using Matlab function “rand”, which generates random signal between 0 and 1, and this causes an offset. Therefore, a DC component is seen in Figure 5.4. DC component is deliberately added to the original signal to show that the system can also eliminate DC noise.

5.1.1 The Effect of Tap Length on LMS Performance

In order to show the effect of tap length on classical LMS algorithm, several simulations are realized for a constant step size value of $\mu = 0.007$ and different tap lengths. The results are shown in Figure 5.5 that MSE in dB is calculated by (5.1). Original sinusoidal signal and noisy sinusoidal signal consist of 10000 samples. In Table 5.1, Mean Square Error (MSE) is also calculated for first 20% (samples from 1 to 2000) part and last 20% (samples from 8001 to 10000) part of the signal to see convergence rate and ability to cancel error at the end of simulation.

$$MSE = \frac{\sum_{n=1}^{N} |e(n)|^2}{N} \tag{5.1}$$

It can be seen from Figure 5.5 and Table 5.1 that the efficiency of the adaptive filter is increasing up to a level by increasing tap length and become almost constant after tap length of 30.

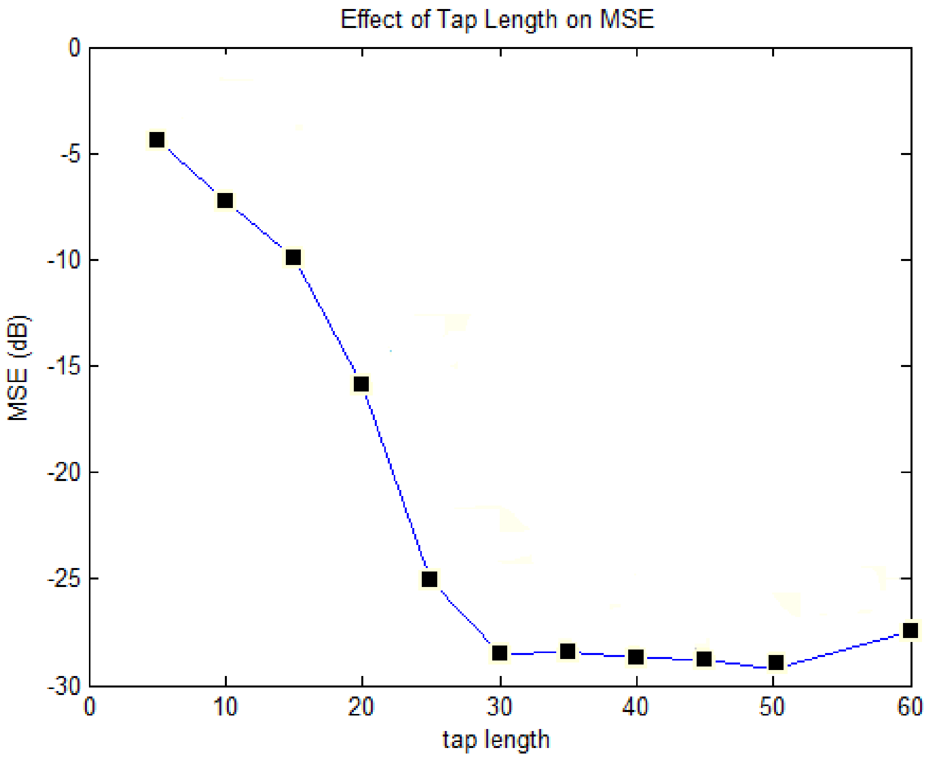


Figure 5.5: Tap Length Effect on MSE

Table 5.1: Tap Length Effect on MSE Along with First and Last 20% Part for $\mu = 0.007$

Tap Length	MSE (dB)	MSE (for fist 20% part)	MSE (for last 20% part)
5	-4,4418	-4,1671	-4,4952
10	-7,274	-7,2623	-7,2809
15	-9,9012	-9,2243	-10,0075
20	-15,8815	-14,3417	-16,3553
25	-25,0603	-21,4577	-26,5491
30	-28,5722	-23,4094	-31,8017
35	-28,404	-23,3256	-31,5678
40	-28,7175	-23,3207	-32,1697
45	-28,8197	-23,1194	-33,3321
50	-29,2351	-23,2259	-35,0805
60	-27,4876	-20,9818	-36,8576

The effect of tap length on error and mean square error is shown in Figure 5.6 and Figure 5.7, respectively. Step size is also selected as $\mu = 0.007$ for both of these time domain figures. For Figure 5.7, MSE for each sample is evaluated with (5.1).

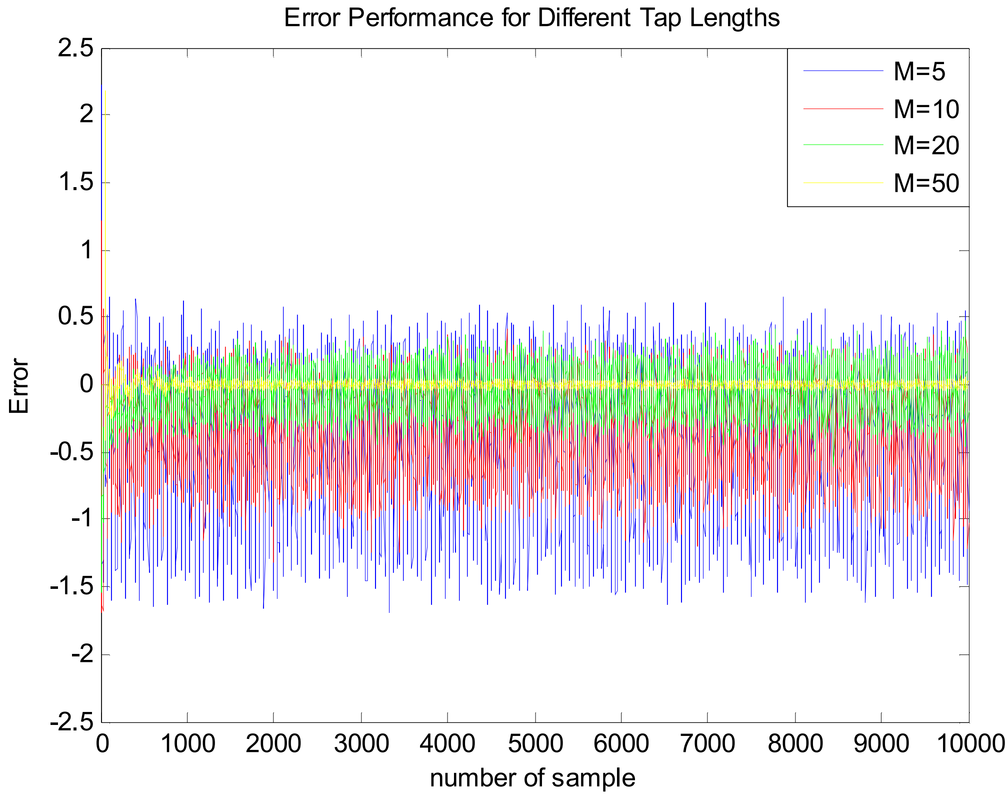


Figure 5.6: Error Graph of LMS for Different Tap Lengths

The effect of tap length can be seen clearly from these figures that if tap length is not selected properly, performance of the system will decrease significantly. So, tap length must be selected sufficiently large. Nevertheless, assigning tap length to very large values causes some other problems that process time will increase and adaptation noise will increase when selecting unnecessary large tap length.

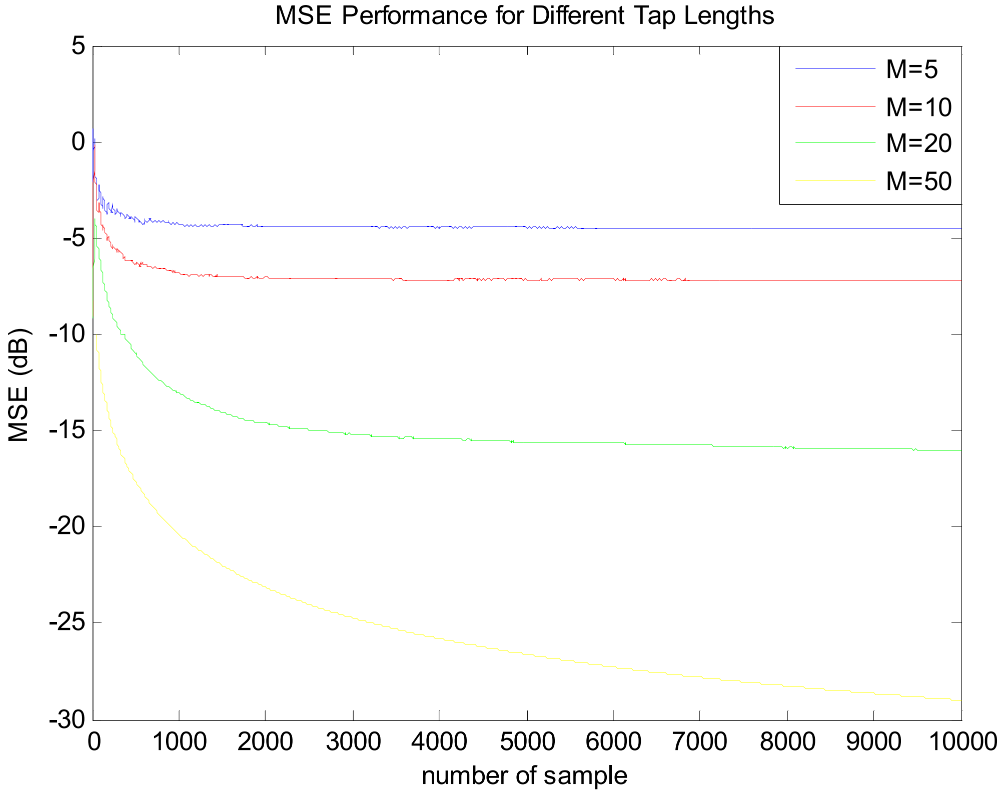


Figure 5.7: MSE Graph of LMS for Different Tap Lengths

5.1.2 The Effect of Step Size on LMS Performance

Step size are alters the convergence speed and error directly for an LMS adaptive filter. Therefore, to demonstrate the effect of step size on classical LMS algorithm, the simulations with different adaptive step sizes are realized. In these simulations, tap length is selected as 20 and results are given in Figure 5.8 and Figure 5.9.

The selection of smaller step size cause slower convergence speed, which is shown in Figure 5.8.In fact, step size parameter causes a tradeoff between convergence and steady state error. If step size selected small, error could be small but it will have slow convergence speed and large error and fast convergence speed will occur when the step size selected bigger as it is shown in Figure 5.9.

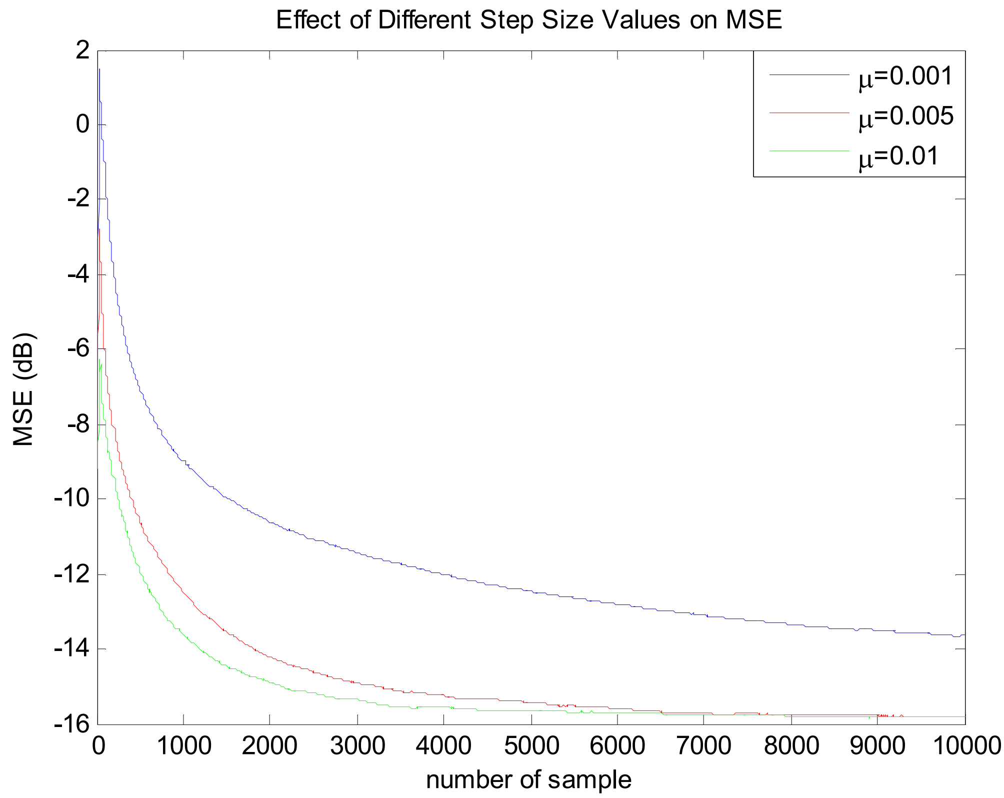


Figure 5.8: MSE Graph of LMS for Different Step Sizes

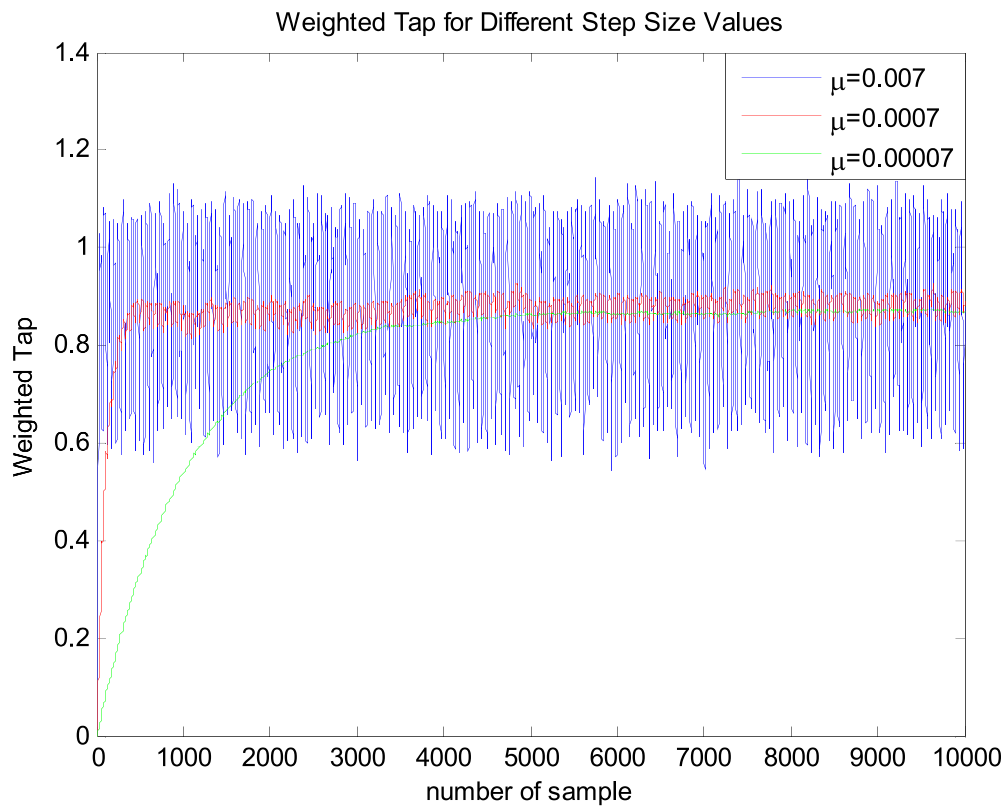


Figure 5.9: Weighted Tap Graph of LMS for Different Step Sizes

5.1.3 The Effect of Sign Algorithms on LMS Performance

Sign-sign LMS algorithm and its variants such as sign-data LMS and sign-error LMS algorithms are used in DSP applications frequently. These algorithms give an improvement about decreasing computational complexity. However, they usually cause poorer performance for the adaptive filter. But, the effect of these algorithms on system performance is depending on input signal.

Result of simulations for these three structures can be seen in Figure 5.10 (step size is selected as 0.007 and tap length is selected as 20). It is shown from figure that sign-error gives best MSE performance and sign-sign provides worst MSE performance. On the other hand, sign-sign have minimum computational complexity. These results can be also seen at Table 5.2.

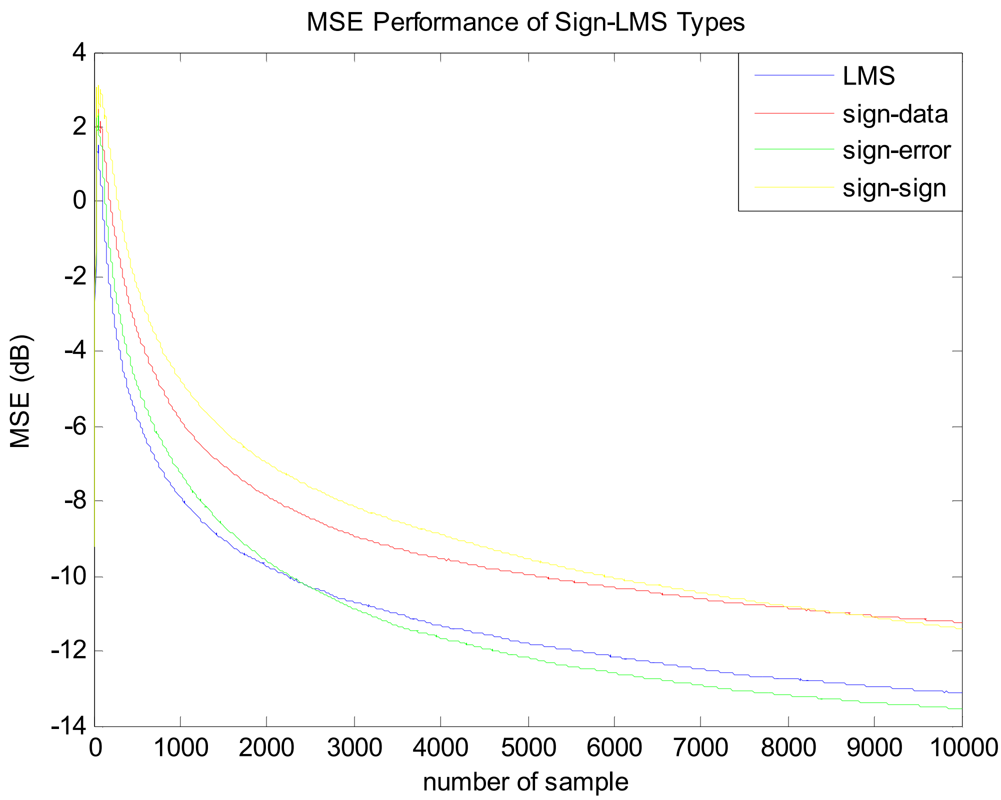


Figure 5.10: Effect of Sign-Sign Algorithms on MSE Performance of LMS

Table 5.2: Comparison MSE Performances of Sign Algorithms

	MSE (dB)	MSE (for first 20% part)	MSE (for last 20% part)
LMS	-12,1861	-7,7785	-17,2591
sign-data LMS	-9,1809	-5,0618	-12,3023
sign-error LMS	-13,8528	-7,4700	-29,3749
sign-sign LMS	-10,0859	-4,7283	-16,6332

As a result of Table 5.2, it can be seen that sign-error LMS algorithm has the best MSE performance for overall and last 20% part. Although, LMS algorithm has the best performance for first 20% part. But, result of sign structure depends on the input signal quietly. Therefore, these results can be changed for different input signals.

5.1.4 Process Time Comparison

In this part, process time of classical LMS, normalized VLMS and VSLMS algorithms are compared and the results are shown in Table 5.3. These results are in MATLAB environment obtained with a PC, which has Intel Core i3-370M processor and 3GB Ram.

Table 5.3: Process Time Comparison of LMS, Normalized VLMS and VSLMS Algorithms

	LMS	Normalized VLMS	VSLMS
Process Time (second)	5,766542	7,659834	7,875496

In order to compare process times of these algorithms, a freewheeling motor sound is used and this signal consists of 54810 samples. Most of the DSP systems use a CODEC, which has 8 kHz sample frequency to get analog data to electrical signal from microphone and to convert electrical signal to analog signal with loudspeaker. Therefore, duration of the freewheeling motor sound can be considered as 6,85125 seconds.

As a result of process time comparison of the algorithms, it is seen that LMS algorithm is suitable to use in real time applications. While, process time of Normalized VLMS and VSLMS algorithms exceed the duration of the input signal. Therefore, sign structures can be used in order to decrease the process time.

5.2 ANC Tests for Freewheeling Motor Sound

In this part, a freewheeling motor sound, shown in Figure 5.11, is used as desired sound, and the motor sound polluted by different noise signals is given in Figure 5.12. Both of these two signals have 54810 samples.

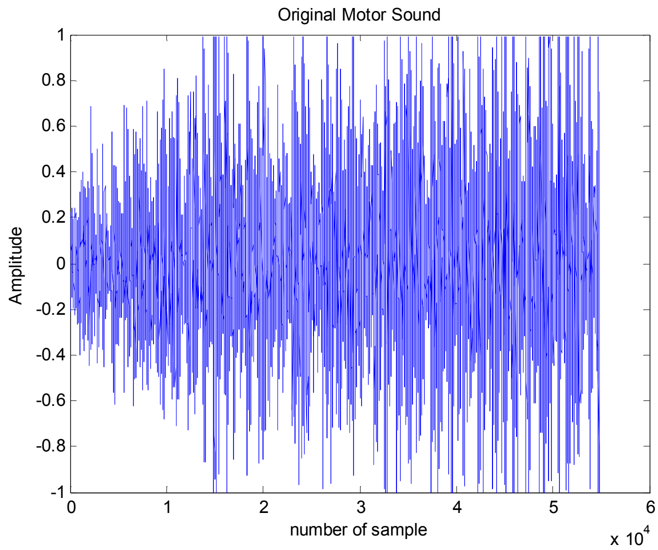


Figure 5.11: Freewheeling Motor Sound

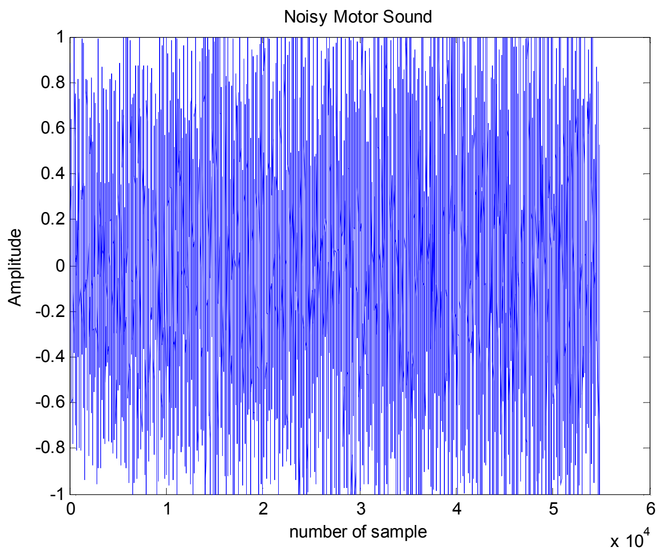


Figure 5.12: Noisy Motor Sound

Frequency components of freewheeling motor sound and noisy motor sound can be seen in Figure 5.13 and Figure 5.14, respectively, to recognize differences between these two signals.

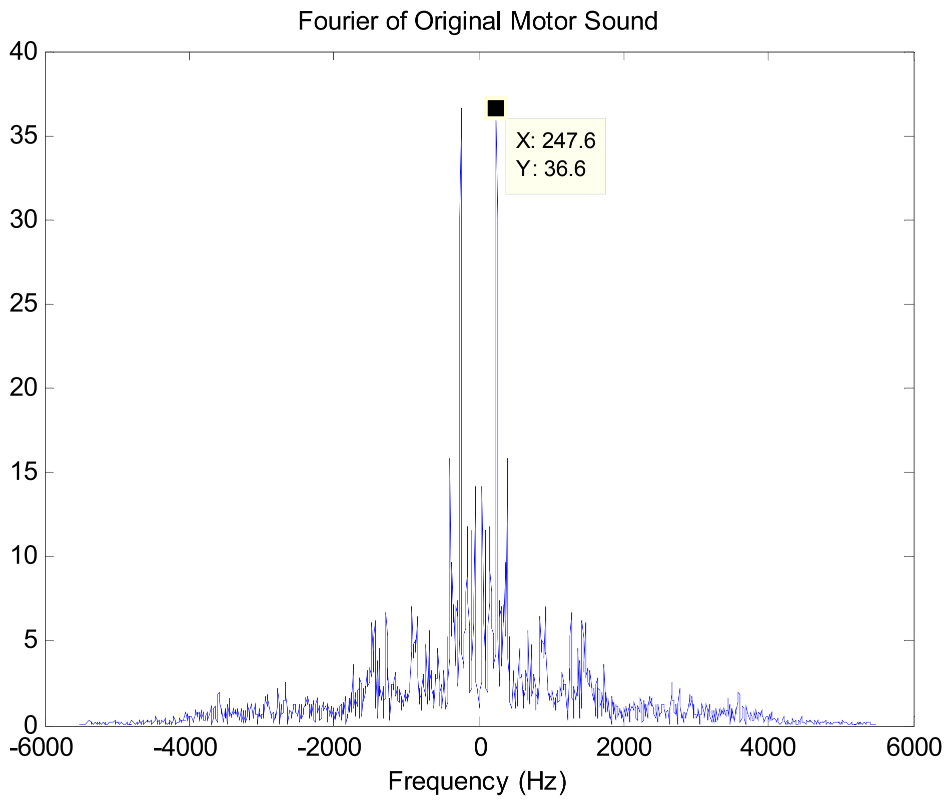


Figure 5.13: Fourier Transform of Freewheeling Motor Sound

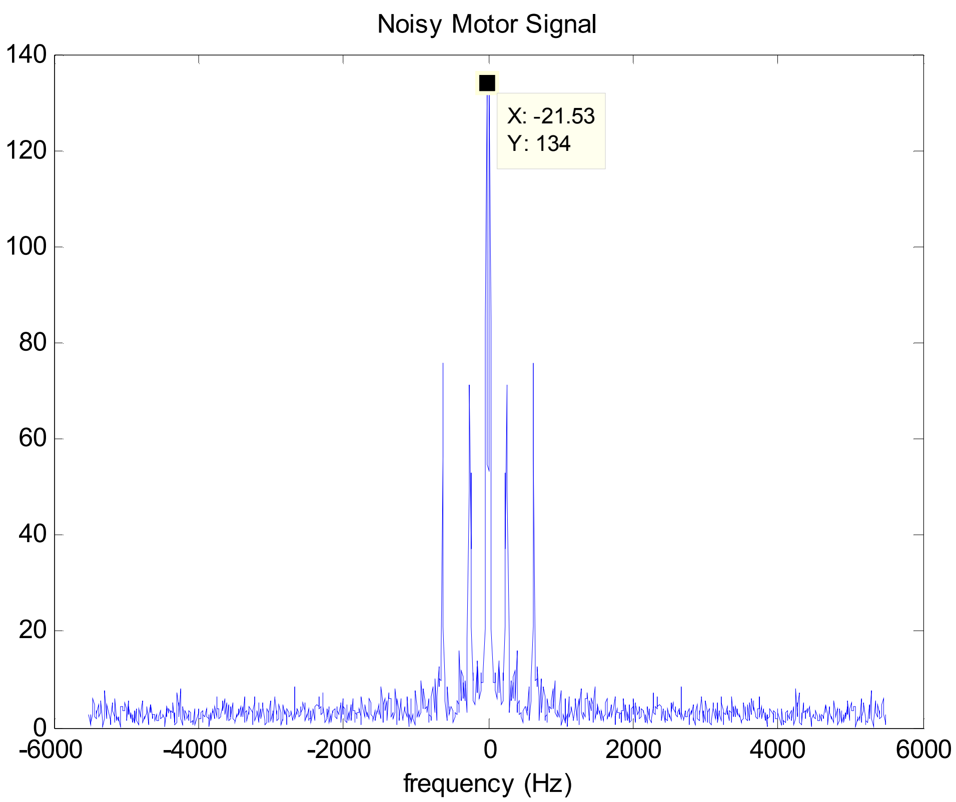


Figure 5.14: Fourier Transform of Noisy Motor Sound

As being initial tests, these two signals are used as inputs for classical LMS, Normalized – Variable length LMS (VLMS) and Variable Step Size LMS (VSLMS) algorithms. Tap length is selected 10 and step size is selected as 0.0007 for classical LMS algorithm and selected parameters for VSLMS algorithm are $\alpha = 1$ and $\beta = 1$. Graphs of errors belonging to these adaptive filters are shown in Figure 5.15, Figure 5.16 and Figure 5.17. Comparison of three algorithms is also shown in Figure 5.18.

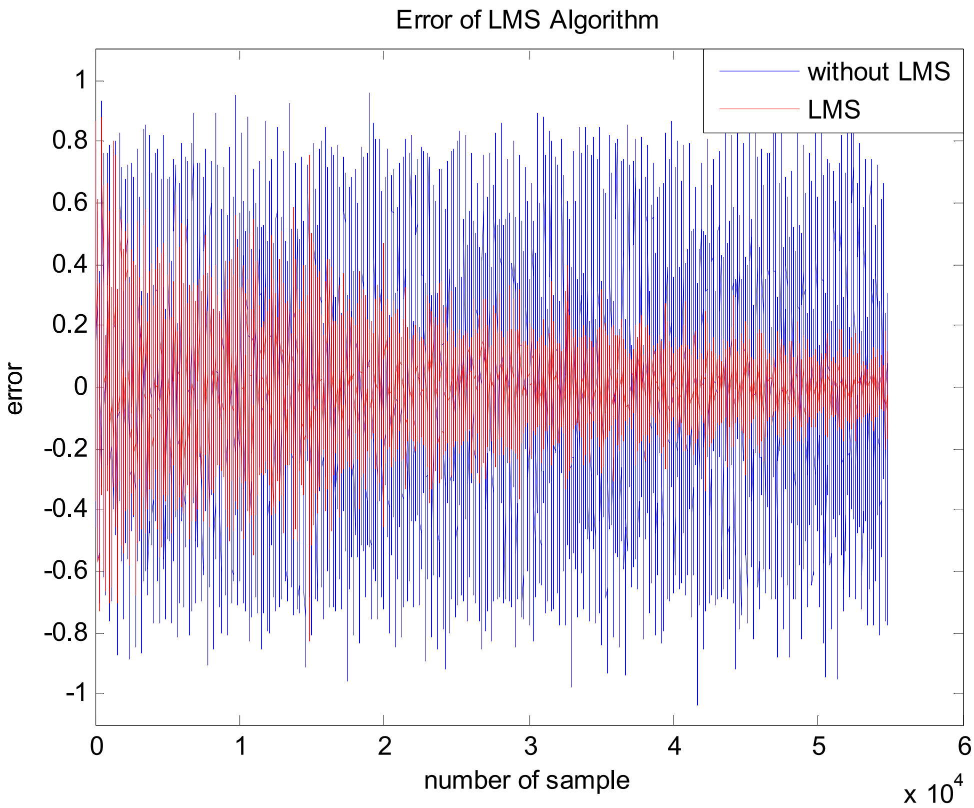


Figure 5.15: The Error Signal without and with LMS

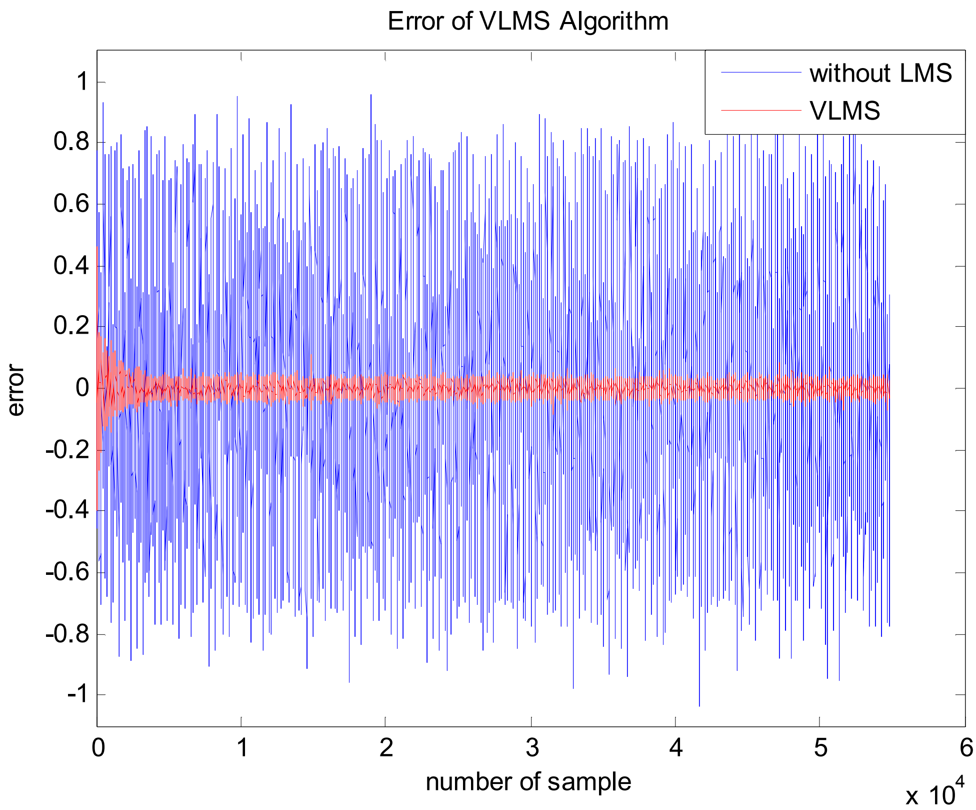


Figure 5.16: Result for Normalized VLMS algorithm

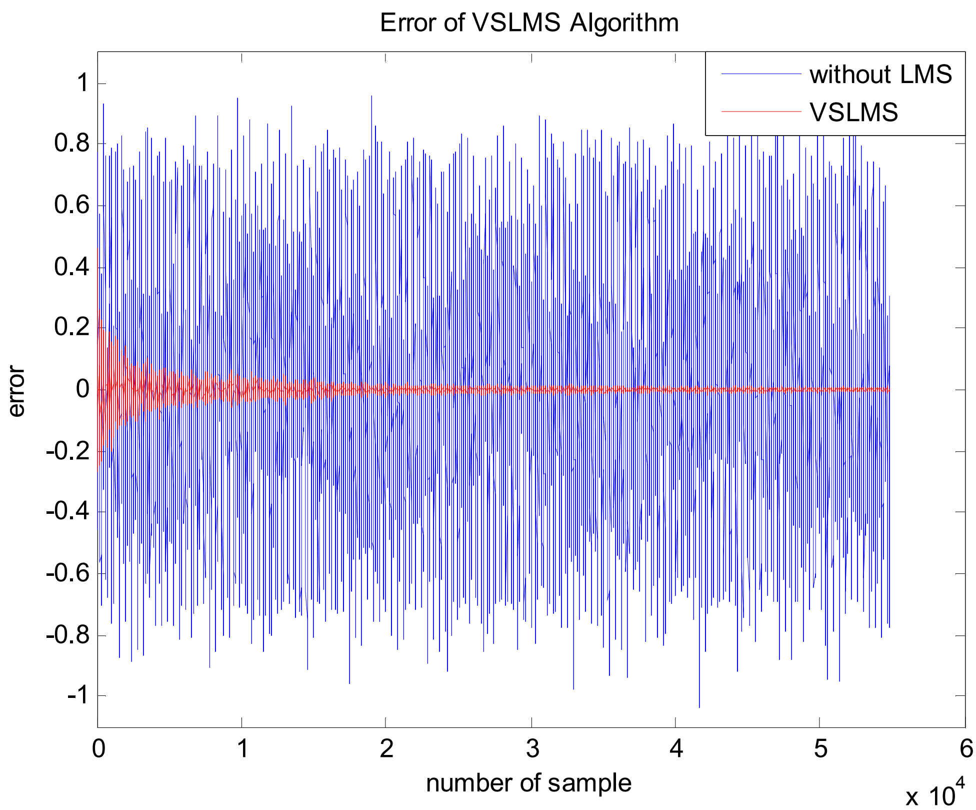


Figure 5.17: Result for VSLMS algorithm

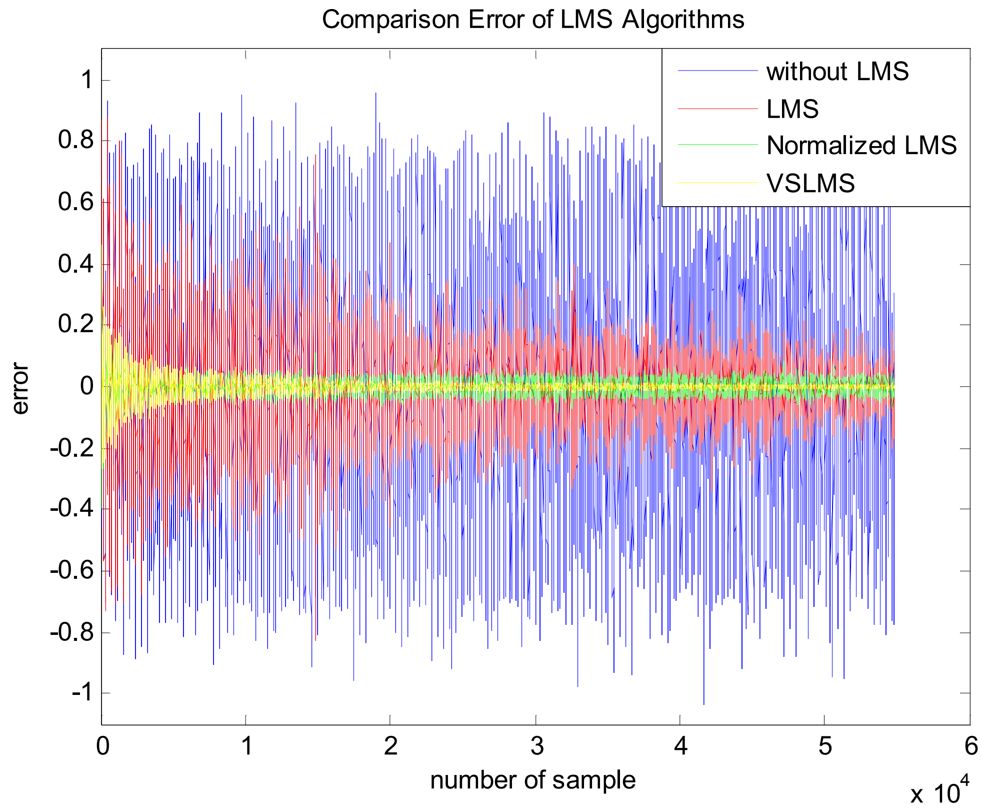


Figure 5.18: The Comparison of LMS-VLMS-VSLMS Algorithms

As a result of the last four figures, it can be said that normalized VLMS algorithm has the fastest convergence speed. Although VSLMS algorithm has slower convergence speed than normalized VLMS, this algorithm gives the best error cancellation performance. Besides the LMS algorithm has the worst performance with respect to convergence and error cancellation.

Table 5.4 has the numerical MSE results for freewheeling motor sound. Although VLMS and VSLMS algorithms have near overall MSE performance and MSE performance for first 20% part of signal, MSE performance for last 20% part is best for VSLMS algorithm. So, selecting VSLMS algorithm is the best option because last performance is important for this application.

Table 5.4: Comparison of LMS Algorithms for Motor Sound

	MSE (dB)	**MSE (for fist 20% part)**	**MSE (for last 20% part)**
LMS	-19,2143	-14,8737	-25,6833
VLMS	-33,8604	-29,5623	-36,3915
VSLMS	-34,8728	-28,2665	-50,1812

The performance of normalized LMS and normalized VLMS are also compared in Figure 5.19 to see the effect of VLMS. VLMS is superior to NLMS with respect to convergence speed but, they have similar error filtering performance.

The change in step size values throughout the whole signal is also investigated for both algorithms. The results are given in Figure 5.20 that step size changes within a larger interval for VSLMS algorithm. At initial part of algorithm, VSLMS filter have biggest step size values and it provides fast convergence speed. Then, value of step size decreases and gets minimum value at the end of process. Minimum error can be obtained with this step size reduction.

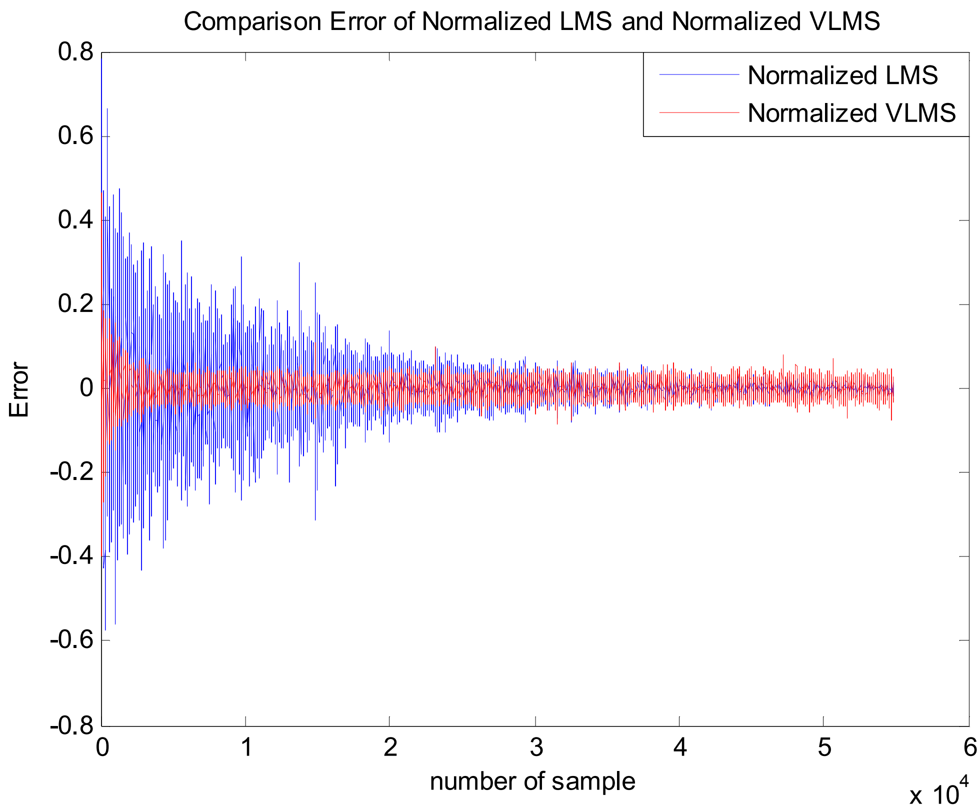


Figure 5.19: The Comparison of Normalized LMS and Normalized VLMS

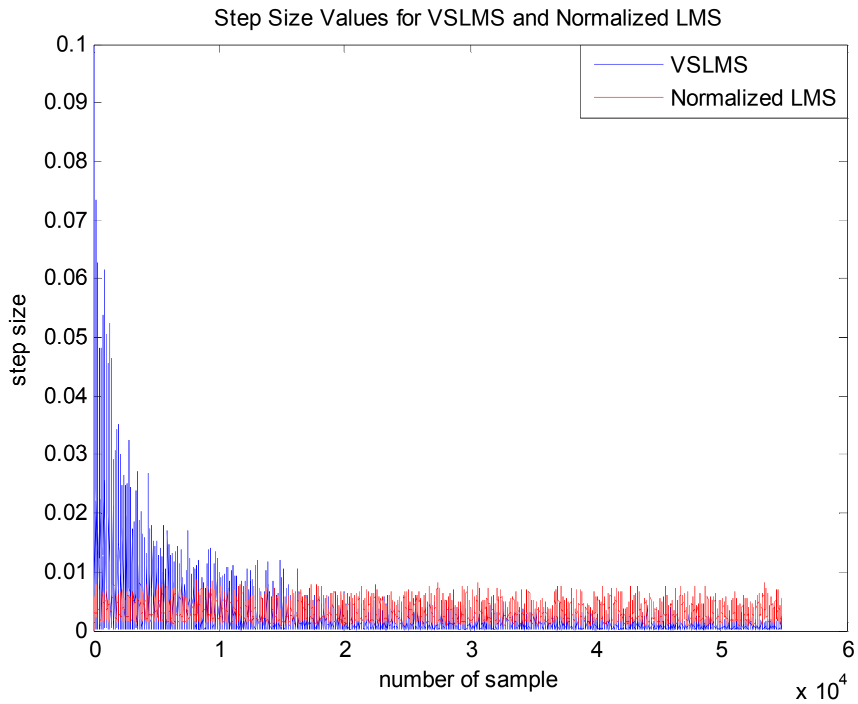


Figure 5.20: The Comparison of Step Size Changes for Normalized LMS and VSLMS

For VLMS algorithm, the tap length values as time progresses are also examined which is shown in Figure 5.21. According to this figure, tap length is mostly alternating between 128 and 256 mostly for the freewheeling motor sound.

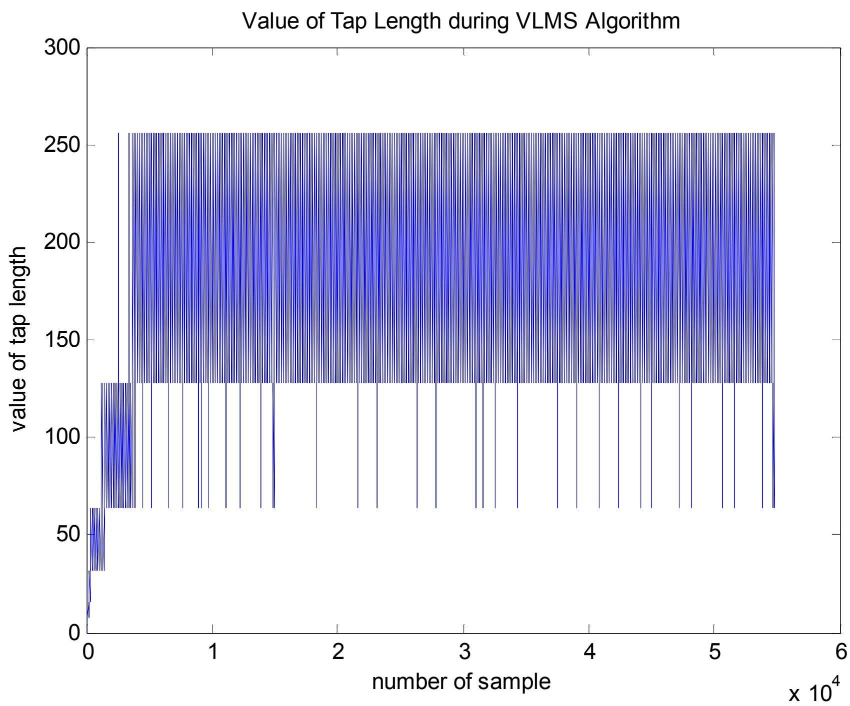


Figure 5.21: Tap Length Changing during VLMS Algorithm

As the last results for the test of freewheeling motor sound, MSE performance of VSLMS algorithm for different tap length values is studied. The results can be seen from Table 5.5 that VSLMS algorithm is almost not affected from tap length.

Table 5.5: Tap Length Effect on VSLMS Algorithm

Tap Length	MSE (dB)	MSE (for fist 20% part)	MSE (for last 20% part)
4	-35,0626	-28,4587	-50,6379
6	-35,0419	-28,4339	-50,3788
10	-34,9760	-28,3700	-50,2257
15	-34,9116	-28,3092	-50,2011
20	-34,8728	-28,2665	-50,1812
30	-34,7785	-28,1619	-50,2314
50	-34,5782	-27,9157	-50,5073
100	-34,0408	-27,2786	-50,9163

5.3 ANC Tests for Accelerating Motor Sound

In this part, different types of LMS algorithm are tested for accelerating motor sound. Original and noisy sound signals are shown in Figure 5.22 and Figure 5.23, respectively. Noisy sound signal includes some sinusoidal signals, random noise and sound of a jet engine.

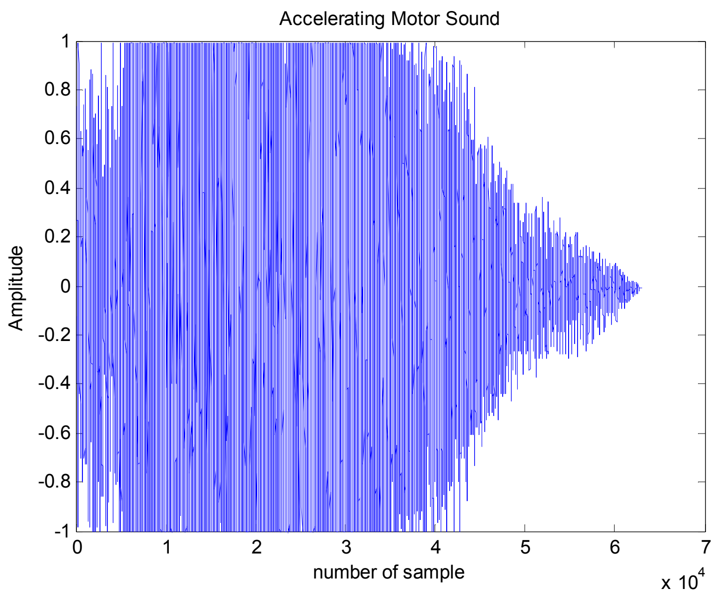


Figure 5.22: An Accelerating Motor Sound

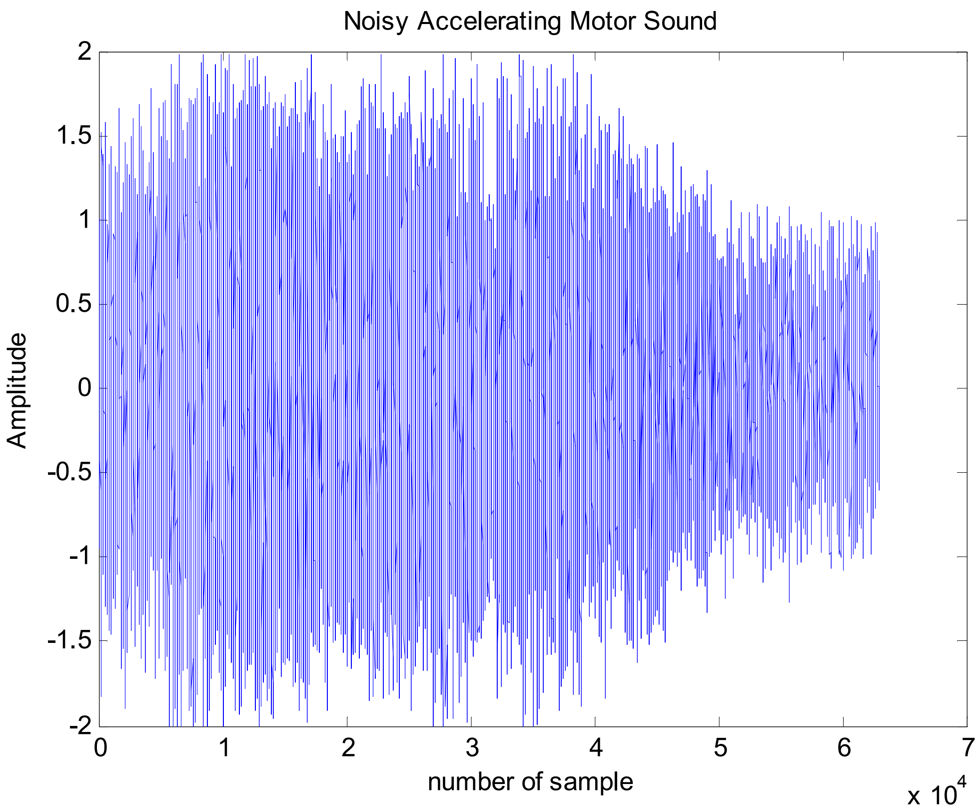


Figure 5.23: Noisy Accelerating Motor Sound

Sound of a jet motor is added to two nonoverlapping intervals of the motor sound to get noisy signal. There are two reasons for this process. Sound of jet engine has 32000 samples while accelerating motor sound has 63000. So, same jet engine signal is added by starting from 1th and 32001th samples. The other reason is to test the performance at the algorithms to abrupt changes. This change and response of LMS algorithms to this change can be seen in Figure 5.24, Figure 5.25 and Figure 5.26 for classical LMS, VLMS, VSLMS, respectively.

It is easily seen from Figure 5.25 that Normalized VLMS algorithm has worse performance after the sharp change at input signal. However, VSLMS algorithm is not affected from this abrupt change so much as shown in Figure 5.26 and it has the lowest error among all algorithms at the end of the process. So, it can be said that VSLMS algorithm has best performance at sharply changing signals relative to LMS and Normalized VLMS algorithms.

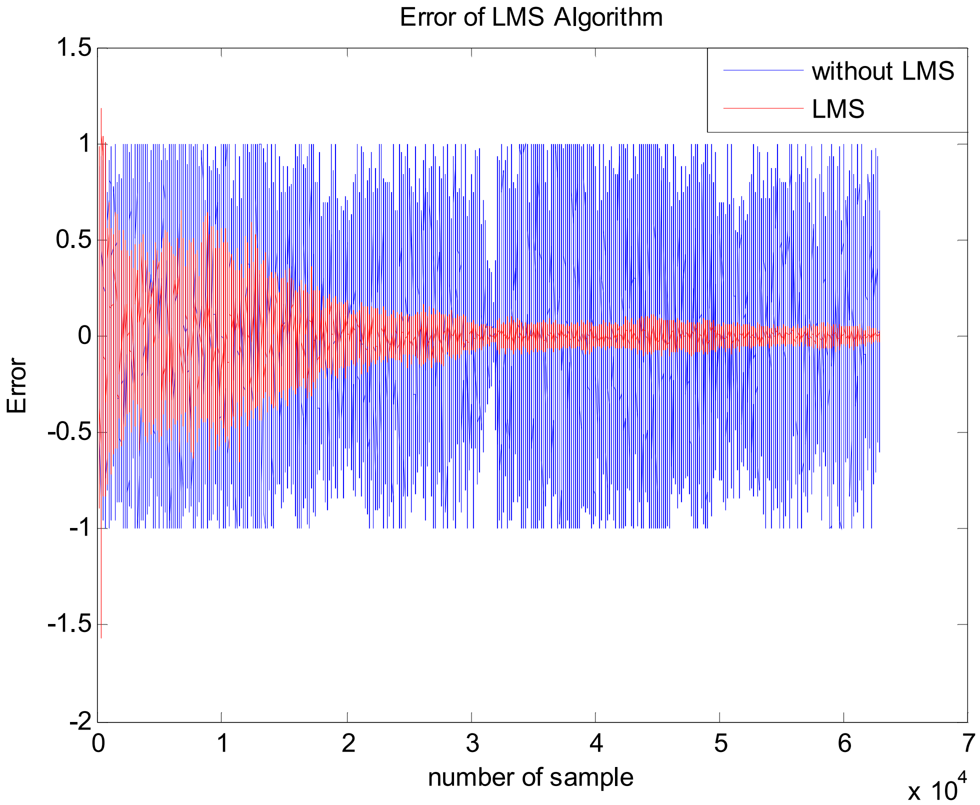


Figure 5.24: Test Results of LMS Algorithm for Noisy Accelerating Motor Sound

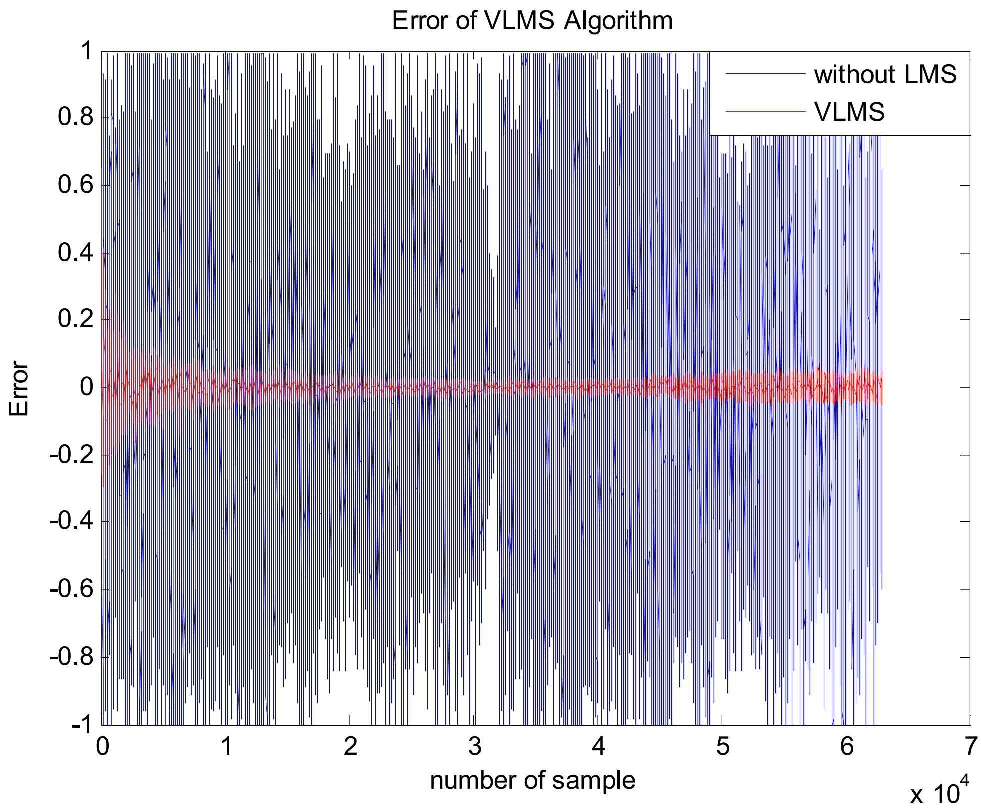


Figure 5.25: Test Results of Normalized VLMS Algorithm for Noisy Accelerating Motor Sound

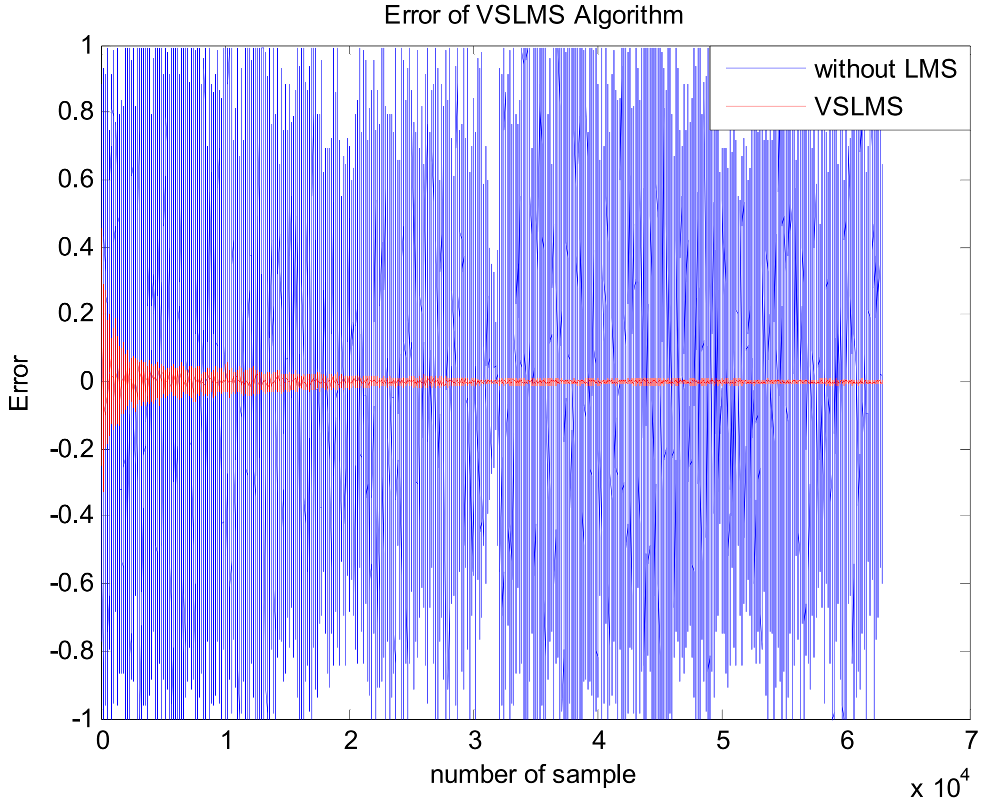


Figure 5.26: The Results for VSLMS Algorithm

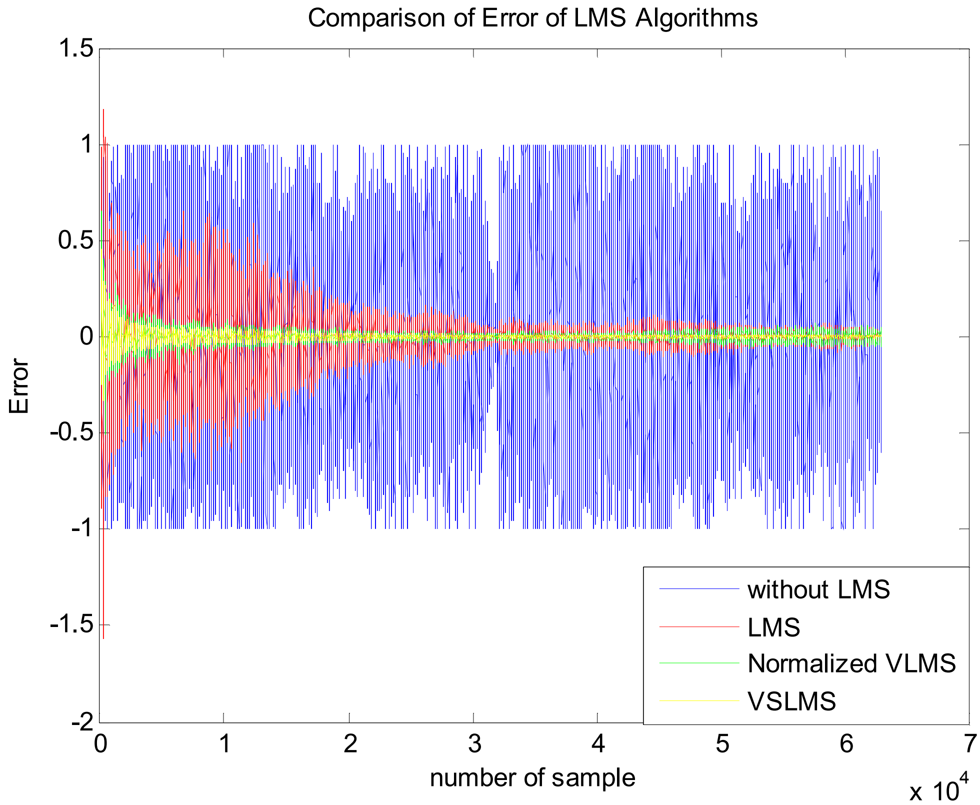


Figure 5.27: Comparison of LMS-VLMS-VSLMS Algorithms

The graph of error performance comparison of classical LMS, Normalized VLMS and VSLMS is shown in Figure 5.27. It is seen that classical LMS and Normalized VLMS are affected dramatically with the sudden change of sound. On the other side, both of them have slower convergence than VSLMS algorithm.

Result of accelerating motor sound simulation is shown at Table 5.6. VSLMS algorithm has best performance for all of three parts.

Table 5.6: Comparison of LMS Algorithms for Accelerating Motor Sound

	MSE (dB)	MSE (for fist 20% part)	MSE (for last 20% part)
LMS	-19,6445	-13,6484	-32,5902
VLMS	-32,0181	-26,1443	-35,5207
VSLMS	-35,4266	-28,7961	-49,8739

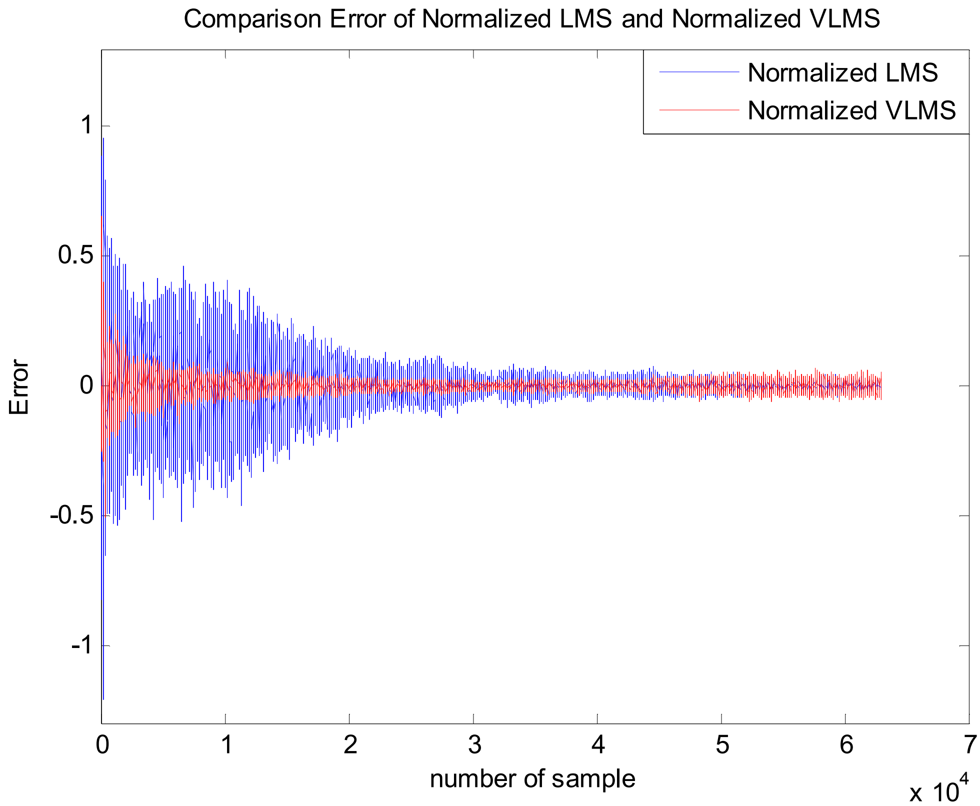


Figure 5.28: Comparison of Normalized LMS and VLMS

Normalized LMS and Normalized VLMS algorithms are tested in Figure 5.28 to show the effect of VLMS algorithm. Both of these algorithms use same normalized step size algorithm. Therefore, this result shows difference between LMS and VLMS algorithms. VLMS algorithm provides higher convergence speed according to this result. Their error performances are nearly same at last 20% parts although, VLMS algorithm much better than LMS algorithm at first 20% part of signal.

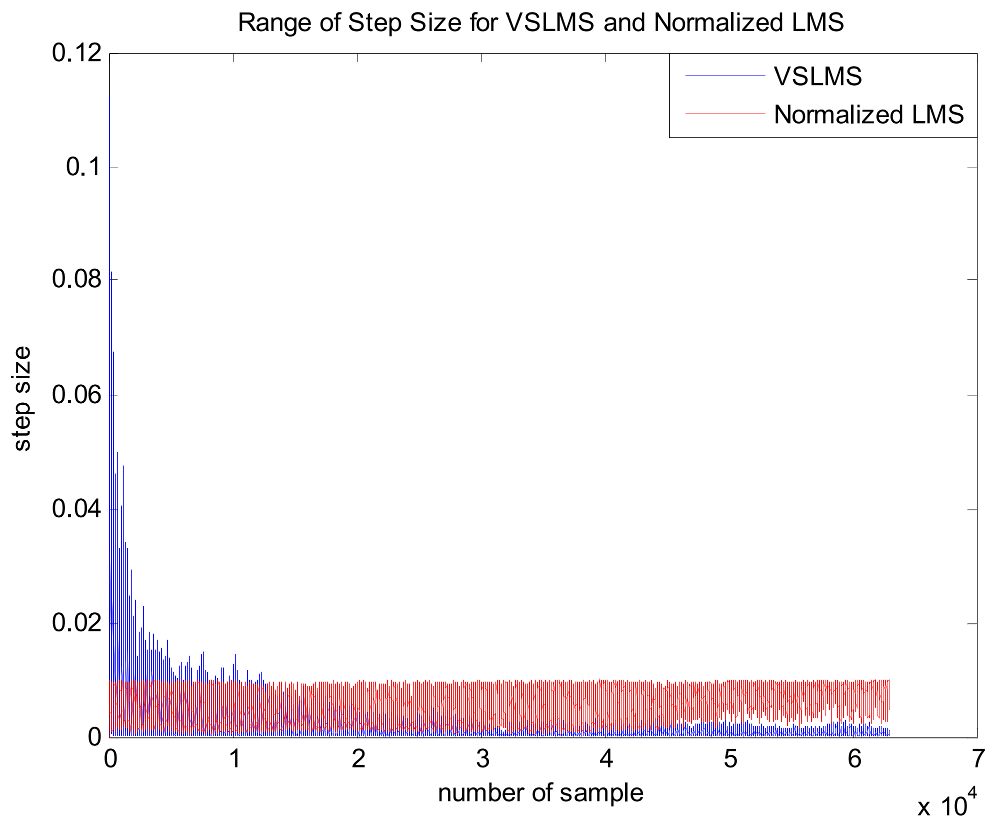


Figure 5.29: Comparison Step Size Changes for Normalized LMS and VSLMS

Changes in step size values are also shown in Figure 5.29 for VSLMS and Normalized LMS algorithms. Initial step size values of VSLMS algorithm are higher than Normalized LMS and it provides higher convergence speed. But, step size becomes its smallest value at the end of the simulation. For this reason, VSLMS have best error performance at these small step size values. On the other hand, Normalized LMS depends on the magnitude of input signal. So, there are no sharp changes on step size values. Therefore, their error performance has not changed enormously throughout the process.

Tap length values for VSLMS algorithm is shown in Figure 5.29. Tap length has maximum value between 30000th and 40000th samples because there is a sharp change between these samples. Since tap length is initially defined as 4, very short tap lengths are observed in the early intervals of the signals.

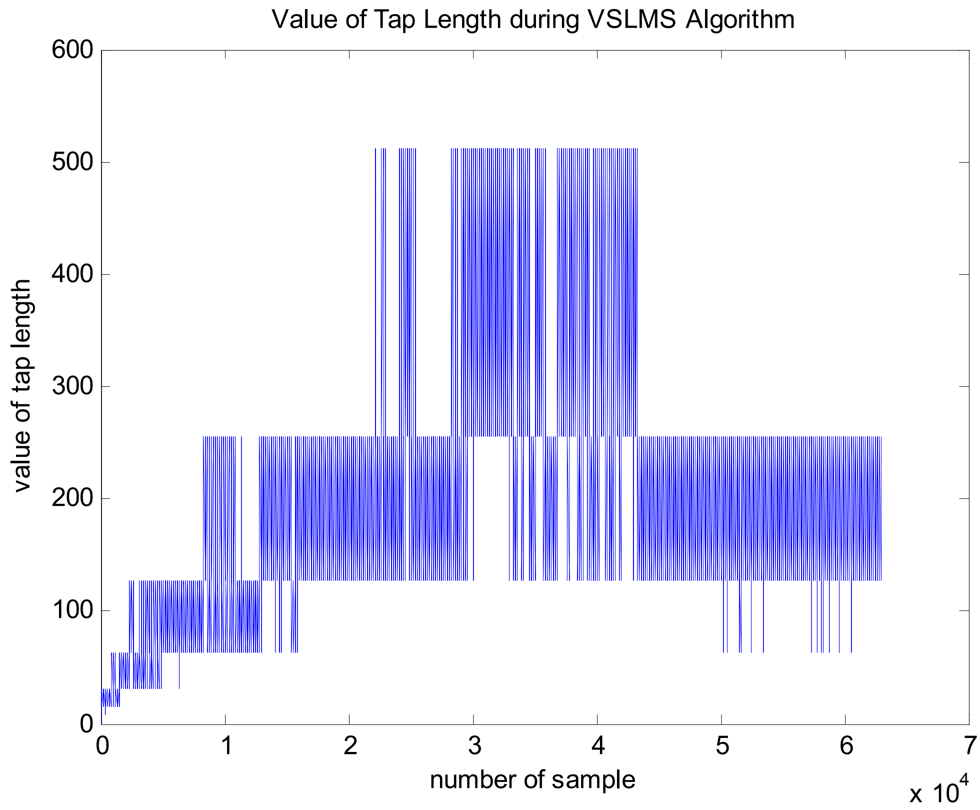


Figure 5.30: Tap Length Changing during VLMS Algorithm

5.4 ANC Tests for Motorbike Sound

In this part, an original motorbike sound and a noisy motorbike sound are used to test LMS, Normalized VLMS and VSLMS algorithms. Original motor signal and noisy motorbike signals can be seen in Figure 5.31 and 5.32, respectively. Sinusoidal signals, which have different frequencies, and random noise are added to motorbike signal to obtain noisy signal.

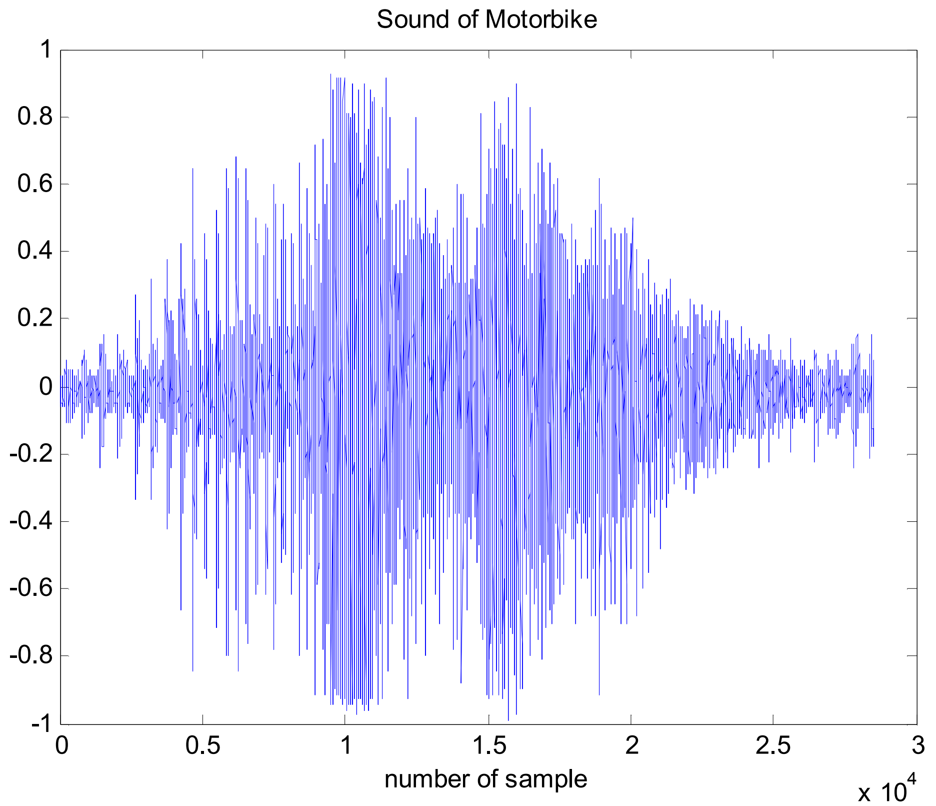


Figure 5.31: Sound of a Motorbike

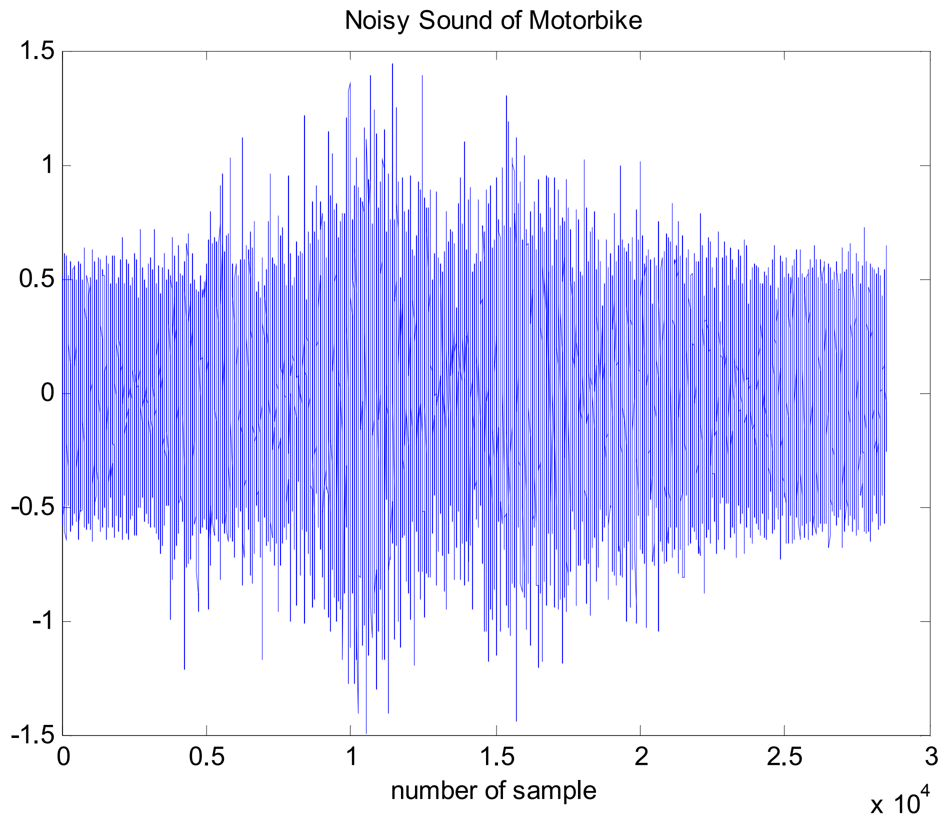


Figure 5.32: Noisy Sound of a Motorbike

Error performance of classical LMS, Normalized VLMS and VSLMS can be seen in Figure 5.33, Figure 5.34 and Figure 5.35, respectively. As a result of these figures, it can be said that both Normalized VLMS and VSLMS algorithms have huge advantage over LMS algorithm to cancel noise and to increase convergence speed. Furthermore, Normalized VLMS algorithm has fastest convergence speed and best error performance up to 15000th sample. VSLMS algorithm has worst performance at near the 10000th sample. But, it has best error cancelling performance at the end of process. This situation can be seen in Figure 5.36 clearly.

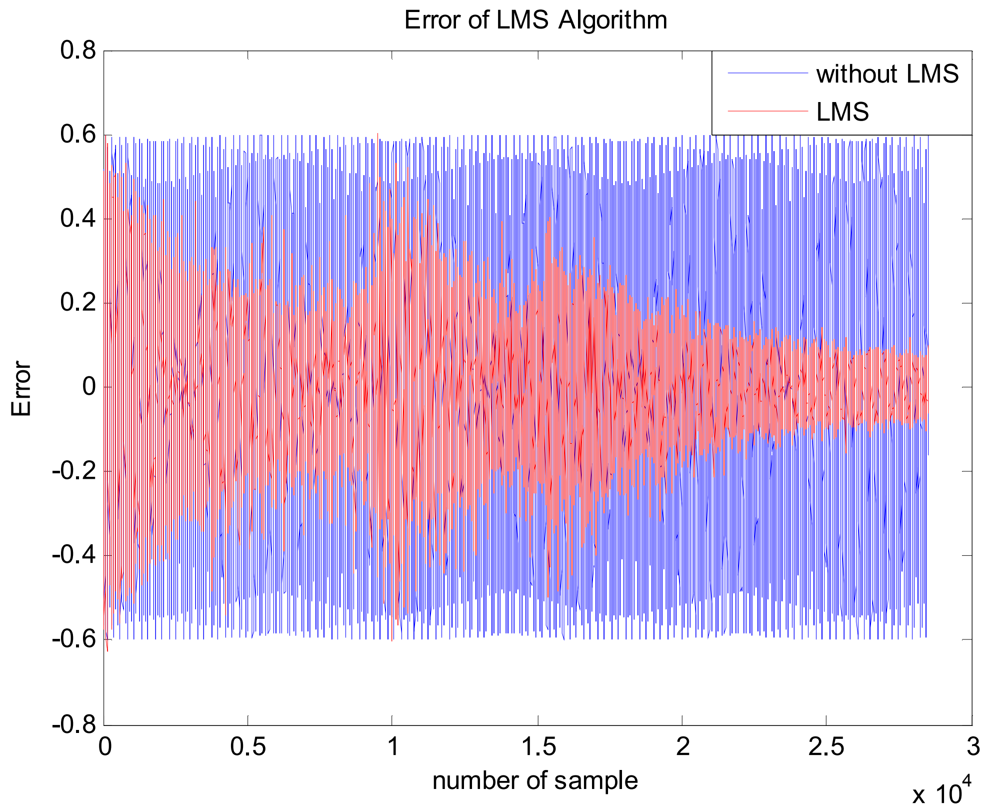


Figure 5.33: The Result for LMS Algorithm

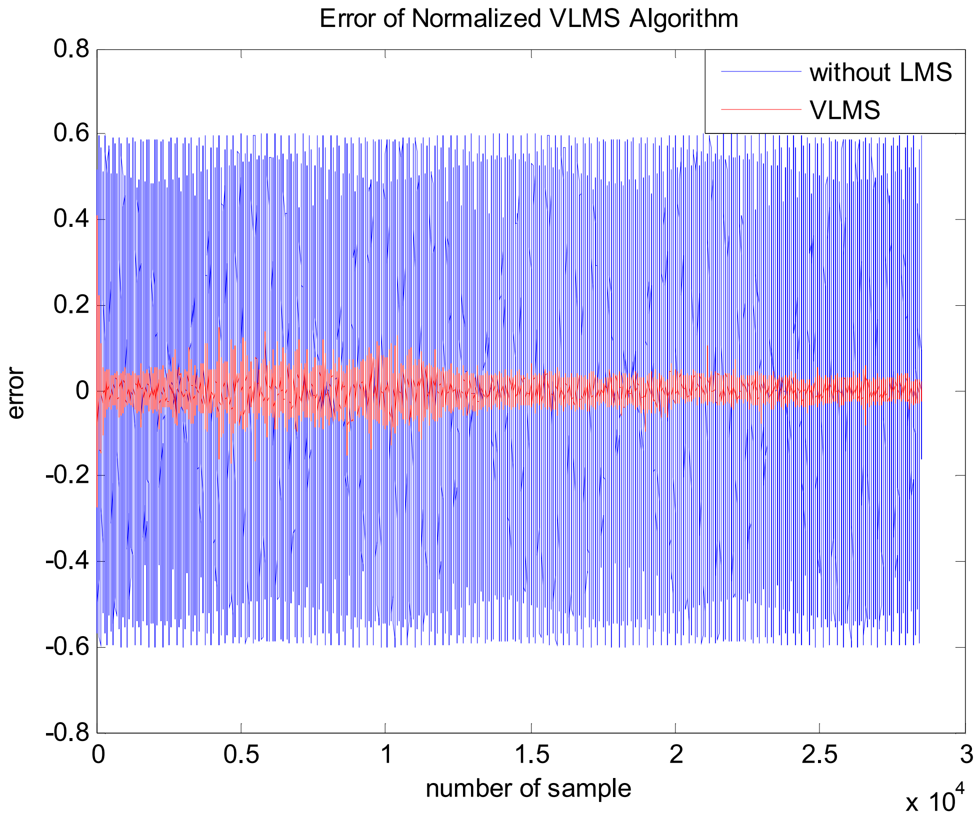


Figure 5.34: The Result for Normalized VLMS Algorithm

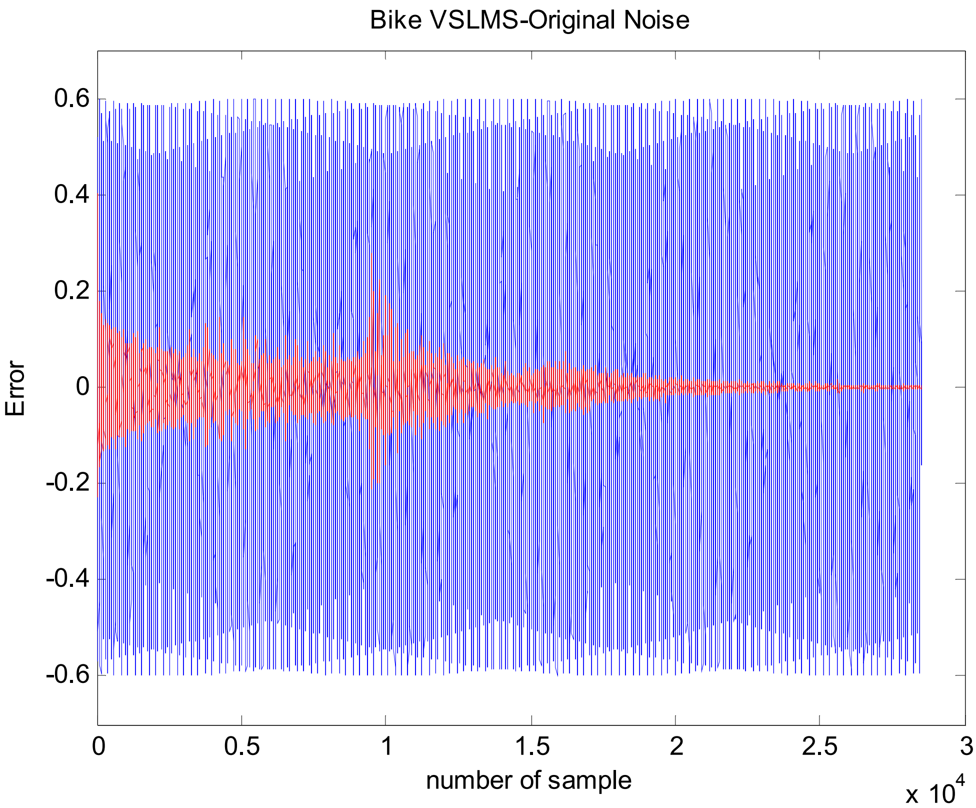


Figure 5.35: The Result for VSLMS Algorithm

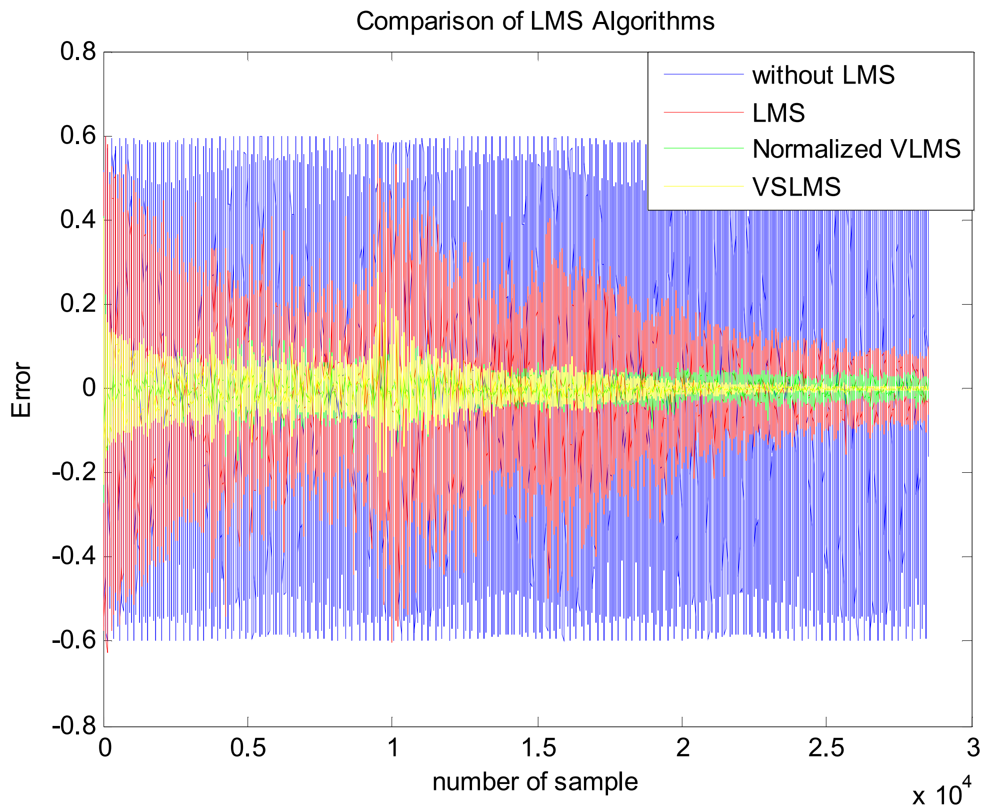


Figure 5.36: Comparison of LMS-VLMS-VSLMS Algorithms

Table 5.7 contains simulation results for motorbike sound. VLMS algorithm has slightly better performance than VSLMS algorithm for overall MSE performance and MSE performance for first 20% part. But, VSLMS algorithm has the best performance for last 20% part.

Table 5.7: Comparison of LMS Algorithms for Motorbike Sound

	MSE (dB)	MSE (for fist 20% part)	MSE (for last 20% part)
LMS	-18,4277	-14,9613	-29,1091
VLMS	-31,7583	-28,6228	-36,0870
VSLMS	-30,6540	-26,7100	-51,0257

Normalized LMS algorithm and Normalized VLMS algorithm are also compared in Figure 5.37. According to this result, VLMS algorithm has higher convergence speed, and it has almost same error during the whole process. Besides, they have similar error cancelling performance at the end of the process.

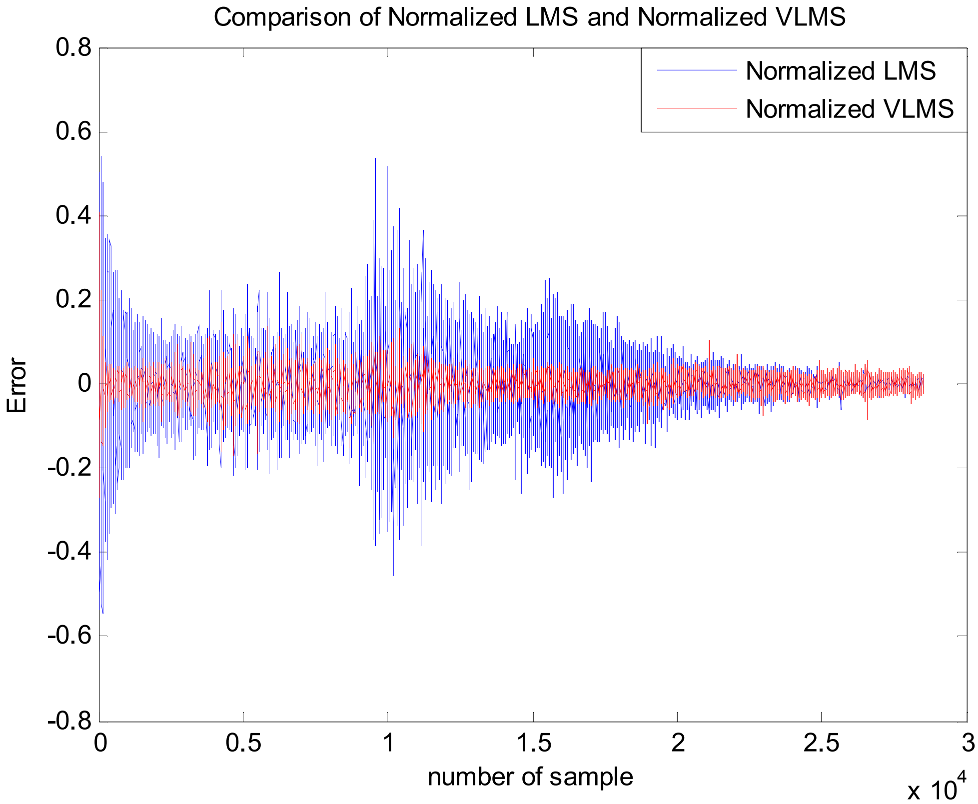


Figure 5.37: Comparison Normalized LMS and Normalized VLMS

Step size changes during filtering process are investigated for Normalized LMS and VSLMS algorithms and the result of this comparison is shown in Figure 5.38. Initial step size value has maximum value for VLMS algorithm to get higher converge speed. But, there is a spike near the 10000th sample. So, step size value is also increased to higher values at these samples. Then, it has smaller values to get better error performance. On the other hand, step size has almost same value for Normalized LMS algorithm; therefore, its convergence is slower.

Tap length changes for VSLMS algorithm is shown in Figure 5.39. In the first half of filtering process, it mostly changes between 64 and 128 while it changes between 128 and 256 in the second part.

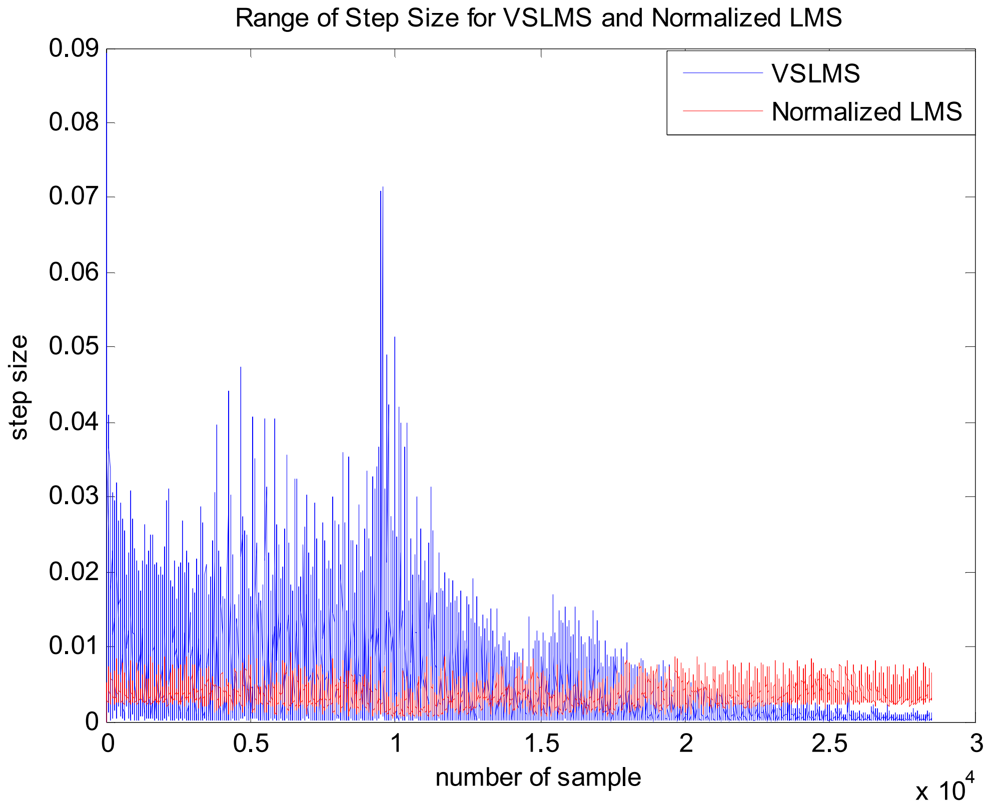


Figure 5.38: Comparison Step Size Changes for Normalized LMS and VSLMS

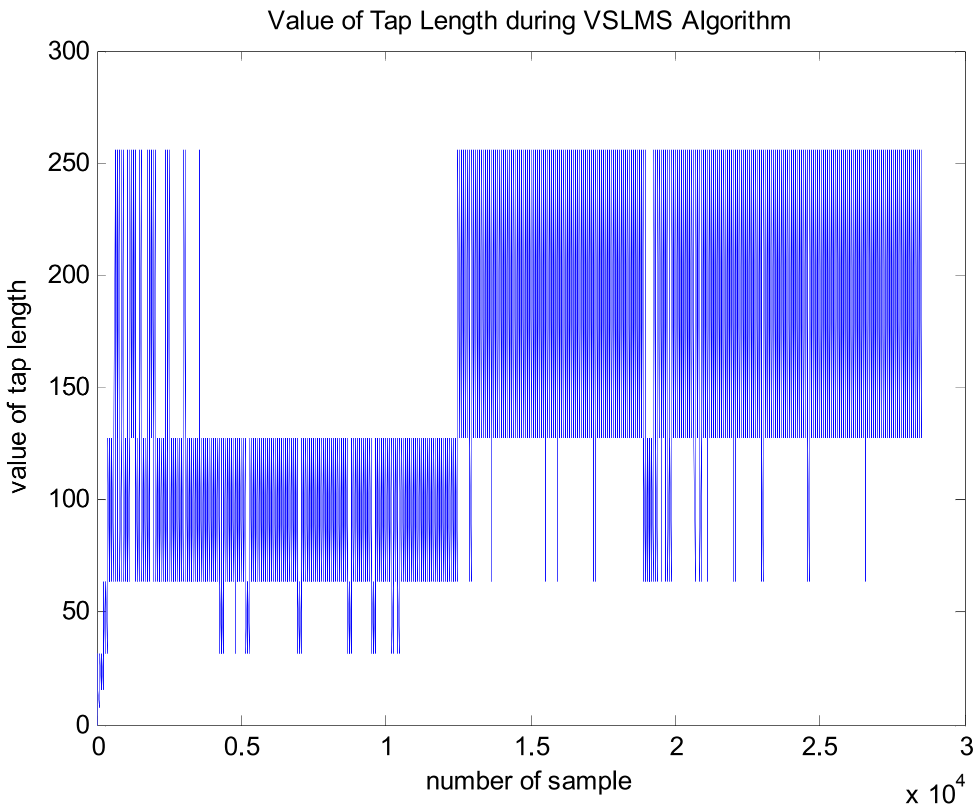


Figure 5.39: Tap Length Changing during VLMS Algorithm

The effect of tap length on VSLMS algorithm is also tested. Result of this test is shown in Table 5.8. It can be easily seen that there is no considerable effect of tap length on VSLMS algorithm. First 20% part of signal is also investigated to see effect on convergence and it is also observed that there is no significant effect of tap length on convergence speed.

Table 5.8: Tap Length Effect on VSLMS Algorithm

Tap Length	MSE (dB)	MSE (for fist 20% part)	MSE (for last 20% part)
4	-30,903	-26,0621	-50,8675
6	-30,985	-27,0048	-50,242
10	-30,7847	-26,5623	-50,8889
15	-30,909	-27,3483	-51,0126
20	-30,654	-26,71	-51,0257
30	-30,7342	-27,271	-51,567
50	-30,3247	-26,7958	-51,7312

6) CONCLUSION

In this thesis, an adaptive active noise control system to cancel motor noise for a driver inside a car environment is presented. Initially, the definition of active noise is given, then, the types of adaptive active noise control are mentioned. Among these types, feedforward control is selected for the proposed method due to the availability of taking reference signal from the noise source in the car environment. As being simpler than other adaptive algorithms such as RLS, LMS is used as the main signal processing in the system. Therefore, initially, the theory of classical LMS and their extended versions such as normalized LMS and sign-sign algorithms are explained. Then, more recent and advanced types of LMS such as VLMS and VSLMS, which have crucial superiorities to classical LMS in terms of steady state error and convergence, are introduced.

In the fifth chapter of this thesis, various simulations are realized to demonstrate the cancellation of motor noise inside the car for driver. LMS, normalized LMS, normalized VLMS and VSLMS algorithms are used in these simulations.

The effect of step size and tap length on performance of error cancellation and convergence are firstly shown. For this purpose, only classical LMS is handled and several simulations are performed for different step size and tap length values. As the results of these simulations, it is observed that there is a tradeoff between the performances of error and convergence for both step size and tap length parameters. Equivalently, fixing these parameters to some constant values improves the performance of either error or convergence; but, degrades the performance of the other one.

In the following simulations, variable tap length and variable step size algorithms are studied. The aim of this study is to prevent drawbacks causing from constant step size and tap length values. For this purpose, VLMS and VSLMS algorithms are simulated and their performances are compared.

VLMS is an algorithm using constant step size values. Nevertheless, improper selection of the step size value causes decreasing in the performance of the system. Therefore, normalized structure is added to VLMS algorithm, which has minimum computational complexity, to avoid the effect of unsuitable selection of step size.

VLMS algorithm sets the required tap lengths at each iteration. Error cancellation performance of the system increases when higher tap lengths are selected. On the other side, if lower step size is selected, system can have lower processing time.

The performance of the normalized VLMS algorithm can be changed by the input signal due to the nature of normalized structure. Therefore, it is observed in the simulations that step size of normalized VLMS algorithm has nearly same values during the process. For this reason, the system has high convergence speed and but, the error can not be annihilated exactly.

In the view of the results of VSLMS algorithm, it is shown that the step size has the largest value at the start of VSLMS algorithm. Therefore, highest convergence speed is obtained in earlier part of the whole signal. Then, the value of step size is decreased by the algorithm and gets its minimum value in the steady-state condition. Connectedly, this small step size provides the minimum error in the steady-state.

Sign-data, sign-error and sign-sign structures are also employed in the simulations to decrease computational complexity. The effects of these structures on performance are tested and it is observed that performances of these structures highly depend on the input signal. These structures are utilized especially in DSP algorithms to yield real-time applications. However, usage of these structures causes degradation in the performance.

In the given simulations, normalized LMS is also compared to normalized VLMS algorithm to demonstrate the effect of VLMS algorithm. According to the results of these simulations, VLMS algorithm has higher convergence speed. However, the errors in the last parts of simulations are found to be nearly same.

As the result of VLMS, VSLMS and LMS algorithms for pure sinusoidal and different motor sounds, it is concluded that the overall MSE performance of the system is very close for VLMS and VSLMS algorithms; but, these algorithms have highly better MSE performance than LMS. On the other hand, VSLMS algorithm has the best performance with respect to the last 20% part of whole signal, which is important for this study considering steady-state performance. Therefore, VSLMS algorithm is found to be the best option to cancel motor noise inside the car.

6.1) Future Work

This thesis is based on the active noise cancellation for a motor noise of a car. In this study, the algorithms are constructed in the computer environment (MATLAB) and the situations for different motor noises are only realized with computer simulations. All required materials for theory and simulation are included in this work. Hence, DSP implementation of the algorithm, therefore, system, is the next step for this thesis.

Active noise cancellation system is used in many areas and its performance highly depends on environment. The driver of a car is the main focused subject in this thesis. For this purpose, it is expected that this system can be demanded by the car manufacturers especially. Besides, it can be adopted other applications easily.

Chip technology is progressed day by day and it provides the improvement of DSP structures. Today, DSPs have capabilities 8000 MIPS (million instructions per second) and more (Texas Instruments, 2009). Therefore, it is not considered to struggle with any problem in real time applications with these mentioned processing speeds.

Sign-sign algorithm provides an important decrease in the process time. It also improves the performance of filter despite the increase in MSE for certain signals. Hence, sign-sign part of the algorithm might be excluded. However, removal of this algorithm substantially effects (increases) the process time.

Initial values of tap length are selected as low values in the simulations. But, it may be required higher values. If first value of tap length is not chosen appropriately, the converge speed of the ANC system will decrease and noise will be attenuated effective in the late times. Similarly, changing α and β values, which are situated in variable step size algorithm, will also increase MSE performance. Therefore, the optimum values for these parameters should be considered for the given real-time application.

It is aimed that use FxLMS algorithm for real time application of this study. Therefore, this algorithm will be investigated and used to cancel motor noise of a car.

APPENDIX A: GRAPHICAL USER INTERFACE

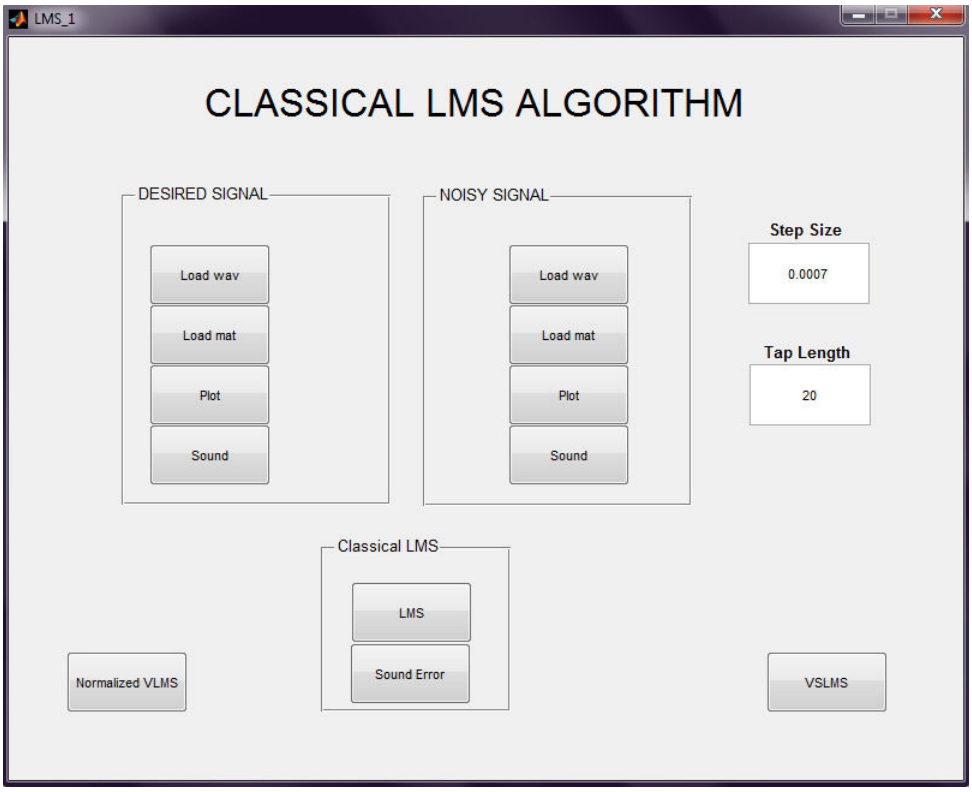


Figure A.1: GUI for Classical LMS Algorithm

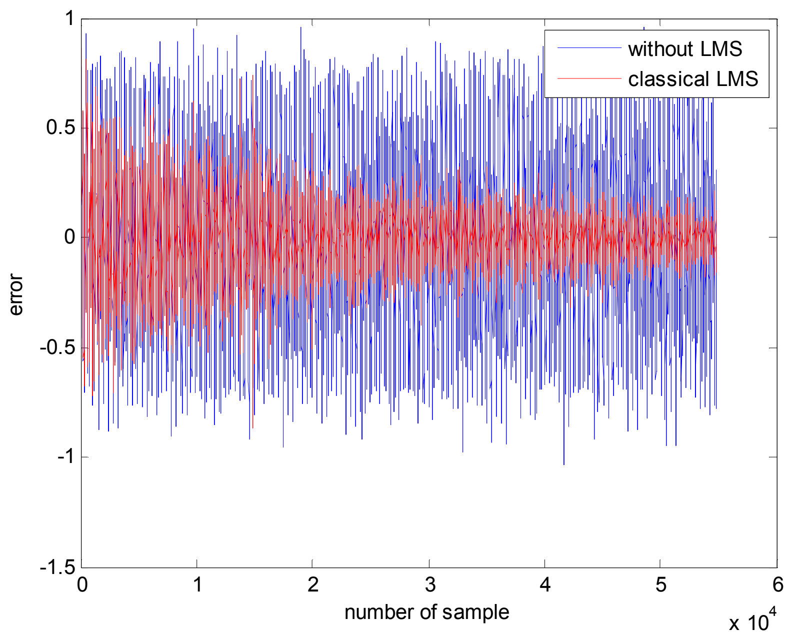


Figure A.2: The Result of GUI for Classical LMS Algorithm

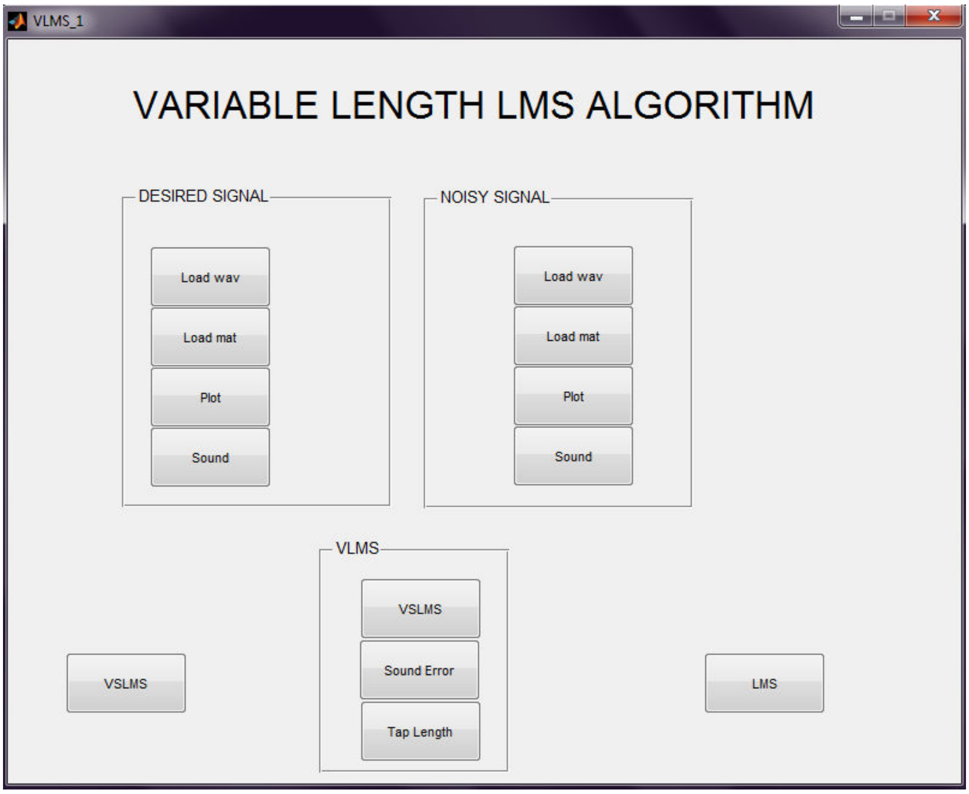


Figure A.3: GUI for Normalized VLMS Algorithm

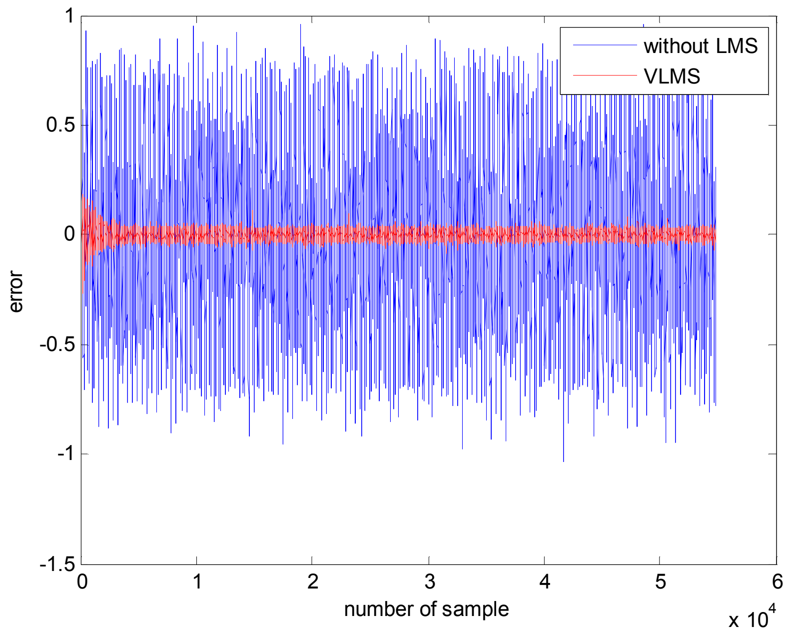


Figure A.4: The Result of GUI for Normalized VLMS Algorithm

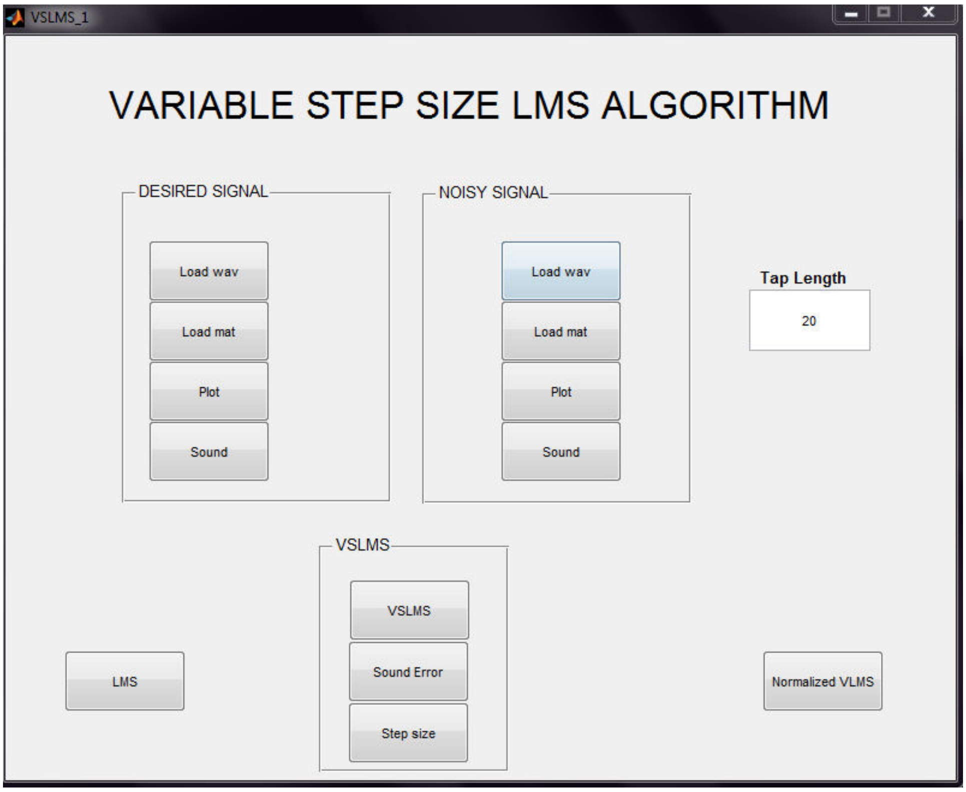


Figure A.5: GUI for Variable Step Size LMS Algorithm

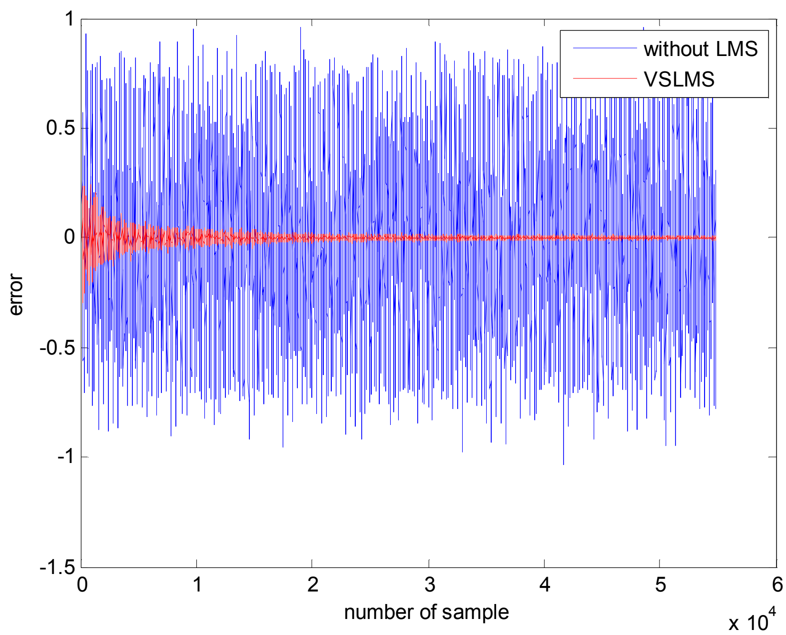


Figure A.6: The Result of GUI for Normalized VLMS Algorithm

BIBLIOGRAPHY

Aboulnasr, T. and Mayyas, K., 1997, A Robust Variable Step-Size LMS Type Algorithm: Analysis and Simulations, IEEE Transactions on Signal Processing, Volume 45(3):631-639

Akhtar, M.T., Abe, M. and Kawamata, M., 2006, A New Variable Step Size LMS Algorithm-Based Method for Improved Online Secondary Path Modeling in Active Noise Control Systems, IEEE Transactions on Audio, Speech, and Language Processing, 14(2): 720-726

Alwan, N.A.S, 2006, On the Effect of Tap Length on LMS Adaptive Echo Canceller Performance, The 2006 International Conference on Computer Engineering and Systems, 197-201

Borisagar, K.R. and Kulkarni, G.R., 2010, Simulation and Comparative Analysis of LMS and RLS Algorithms Using Real Time Speech Input Signal, Global Journal of Researches in Engineering, 44(5): 44-47

Cuesta, M., Bravo, T., Cobo, P., Ranz, C. and Siguero M., 2000, Designing practical active noise control systems, XV Symposium Nacional de la Unión Científica de Radio

Douglas, S.C., 1994, A Family of Normalized LMS Algorithms, IEEE Signal Processing Letters, Volume 1(3): 49-51

Elliott S.J. and Nelson P.A., 1993, Active Noise Control, IEEE Signal Processing Magazine, 10(4):12-35

Erkan, F., 2009, Design and Implementation of a Fixed Point Digital Active Noise Controller Headphone, Msc. Thesis, ODTU, 106p.

Gu, Y., Tang, K. and Cui, H., 2004, Sufficient Condition for Tap Length Gradient Adaption of LMS Algorithm, IEEE International Conference on Acoustics, Speech, and Signal Processing, Volume 2:461-464

Hansen, C.H., 2003, Understanding Active Noise Cancellation, Spon Press, New York, 162p.

Haykin, S., 1996, Adaptive Filter Theory, Prentice Hall Inc., New Jersey, 976p.

Honda, “Active Noise Cancellation”, http://honda.co.nz/technology/driving/anc/, (2012-06-25)

BIBLIOGRAPHY (continue)

Hu, M., Tang, W. and Cai, C., 2010, A New Variable Step-Size LMS Adaptive Filtering Algorithm for Beamforming Technology, 9th International Symposium on Antennas Propagation and EM Theory (ISAPE), 101-104

Hui, C., Yanguang, H., Haibin, L. and Xinping, G., 2010, A New Variable Tap-Length LMS Algorithm and Application in Fixed Satellite Communications,6th International Conference on Wireless Communications Networking and Mobile Computing (WiCOM)

Kestell, C.D. and Hansen, C.H., An Overview of Active Noise Control, 1999, Special Issue of Safety Science Monitor, Volume 3

Kuo, S.M., Panahi, I., Chung, K.M., Horner, T., Nadeski, M. and Chyan, J., 1996, Design of Active Noise Control Systems With the TMS320 Family, Texas Instruments Incorporated, 162p.

Kuo, S.M., 1999, Active noise control: a tutorial review, Proceedings of the IEEE, 87(6):943-973

Kwong, R.H. and Johnston, E.W., 1992, A Variable Step Size LMS Algorithm, IEEE Transactions on Signal Processing, Volume 40(7):1633-1642

Li, X., Fan, Y. and Peng, K., 2009, WiCom '09. 5th International Conference onWireless Communications, 1-4

Liu, F.C., Zhang, Y.X. and Wang Y.J., 2009, A Variable Step Size LMS Adaptive Filtering Algorithm Based on the Number of Computing Mechanism, International Conference on Machine Learning and Cybernetics, Volume 4:1904-1908

Lueg, P., 1936, Process of Silencing Sound Oscillations

Minguez, A., Recuero, M., Ulin, V. and Gil, J. S., 1999, Engine Noise Cancellation Inside an Automobile, International Symposium on Active Control of Sound and Vibration (ACTIVE 99), Vol 1&2:765-774

Pritzker, Z. and Feuer, A., 1991, Variable Length Stochastic Gradient Algorithm, IEEE Transactions on Signal Processing, Volume 39(4):997-1001

Poularikas, A.D. and Ramadan Z.M., 2006, Adaptive Filtering Primer with Matlab, Taylor & Francis Group, New York

BIBLIOGRAPHY (continue)

Rath, S.S and Chakraborty, M., 2010, A Low Complexity Realization of the Sign-LMS Algorithm, International Conference on Green Circuits and Systems (ICGCS)

Rusu, C. and Cowan, C.F.N., 2001, Novel Stochastic Gradient Adaptive Algorithm with Variable Length, European Conference on Circuit Theory and Design, 341-344

Slock, D.T.M, 1993, On the Convergence Behavior of the LMS and the Normalized LMS Algorithms, IEEE Transactions on Signal Processing, Volume 9:2811-2825

Stranneby, D. and Walker, W., 2004, Digital Signal Processing and Applications, Elsevier, United Kingdom, 357p.

Synder, S.D., 2000, Active Noise Control Primer, Springer Inc., New York

Tan, L., 2008, Digital Signal Processing Fundamentals and Applications, Elsevier, United Kingdom, 817p.

Texas Instruments, 2009, "TMS320C6414T, TMS320C6415T, TMS320C6416T Fixed-Point Digital Signal Processors Data Sheet", http://www.ti.com/lit/ds/symlink/tms320c6416t.pdf

Vijaykumar, V.R., Vanathi, P.T. and Kanagasapabathy, P., 2007, Modified Adaptive Filtering Algorithm for Noise Cancellation in Speech Signals, Elektronika IR Elektrotechnika, Volume 2:17-20

Wang, L., Gan, W.S. and Kuo, S.M., 2008, Integration of Bass Enhancement and Active Noise Control Systemin Automobile Cabin, Hindawi Publishing Corporation Advances in Acoustics and Vibration Volume 2008

Won, Y.K., Park, R.H., Park, J.H. and Lee, B.U., 1994, Variable LMS Algorithms Using the Time Constant Concept, IEEE Transactions on Consumer Electronics, 40(3): 655-661

Yan, Y., Zhao, J., Wang, Z. and Yan, Y., 2010, An novel Variable Step Size LMS Adaptive Filtering Algorithm Based on Hyperbolic Tangent Function, International Conference on Computer Application and System Modeling, Volume 14:233-236

Yu, H., Liu, Z. and Li, G., 2008, A VSLMS Style Tap-length Learning Algorithm for Structure Adaptation, 11th IEEE Singapore International Conference on Communication Systems

BIBLIOGRAPHY (continue)

Zhang, Y., Chambers, J.A., Sanei, S., Kendrick, P. and Cox, T.J., 2007, A New Variable Tap-Length LMS Algorithm to Model an Exponential Decay Impulse Response, IEEE Signal Processing Letters, 14(4): 263-266

Zhou, Y.L., Zhang, Q.Z., Li, X.D., Gan, W.S., 2004, Analysis and DSP implementation of an ANCsystem using a filtered-error neural network, Journal of Sound and Vibration, 285(1-2):1-25