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SUPPRESSION OF ACOUSTIC FEEDBACK IN HEARING AIDS USING DUAL ADAPTIVE FILTERING

by

Madan Neupane

A THESIS

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DEPARTMENTAL ACCEPTANCE

The thesis entitled "**Suppression of Acoustic Feedback in Hearing Aids using Dual Adaptive Filtering**", submitted by **Madan Neupane** in partial fulfillment of the requirement for the award of the degree of "**Master of Science in Information and Communication Engineering**" has been accepted as a bonafide record of work independently carried out by him in the department.

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ABSTRACT

Acoustic feedback is a major problem in most of the hearing aid users. This feedback corrupts the speech signal and causes instability. In this thesis, a new solution approach for the suppression of continuous acoustic feedback in the digital hearing aids has been dealt with. In this method, two adaptive filters work in tandem to mitigate the acoustic feedback. The error signal of the first adaptive filter is used as a desired response for the second adaptive filter and the filter weights are adapted using Normalized Least Mean Square (NLMS) and modified NLMS algorithms which is a novel approach presented in this thesis. Due to the correlation between input and desired response, a bias is found in the adaptive filter's estimate of the feedback path. An appropriate delay is inserted at the output of the hearing aid to reduce this bias. Based on this delay based processing, a new strategy is proposed to exchange the weights between the two adaptive filters. Unlike previous techniques, initial weights of the adaptive filters are chosen other than either 1's or 0's such that faster convergence is achieved. Computer simulations are performed and the results verify the effectiveness of the proposed method.

Keywords: Hearing Aids, Acoustic Feedback, NLMS, Adaptive Filters.

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LIST OF ABBREVIATIONS

AFC:	Adaptive Feedback Cancellation
AFR:	Acoustic Feedback Reduction
ANC:	Active Noise Control
BTE:	Behind-The-Ear
DSP:	Digital Signal Processor
FXLMS:	Filtered XLMS
FIR:	Finite Impulse Response
IIR:	Infinite Impulse Response
LMS:	Least Mean Square
NFXLMS:	Normalized filtered XLMS
NLMS:	Normalized Least Mean Square
SNR:	Signal to Noise Ratio

CHAPTER ONE: INTRODUCTION

1.1 Nature of Sound

A sound source, such as clapping two hands together in the air, causes the displacement of air particles. The displacement of air particles at such a location forces the displaced particles closer to other air particles (condensation), resulting in an increase in the density of air. There is then a reactive force, analogous to releasing a compressed spring, which causes the air particles to bounce away from each other (rarefaction), resulting in a decrease in the density of air at that location. Sound waves propagate through a medium such as air, or water, through repeated condensation and rarefaction, and can be understood as a series of rapid changes in the density of a medium.

Sound is often analyzed in terms of amplitude and frequency. Amplitude is the magnitude of vibration of a sound source (how much air is displaced), measured in decibels (dB), and frequency is the rate of vibration of a sound source (how often the air is displaced), measured in Hertz (Hz). The perceptual correlates of amplitude and frequency are loudness, and pitch, respectively. The frequency range of human hearing for young adults is 20-20000 Hz, and the sensitivity for high frequencies generally reduces as a natural progression of aging, known as age-related hearing loss [1].

1.2 The Auditory System

The auditory system, depicted in figure 1.1, consists of three major parts: the outer ear, the middle ear and the inner ear. Each part of the system serves a vital function in our ability to effectively hear sound. The outer ear consists of the pinna and the ear canal. The pinna captures the sound energy and directs it through the ear canal to the ear drum. The middle ear converts the sound waves into mechanical vibrations, which are transmitted to the fluid in the inner ear. The inner ear contains the cochlea and the auditory nerve. The cochlea converts the mechanical signals into neural signals. The auditory nerve transmits these neural pulses to the brain, where they are translated into specific sounds. The auditory signal processing in the cochlea is largely responsible for the hearing-specific properties such as the frequency-specific sensitivity and the low hearing threshold.

The cochlea is divided along its length by the basilar membrane: sound waves result in pressure differences between one side of the basilar membrane and the other and hence, in movement of the basilar membrane. Hair cells are aligned into three to five outer rows (outer hair cells) and one inner row (inner hair cells) that extend along the membrane. These outer and inner hair cells have stereocilia or “hairs” that stick out and are in contact with a second membrane, called the tectorial membrane. When the basilar membrane moves up and down, the stereocilia at the top of the hair cells, bend back and forth. The mechanical properties of the basilar membrane vary progressively along its length so that each region of hair cells on the basilar membrane responds best to a specific characteristic frequency: hair cells in the base of the cochlea respond to high frequencies, while hair cells situated in the apex of the of the cochlea react to low frequencies. This explains the frequency-specific sensitivity of the ear, which can be compared with a filter bank.

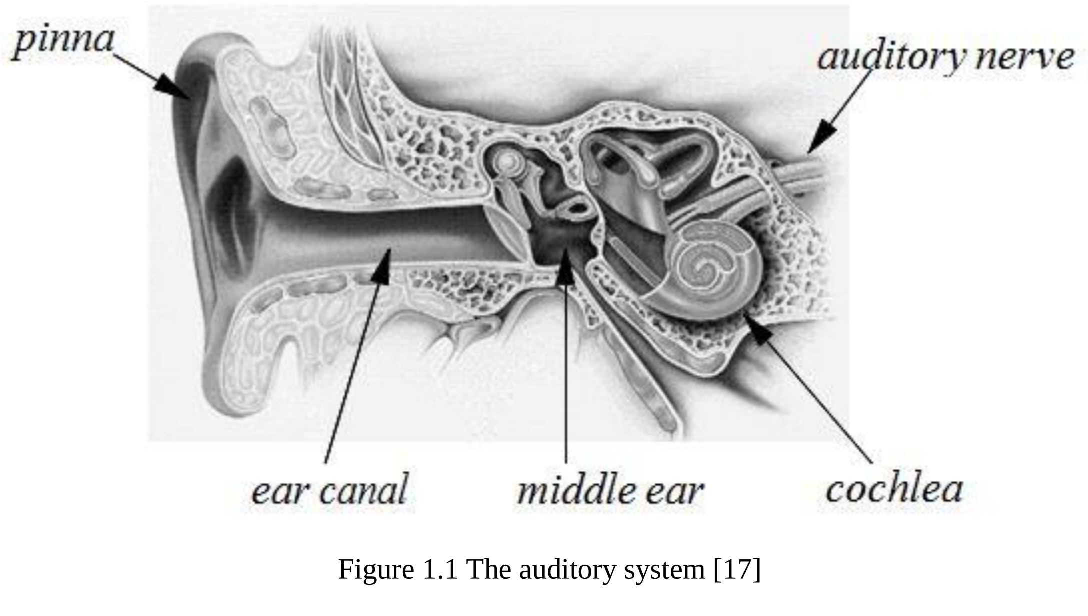

Figure 1.1 The auditory system [17]

The movement of the stereocilia of the inner hair cells leads to the generation of neural pulses in the auditory nerve. Hence, the inner hair cells convert mechanical motion into neural activity. The outer hair cells have a different function in the cochlea: they selectively amplify the vibrations of the basilar membrane in a highly nonlinear way. The outer hair cells are responsible for the high frequency resolution and the high sensitivity to weak sounds (i.e., the low hearing thresholds) of the auditory system. In addition, they produce nonlinear, compressive input-output functions on the basilar membrane for frequencies close to the characteristic frequency, which allows acoustic information over a wide dynamic range to be transferred to the brain [2].

1.3 Hearing Impairment

Hearing loss is one of the most prevalent chronic health conditions, affecting large number of world's population. Because of the increased exposure to noise in daily life, this number is expected to further increase in the future. Therefore it is necessary to amplify the perceived sound signal and also reduce the background noise with respect to the desired speech signal. Hearing aid, a small amplifying device which fits on the ear, worn by a partially impaired person, is used for this purpose.

According to the part of the auditory system that is affected, hearing loss is classified into conductive, sensorineural or mixed hearing loss. Conductive hearing loss is caused by problems in the outer and middle ear that interfere with the transmission of sound to the inner ear. This type of hearing loss can be corrected by medical intervention or by (frequency-dependent) amplification of sound. Sensorineural hearing loss refers to problems in the inner ear, i.e., either the cochlea (i.e., cochlear hearing loss) or the auditory nerve. In about 90 % of the cases, hearing loss belongs to this last category [3].

Majority of cases of sensorineural hearing loss are cochlear hearing loss and are caused by damage to hair cells in the cochlea so that the conversion from mechanical movement to neural activity is affected. Since cochlear hair cells, once destroyed, do not regenerate, this type of hearing loss is permanent. The most common causes for the destruction of hair cells are aging and exposure to loud sound. The hair cells in the base of the basilar membrane are usually first damaged so that hearing loss first occurs at the high frequencies.

Usually, the outer hair cells are more susceptible to damage than the inner hair cells. Damage to the outer hair cells produces several changes in the perception of sound: an increased hearing threshold (i.e., loss of sensitivity to weak sounds), a reduced frequency selectivity and a reduced dynamic range.

In addition to outer hair cell damage, also damage to the inner hair cells gives rise to an elevated hearing threshold. Inner hair cell damage results in a less efficient transduction of mechanical vibrations into neural activity, so that the amount of basilar membrane vibration needed to reach the threshold is larger than normal. Other consequences of inner hair cell damage are a reduced flow of auditory information in the auditory nerve, and, in extreme cases, no transfer of activity at some regions of the basilar membrane, so-called dead regions.

Depending on the amount of inner and outer hair cell damage, the hearing loss varies from mild (i.e., between 20 dB to 40 dB), moderate (i.e., between 40 dB and 70 dB), severe (i.e., between 70 dB and 90 dB) to profound or “deafness” (i.e., larger than 90 dB) [3].

1.4 Hearing Aids

A digital hearing aid is a compact sound-amplifying device designed to aid people who have a hearing impairment. Digital hearing aids use discrete signal samples of the microphone signal and the speaker signal to perform the necessary signal processing for hearing-impaired listeners. Such processes include adaptive feedback cancellation, noise suppression, hearing loss compensation and dynamic range compression (DRC) applied on the spectrally distributed signals. In general, a hearing aid performs compensation of hearing loss, noise suppression to reduce ambient noise in the incoming signal and DRC to provide a comfortable listening experience in the forward path.

There are four common types of hearing aid models:

– In The Canal (ITC)

– Completely In The Canal (CIC)

– In The Ear (ITE)

– Behind The Ear (BTE).

The BTE hearing aid has the largest physical size. The CIC hearing aid and the ITC hearing aid are becoming more popular since they are small and can be hidden in the ear. A hearing aid comprises at least a microphone, an amplifier, a receiver, an ear mold, and a battery. Modern hearing aids are digital and also include an analog to digital converter (ADC), a digital signal processor (DSP), a digital to analog converter (DAC), and a memory. Larger models, ITE and BTE, also include a telecoil in order to work in locations with induction-loop support. Some hearing aids have directionality features, which mean that a directional microphone or several microphones are used [2, 4].

1.5 Motivation

Acoustic feedback creates a closed signal loop, which, under certain conditions, causes the so-called howling effect. These conditions depend on the magnitude and the phase of the feedback loop, which consists of the acoustic feedback path and the amplification of the system. In the case of hearing aids, the howling effect is highly annoying for the hearing aid user and his/her environment. Moreover, the acoustic feedback limits the maximum amplification that can be used in hearing aids. Hence, the reduction of the acoustic feedback is a very important task in the context of hearing aids. Acoustic feedback results in severe distortion of the desired signal and howling if the hearing aid gain is increased. As a result, the maximum amplification that can be used in a commercial hearing aid is often too small to compensate for the hearing loss in a patient. Therefore, an urgent demand exists for efficient and well working signal processing algorithms for noise reduction and acoustic feedback suppression [1].

Many adaptive feedback cancellation (AFC) techniques have been proposed in order to minimize the effect of the feedback on the hearing aids [1-6]. The adaptation control is difficult due to the correlated input and feedback signals that could lead to a biased filter and severe signal distortion at the hearing aid output [4]. The algorithms for AFC should provide a compromise between fast convergence speed, and low steady state level. Another requirement is a low computational complexity and good sound quality. It is known that there is a bias in the estimate of feedback path in case of AFC due to correlation between the input and output signals of the hearing aids. There are several techniques that reduce the bias (e.g. by adding probe signal to output [5], inserting the de-correlation filter [7] or time delays in the forward or filter.

However, still an efficient approach towards the minimization of biased solution is needed which motivated in the design of this acoustic feedback suppression system.

1.6 Problem Definition

Acoustic feedback is a major problem in the hearing aids, limiting the maximum gain available to the user, and making the hearing aids oscillating at higher gain thus producing annoying sounds of whistling, screeching or howling [9]. A generic digital hearing aid system is shown in Fig. 1.2, where $G(z)$ represents the forward path of the hearing aid and comprises all signal processing for noise reduction and signal amplification, and $s(n)$ is the desired input signal to be processed by $G(z)$. Assume that the components for the adaptive feedback cancelation (AFC) (shown in a dashed box) are not present, and hence, $u(n) = x(n)$. The input signal $x(n)$ [which should ideally be equal to $s(n)$] picked up by the microphone is processed by $G(z)$ and the output signal $y(n)$ is generated. The output signal $y(n)$ to the loudspeaker is not only propagated to the user ear, but is also fed back via acoustic feedback path $F(z)$ to the input microphone thus generating a corrupted input signal $u(n) = x(n) = s(n) + y_f(n)$, where $y_f(n)$ is the feedback component due to the output $y(n)$ [13].

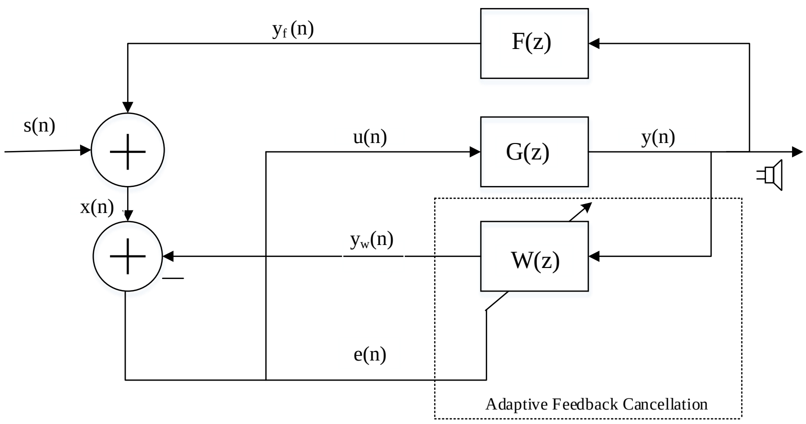

Figure 1.2 A simplified block diagram of hearing aid employing NLMS algorithm-based conventional adaptive filtering approach for AFC [13]

Acoustic feedback in hearing aids occurs when the aid's receiver produces an acoustic signal that leaks back to the microphone. Feedback usually results from leakage from the ear canal via a vent or from mechanical coupling of receiver motion via the hearing aid housing. Although there are a number of signal-processing elements involved, for present purpose the essence of the problem can be pictured as in figure

1.2, where H represents the net feedback path and G represents the intended transfer function of the hearing aid. The transfer function of this system is $H(z) = \frac{G(z)}{1-G(z)F(z)}$ which shows that due to acoustic feedback the hearing aid will be unstable if $G(z)$ is large enough so that $G(z)F(z) = 1$ at some frequency. Stated differently, when a frequency component of the feedback signal arrives at the microphone in phase with and with magnitude equal to or greater than the sound that produced it, oscillation will occur, driving the hearing aid at its maximum level and rendering it useless. The conditions for oscillation in hearing aids are common. Thus, when escaped sound reaches the microphone, it can easily have magnitude close to that of the input. [3] Also the input and desired-response signals of $G(z)$, $y(n)$ and (n) , respectively, are correlated with each other and would result in a biased convergence.

1.7 The main objectives of this thesis are:

(i) To propose a new adaptive algorithm for the suppression of acoustic feedback in digital hearing aids

(ii) To compare the new model with conventional NLMS system

1.8 Significance of this thesis:

(i) New hearing aid systems with better performance can be manufactured based on the research results obtained. Can act as a design reference for the manufacturing companies.

(ii) Good alternative solution to the feedback and bias problem than the previous ones.

(iii)Can act as a basis for those researchers who are intended to work in the areas of adaptive filter design and hearing aid technology.

1.9 Organization of Report

The thesis is organized in six chapters. Chapter 2 introduces the relevant research techniques of previous authors that had been done previously and briefly discusses the limitations of their research. Chapter 3 presents the adaptive filtering techniques and related theory used in this thesis work. Chapter 4 illustrates the overall methodology employed to achieve the objectives stated earlier in this thesis. Chapter 5 focuses on the simulation results and its analysis. Finally chapter 6 focuses on conclusion.

CHAPTER TWO: LITERATURE REVIEW

A literature review shows that a number of approaches have been proposed to solve the problem of acoustic feedback [1] – [6]. The most successful approach is based on adaptive filtering as shown in figure 1.2, where $W(z)$ is adapted (usually by the normalized least mean square (NLMS) algorithm [7]) to model $F(z)$. It is evident from figure 1.2 that the input $y(n)$ and the desired response $x(n)$ to (z) , are correlated with each other. This scheme, therefore, cannot be used for continuous AFC [8], and hence the acoustic feedback cannot be estimated accurately. A simple approach to decorrelate these two signals is to use an appropriate delay either in the cancelation path [1] or in the forward path [9], however, it degrades the speech quality.

Another solution is to filter the error and/or input signal of $W(z)$ through appropriate decorrelation filters, before being used in the update equation of the NLMS algorithm [10], resulting in the so- called Filtered-x adaptive algorithm. It is not, however, easy to design an appropriate decorrelation filter [11]. Yet another solution is a noncontinuous adaptation or an open-loop algorithm in which the hearing aid forward path is broken and a probe noise is injected during particular intervals, for example, when howling is detected by an appropriate oscillation detector [12]. The ON/OFF switching of the probe signal produces annoying effects to the hearing aid user.

Working principle of the different AFR subsystems in the proposed hearing aid model has been dealt in [15]. These subsystems adapt the feedback-reduction FIR filter based on the LMS algorithm or a filtered version of this algorithm, i.e., the FXLMS. Moreover, the normalized versions of both algorithms (i.e., NLMS and NFXLMS) are also proposed to adapt. The way of measuring the performance of the different hearing-aid categories under study has been presented, which is based on subjective and objective measurements [15].

An approach has been proposed that improves the identification and cancellation of the feedback path by reducing the impact of the desired signal on the adaptation of the feedback canceller. This method allows for the canceller's coefficients to continuously adapt allowing it to track variations in the feedback path. The suggested microphone layout assumes that the speech signals received by both microphones are similar, but the feedback received by the second microphone has greater attenuation than the first. Two adaptive filters were used, the first was used as the feedback canceller and the second was used to match the desired speech signal recorded by the dual microphones. With such arrangement, the speech signal from the second microphone is subtracted from the error signal before adapting the canceller [16].

Understanding speech in noise and acoustic feedback belong to the major problems of current hearing aid users. With the advent of low power DSPs, an urgent demand exists for efficient and well-working algorithms that offer a solution to these problems. In this thesis, the authors have developed several digital signal processing techniques for noise reduction and feedback cancellation. In order to be able to deal with time-varying acoustic environments and non-stationary signals, all the proposed algorithms are adaptive. In the algorithmic design, the specific design criteria for hearing aids, such as small-sized systems, low computational complexity and a low processing delay, have been taken into account [17]. A mechanism for the compensation for the effects of the remote controller on the error signal was proposed, resulting in a new adaptive algorithm for remote ANC applications [18].

The first and probably still the most common electronic solutions for acoustic feedback in commercial hearing aids are the reduction of the high frequency gain and the use of notch filters [20, 21]. Typically, the feedback path provides less attenuation at high frequencies [22], where most hearing aid users have the largest hearing loss. As a result, acoustic feedback often first occurs in the high frequency range. Attenuating the high frequencies reduces the risk of acoustic feedback, but also compromises the audibility of the high frequencies. To minimize the detrimental effect of gain limitation, some hearing aid manufacturers use one or several notch filters, so that the gain is only reduced in narrow bands around the critical frequencies [20, 21].

The first application of adaptive feedback cancellation techniques in commercial hearing aids appeared in the Danavox BTE DFS Genius [23, 24] followed by the digital Danalogic hearing instruments of GN Danavox [25]. In the first design, the acoustic feedback path was identified based on an external probe signal that was inserted in the loudspeaker. With this feedback suppression system, the maximum stable gain before instability was found to be increased by about 10 dB. Nowadays, adaptive feedback cancellation techniques are still only encountered in the most advanced digital hearing aids (e.g., Oticon Adapto, Widex Senso Diva, GN ReSound Canta 4 and Canta 7). To preserve signal quality, the use of an external probe signal is limited or avoided as much as possible [20].

Most sound signals in every-day-life are spectrally colored, e.g., speech, music. To reduce the bias of the feedback canceller and the resulting distortion of the desired signal, the adaptation of the feedback canceller is controlled. Often, the adaptation speed is kept small. When feedback or a sudden change in feedback path is detected, the adaptation speed is temporarily increased (e.g., Widex Senso Diva Oticon Adapto [26, 27]). In order to further limit signal distortion, the adaptation of the feedback canceller is sometimes restricted to the high frequencies (e.g., Oticon Adapto). Constrained adaptation or a slow adaptation speed, however, only limit the bias of the feedback canceller to some extent, while considerably compromising the tracking of changes in the feedback path. As a result, acoustic feedback still often occurs, e.g., when placing a telephone set close to the ear or when taking off the hearing aid during operation. In addition, the maximum amplification that is available with commercial hearing aids is still too limited to compensate for the hearing loss in each individual patient. Furthermore, to improve listening comfort and binaural hearing, there is a growing tendency in the hearing aid industry towards hearing aids with open fittings (e.g., ReSoundAir™ of GN ReSound, OpenEar Acoustics™ of Oticon), making the risk for acoustic feedback even higher [27]. Consequently, there is a high demand for adaptive feedback cancellation techniques that provide a reliable feedback path estimate without compromising the tracking performance or the signal quality.

CHAPTER THREE: ADAPTIVE FILTERS AND ALGORITHMS

3.1 Filtering

The advances in digital circuit design have been the key technological development that sparked a growing interest in the field of digital signal processing. The resulting digital signal processing systems are attractive due to their low cost, reliability, accuracy, small physical sizes, and flexibility.

One of the examples of a digital signal processing system is a filter. Filtering is a signal processing operation whose objective is to process a signal in order to manipulate the information contained in it. In other words, a filter is a device that maps its input signal to another output signal facilitating the extraction of the desired information contained in the input signal. A digital filter is the one that processes discrete-time signals represented in digital format. For time-invariant filters the internal parameters and the structure of the filter are fixed, and if the filter is linear then the output signal is a linear function of the input signal. Once prescribed specifications are given, the design of time-invariant linear filters entails three basic steps, namely: the approximation of the specifications by a rational transfer function, the choice of an appropriate structure defining the algorithm, and the choice of the form of implementation for the algorithm [14].

3.2 Adaptive Filtering

A filter is designed and used to extract or enhance the desired information contained in a signal. An adaptive filter is a filter with an associated adaptive algorithm for updating filter coefficients so that the filter can be operated in an unknown and changing environment. The adaptive algorithm determines filter characteristics by adjusting filter coefficients (or tap weights) according to the signal conditions and performance criteria (or quality assessment). A typical performance criterion is based on an error signal, which is the difference between the filter output signal and a given reference (or desired) signal.

As shown in figure 3.1, an adaptive filter is a digital filter with coefficients that are determined and updated by an adaptive algorithm. Therefore, the adaptive algorithm behaves like a human operator that has the ability to adapt in a changing environment. For example, a human operator can avoid a collision by examining the visual information (input signal) based on his/her past experience (desired or reference signal) and by using visual guidance (performance feedback signal) to direct the vehicle to a safe position (output signal).

Adaptive filtering finds practical applications in many diverse fields such as communications, radar, sonar, control, navigation, seismology, biomedical engineering and even in financial engineering [1–7]. The high-order filter together with a highly correlated input signal degrades the performances of most time-domain adaptive filters. Adaptive algorithms that are effective in dealing with ill-conditioning problems are available; however, such algorithms are usually computationally demanding, thereby limiting their use in many real-world applications.

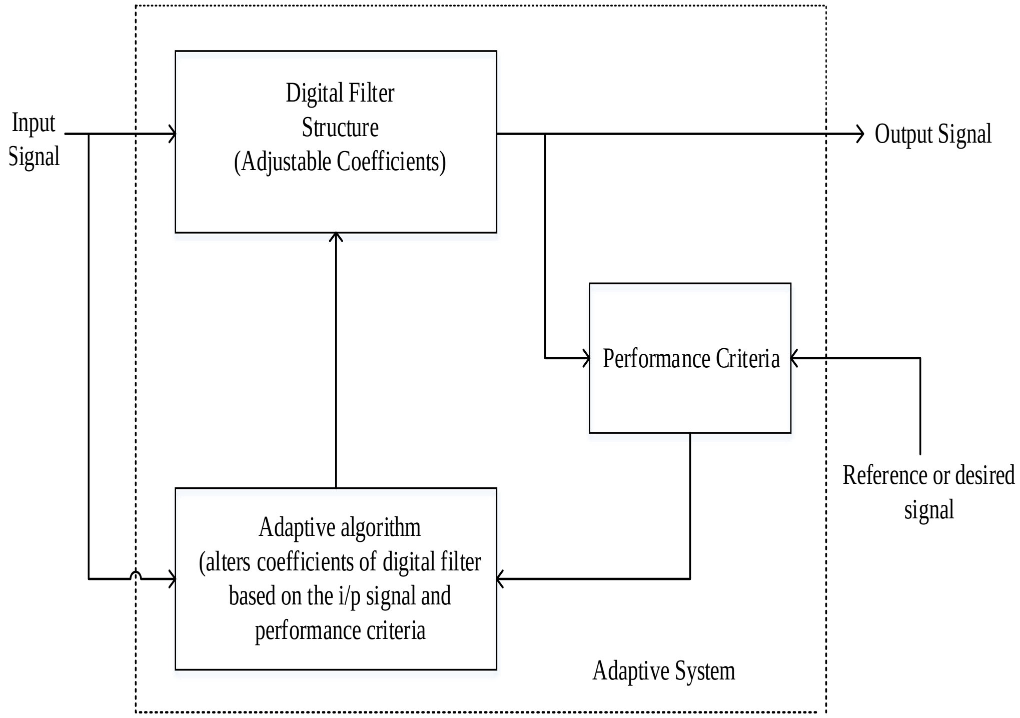

Figure 3.1 Basic Functional Blocks of an Adaptive Filter

3.3 Adaptive Feedback Cancellation (AFC) Methods

In adaptive cancellation methods, the feedback signal is estimated by filtering the hearing aid output with an estimate of H, the acoustic feedback path transfer function. This estimated feedback signal is then subtracted from the hearing aid input. The algorithms for estimation and adaptation vary among implementations.

Continuous adaptation: The continuous-adaptation AFC system is applicable to the systems that continually adjust the adaptive filter weights while simultaneously processing the input signal. Estimates of optimal filter weights are made, usually using modified LMS algorithms, based on the correlation between the error signal and the system output. Usually, a reference path delay is used to compensate for the delay associated with the feedback path. AFC systems that use noise probes results in the increase in stable gain on the order of 10-15 dB.

Non-continuous adaptation: In non-continuous adaptation AFC systems the normal signal path is broken and the filter is adapted, using a broadband noise probe, when some predetermined condition is met. One such approach is to adapt at system turn-on, periodically, and/or when a threshold change in gain is sensed [6].

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There are obvious advantages and disadvantages to non-continuous adaptation. The advantages include shorter probe duration (rather than continuous probe noise), interruption of the feedback loop at the onset of oscillation, and processing of alert or alarm signals without attenuation. One disadvantage of the noncontinuous adaptation methods is that changes in the feedback path that do not immediately cause instability but that may nonetheless be disturbing because of their effects on the overall transfer function are undetected. Other disadvantages are that the signal is interrupted for a brief period and that a high-level noise is presented to the user.

In addition to these obvious factors, there are two others that also must be appreciated. The first stems from the fact that the continuous-adaptation AFC systems are recursive adaptive systems. The second concerns the effects of external signals present during the filter weight adaptation.

a) FIR versus IIR Adaptive Filtering: Despite prior treatments of continuous-adaptation systems as transversal filters that can be simply adapted by an unconstrained LMS algorithm, these systems can be readily seen to be recursive IIR adaptive filters. The recursion arises because the output of the adaptive filter recirculates back to the input of the adaptive filter. Realizing that the continually adapting AFC configurations are recursive adaptive filters, more factors must be considered in their design and in the interpretation of their performance. In particular, recursive adaptive filters have two disadvantages that are not found in non-recursive adaptive filters. First, they become unstable if their poles move outside the unit circle during the adaptation process. This instability must be prevented by limiting the filter weights in some manner during the update. Second, their performance surfaces are generally non quadratic and may have local minima. Both of these factors hinder the use of simple adaptive algorithms.

b) Effects of input signals on weight adaptation: The presence of signals other than the output of the feedback path at the hearing aid microphone can have adverse effects on the performance of AFC systems. This problem is of real concern because the user will rarely be in a perfectly quiet environment (and if he or she were, microphone noise would still be present). Consequently, the adaptation process, whether continuous or noncontinuous, must proceed in the presence of ambient stimuli.

The degrading effect of ambient stimuli on the precision of adaptive feedback equalization and cancellation is the same problem - known as misadjustment - that is encountered in adaptive noise cancellation when uncorrelated signals interfere with the adaptive process [3].

3.4 Adaptive Transversal Filters

An adaptive filter is a self-designing and time-varying system that uses a recursive algorithm continuously to adjust its tap weights for operation in an unknown environment [6]. Figure 3.2 shows a typical structure of the adaptive filter, which consists of two basic functional blocks:

(i) a digital filter to perform the desired filtering and

(ii) an adaptive algorithm to adjust the tap weights of the filter

The digital filter computes the output $y(n)$ in response to the input signal $u(n)$, and generates an error signal $e(n)$ by comparing $y(n)$ with the desired response $d(n)$, which is also called the reference signal, as shown in Figure 3.1. The performance feedback signal $e(n)$ (also called the error signal) is used by the adaptive algorithm to adjust the tap weights of the digital filter. The digital filter shown in Figure 3.2 can be realized using many different structures. The commonly used transversal or finite impulse response (FIR) filter is shown in Figure 3.3. The adjustable tap weights, $w_m(n), m = 0,1, \ldots., M-1,$ indicated by circles with arrows through them, are the filter tap weights at time instance n and M is the filter length. These time-varying tap weights form an $M \times 1$ weight vector expressed as:

$$\boldsymbol{w}(n) \equiv [w_0(n), w_1(n), \ldots, w_{M-1}(n)]^T, \text{-----------------------} \quad (3.1)$$

where the superscript T denotes the transpose operation of the matrix. Similarly, the input signal samples, $u(n-m), m = 0, 1, \ldots, M-1$, form an $M \times 1$ input vector

$$\boldsymbol{u}(n) \equiv [u(n), u(n-1), \ldots, u(n-M+1)]^T \text{-----------------} \quad (3.2)$$

With these vectors, the output signal $y(n)$ of the adaptive FIR filter can be computed as the inner product of $\boldsymbol{w}(n)$ and $\boldsymbol{u}(n)$, expressed as

$$y(n) = \sum_{m=0}^{m-1} w_m(n) u(n-m) = \boldsymbol{w}^T(n)\boldsymbol{u}(n) \text{-------------------} \quad (3.3)$$

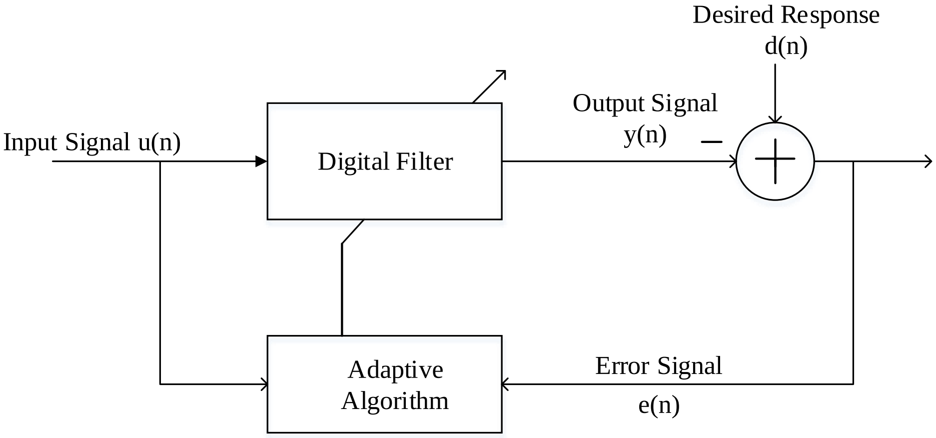

Figure 3.2 Typical structure of the adaptive filter using i/p and error signals to update its tap weights

3.5 Performance Measure

The error signal $e(n)$ shown in Figure 3.2 is the difference between the desired response $d(n)$ and the filter response $y(n)$, expressed as

$$e(n) = d(n) - \boldsymbol{w}^T(n)\boldsymbol{u}(n) \text{ ------------------------------ } (3.4)$$

The weight vector $\boldsymbol{w}(n)$ is updated iteratively such that the error signal $e(n)$ is minimized. A commonly used performance criterion (or cost function) is the minimization of the mean-square error (MSE), which is defined as the expectation of the squared error as

$$J \equiv E\{e^2(n)\} \text{ -- } (3.5)$$

For a given weight vector $\boldsymbol{w} = [w_0, w_1, \ldots, w_{M-1}]^T$ with stationary input signal $u(n)$ and desired response $d(n)$, the MSE can be calculated from Equations (3.4) and (3.5) as

$$J \equiv E\{d^2(n)\} - 2\boldsymbol{p}^T\boldsymbol{w} + \boldsymbol{w}^T\boldsymbol{R}\boldsymbol{w} \text{ --------------------------- } (3.6)$$

where $\boldsymbol{R} \equiv E\{\boldsymbol{u}(n)\boldsymbol{u}^T(n)\}$ is the input autocorrelation matrix and $\boldsymbol{p} \equiv E\{d(n)\boldsymbol{u}(n)\}$ is the cross-correlation vector between the desired response and the input vector. The time index n has been dropped in Equation (3.6) from the vector $\boldsymbol{w}(n)$ because the MSE is treated as a stationary function.

Equation (3.6) shows that the MSE is a quadratic function of the tap weights $\{w_0, w_1, \ldots, w_{M-1}\}$ since they appear in first and second degrees only. For M >2, the error surface is a hyperboloid. The quadratic performance surface guarantees that it has a single global minimum MSE corresponding to the optimum vector $\boldsymbol{w_0}$. The optimum solution can be obtained by taking the first derivative of Equation (3.6) with respect to **w** and setting the derivative to zero. This results in the Wiener–Hopf equation

$$\boldsymbol{R}\boldsymbol{w}_0 = \boldsymbol{p} \text{ -- } (3.7)$$

Assuming that $\boldsymbol{R}$ has an inverse matrix, the optimum weight vector is

$$\boldsymbol{w}_0 = \boldsymbol{R}^{-1}\boldsymbol{p} \quad (3.8)$$

Substituting Equation (3.8) into (3.6), the minimum MSE corresponding to the optimum weight vector can be obtained as

$$J_{min} = E\{d^2(n)\} - \boldsymbol{p}^T\boldsymbol{w}_0 \quad (3.9)$$

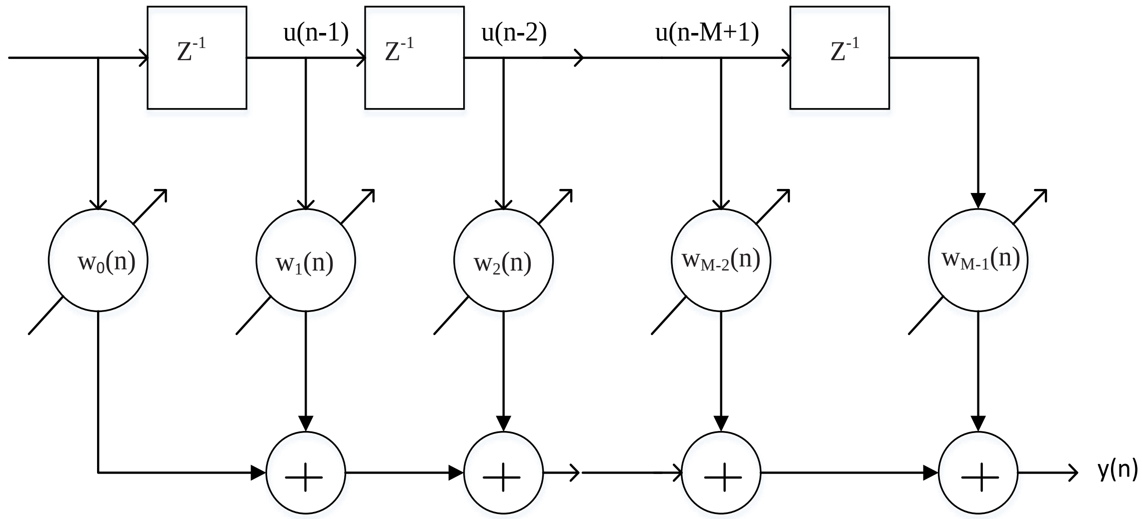

Figure 3.3 An M-tap adaptive transversal FIR filter structure

3.6 Adaptive Filtering Algorithms

An adaptive algorithm is a set of recursive equations used to adjust the weight vector $\boldsymbol{w}(n)$ automatically to minimize the error signal $e(n)$ such that the weight vector converges iteratively to the optimum solution $\boldsymbol{w}_o$ that corresponds to the bottom of the performance surface, i.e. the minimum MSE J_{min}. The least mean-square (LMS) algorithm is the most widely used among various adaptive algorithms because of its simplicity and robustness. The LMS algorithm based on the steepest-descent method using the negative gradient of the instantaneous squared error, i.e. $J \approx e^2(n)$, was devised by Widrow and Stearns [29] to study the pattern-recognition machine. The LMS algorithm updates the weight vector as follows:

$$\boldsymbol{w}(n+1) = \boldsymbol{w}(n) + \mu\boldsymbol{u}(n)e(n), \quad \text{(3.10)}$$

where μ is the step size (or convergence factor) that determines the stability and the convergence rate of the algorithm.

As shown in Equation (3.10), the LMS algorithm uses an iterative approach to adapt the tap weights to the optimum Wiener–Hopf solution given in Equation (3.8). To guarantee the stability of the algorithm, the step size is chosen in the range

$$0 < \mu < \frac{2}{\lambda_{max}}, \quad \text{(3.11)}$$

where λ_{max} is the largest eigenvalue of the input autocorrelation matrix $\boldsymbol{R}$. However, the eigenvalues of $\boldsymbol{R}$ are usually not known in practice so the sum of the eigenvalues (or the trace of $\boldsymbol{R}$) is used to replace λ_{max}. Therefore, the step size is in the range of $0 < \mu < \frac{2}{trace(\boldsymbol{R})}$. Since $trace(\boldsymbol{R}) = MP_u$ is related to the average power P_u of the input signal $u(n)$, a commonly used step size bound is obtained as

$$0 < \mu < \frac{2}{MP_u}. \quad \text{(3.12)}$$

It has been shown that the stability of the algorithm requires a more stringent condition on the upper bound of μ when convergence of the weight variance is imposed [3]. For Gaussian signals, convergence of the MSE requires $0 < \mu < 2/3\ MP_u$.

The upper bound on μ provides an important guide in the selection of a suitable step size for the LMS algorithm. As shown in (3.12), a smaller step size μ is used to prevent instability for a larger filter length M. Also, the step size is inversely proportional to the input signal power P_u. Therefore, a stronger signal must use a smaller step size, while a weaker signal can use a larger step size. This relationship can be incorporated into the LMS algorithm by normalizing the step size with respect to the input signal power. This normalization of step size (or input signal) leads to a useful variant of the LMS algorithm known as the normalized LMS (NLMS) algorithm.

The NLMS algorithm [7] includes an additional normalization term $\boldsymbol{u}^T(n)\boldsymbol{u}(n)$, as shown in the following equation:

$$\boldsymbol{w}(n+1) = \boldsymbol{w}(n) + \mu\frac{\boldsymbol{u}(n)}{\boldsymbol{u}^T(n)\boldsymbol{u}(n)}e(n), \text{----------------------} \quad (3.13)$$

where the step size is now bounded in the range $0 < \mu < 2$. It makes the convergence rate independent of signal power by normalizing the input vector $\boldsymbol{u}(n)$ with the energy $\boldsymbol{u}^T(n)\boldsymbol{u}(n) = \sum_{m=0}^{M-1} u^2(n-m)$ of the input signal in the adaptive filter. There is no significant difference between the convergence performance of the LMS and NLMS algorithms for stationary signals when the step size μ of the LMS algorithm is properly chosen. The advantage of the NLMS algorithm only becomes apparent for nonstationary signals like speech, where significantly faster convergence can be achieved for the same level of MSE in the steady state after the algorithm has converged.

Assuming that all the signals and tap weights are real valued, the FIR filter requires M multiplications to produce the output $y(n)$ and the update equation (3.10) requires $(M+1)$ multiplications. Therefore, a total of $(2M+1)$ multiplications per iteration are required for the adaptive FIR filter with the LMS algorithm. On the other hand, the NLMS algorithm requires additional $(M+1)$ multiplications for the normalization term, giving a total of $(3M+2)$ multiplications per iteration. Since M is generally large for most practical applications, the computational complexity of the LMS and NLMS algorithms is proportional to M, denoted as $O(M)$. Note that the normalization term $\boldsymbol{u}^T(n)\boldsymbol{u}(n)$ in Equation (3.13) can be approximated from the average power P_u, which can be recursively estimated at time *n* by a simple running average as

$$P_u(n) = (1-\beta)P_u(n-1) + \beta u^2(n), \text{---------------------} \quad (3.14)$$

Where, $0 < \beta << 1$ is the smoothing (or forgetting) parameter. The affine projection (AP) algorithm [28] is a generalized version of the NLMS algorithm. Instead of minimizing the current error signal given in Equation (3.4), the AP algorithm increases the convergence rate of the NLMS algorithm by using a set of P

constraints $d(n-k) = \boldsymbol{w}^T(n+1)\boldsymbol{u}(n-k)\, for\, k = 0,1,\ldots,P-1.$ Note that P is less than the length M used in the adaptive FIR filter and results in an under determined case. Therefore, a pseudo-inversion of the input signal matrix is used to derive the AP algorithm as follows:

$$\boldsymbol{w}(n+1) = \boldsymbol{w}(n) + \mu \boldsymbol{A}^T(n)[\boldsymbol{A}(n)\boldsymbol{A}^T(n)]^{-1}e(n) \text{ -------------- } (3.15)$$

$$\boldsymbol{e}(n) = \boldsymbol{d}(n) - \boldsymbol{A}(n)\boldsymbol{w}(n), \text{------------------------------- } (3.16)$$

where the input signal matrix $\boldsymbol{A}^T(n) = [\boldsymbol{u}(n), \boldsymbol{u}(n-1), \ldots, \boldsymbol{u}(n-P+1)]$ consists of P columns of input vectors of length M, $\boldsymbol{e}(n) = [e(n), e(n-1), \ldots, e(n-P+1)]^T$ is the error signal vector and $\boldsymbol{d}(n) = [d(n), d(n-1), \ldots, d(n-P+1)]^T$ is the desired signal vector. The computation of error signals given in Equation (3.16) is based on P constraints (or order) of the AP algorithm. More constraints (i.e. larger P) results in faster convergence but at the cost of higher complexity. When P reduces to one (i.e. a single column), the updating equation in (3.15) becomes a special case of the NLMS algorithm as shown in Equation (3.13). The computational complexity of the AP algorithm is $O(P^2M)$.

Unlike the NLMS algorithm that is derived from the minimization of the expectation of squared error, the recursive least-square (RLS) [28] algorithm is derived from the minimization of the sum of weighted least-square errors as

$$J_{LS}(n) = \sum_{i=1}^{n} \lambda^{n-i} e^2(i), \text{---------------------------------- } (3.17)$$

where λ is the forgetting factor and has a value less than and close to 1. The forgetting factor weights the current error heavier than the past error values to support filter operation in nonstationary environments. Therefore, in the least-square method, the weight vector $\boldsymbol{w}(n)$ is optimized based on the observation starting from the first iteration (i = 1) to the current time ($i = n$). The least-square approach can also be expressed in the form similar to the Wiener–Hopf equation defined in equation (3.7), where the autocorrelation matrix and cross-correlation vector are expressed as

$\boldsymbol{R} \approx \boldsymbol{R}(n) = \sum_{i=1}^{n} \lambda^{n-i} \boldsymbol{u}(i)\boldsymbol{u}^T(i)$ and $\mathbf{p} \approx \mathbf{p}(n) = \sum_{i=1}^{n} \lambda^{n-i} d(i)\boldsymbol{u}(i)$ respectively.

Now the RLS algorithm can be written as:

$$\boldsymbol{w}(n+1) = \boldsymbol{w}(n) + \boldsymbol{g}(n)e(n), \text{---------------------------} (3.18)$$

where the updating gain vector is defined as

$$\boldsymbol{g}(n) = \frac{\boldsymbol{r}(n)}{1 + \boldsymbol{u}^T(n)\boldsymbol{r}(n} \text{--------------------------------------} (3.19)$$

And

$$\boldsymbol{r}(n) = \lambda^{-1}\boldsymbol{P}(n-1)\boldsymbol{u}(n) \text{--------------------------------} (3.20)$$

The inverse correlation matrix of input data, $\boldsymbol{P}(n) \equiv \boldsymbol{R}^{-1}(n)$, can be computed recursively as

$$\boldsymbol{P}(n) = \lambda^{-1}\boldsymbol{P}(n-1) - \boldsymbol{g}(n)\boldsymbol{r}^T(n) \text{-----------------------} (3.21)$$

Note that the AP algorithm approaches the RLS algorithm when P increases to M and $\lambda = 1$. Since both the NLMS and RLS algorithms converge to the same optimum weight vector, there is a strong link between them. Montazeri and Duhamel [10] linked the set of adaptive algorithms including the NLMS, AP and RLS algorithms.

The computational complexity of the RLS algorithm is in the order of $O(M^2)$. There are several efficient versions of the RLS algorithm, such as the fast transversal filter with the reduced complexity to $O(M)$ [28]. Compared to the NLMS and AP algorithms, the RLS algorithm is more expensive to implement. The AP algorithm has a complexity that lies between the NLMS (for $P = 1$) and RLS (for $P = M$) algorithms.

CHAPTER FOUR: METHODOLOGY

4.1 Existing System Model

In figure 1.2, the closed loop transfer function between $y(n)$ and $s(n)$ is given as:

$$H(z) = \frac{G(z)}{1-G(z)F(z)} \text{-------------------------------------} (4.1)$$

Consider the NLMS-algorithm-based conventional method as shown in figure 1.2. The signal pricked up by the input microphone, (n) , is given as

$$x(n) = s(n) + y_f(\mathrm{n}) \text{-------------------------------------} (4.2)$$

Where $y_f(\mathrm{n}) = f(n) * y(n)$ is the feedback component due to the output signal (n) , $*$ denotes linear convolution, and $f(n)$ represents the impulse response of $F(z)$. The error signal for $W(z)$ is generated as:

$$e(n) = x(n) - y_w(\mathrm{n}) = s(n) + y_f(\mathrm{n}) - y_w(\mathrm{n}) \text{----------------} (4.3)$$

which is also used as an input to the hearing aid processing unit $G(z)$, i.e., $u(n) = e(n)$. The coefficient vector for (z) , $w(n) = [w_o(n), w_1(n), \cdots, w_{L-1}(n)]^T$, is updated using the NLMS algorithm as

$$\boldsymbol{w}(n+1) = \boldsymbol{w}(n) + \frac{\mu}{\boldsymbol{y}^T(n)\boldsymbol{y}(n)+\delta}\, g(n)\boldsymbol{y}(n) \text{-------------------} (4.4)$$

where μ is step-size for $W(z)$, and δ is a small positive constant to avoid division by zero. Ideally, $W(z)$ is expected to generate a replica of$y_f(\mathrm{n})$, so that $(n) = e(n) \approx s(n)$. However, the input and desired-response signals of $G(z)$, $y(n)$ and $x(n)$, respectively, are correlated with each other and would result in a biased convergence, i.e., $u(n) = e(n) \rightarrow ZERO$. The objective is to solve this biasing problem and hence realize an efficient method for continuous AFC which shows that due to acoustic feedback the hearing aid will be unstable if $G(z)$ is large enough so that $G(z)F(z) = 1$ at some frequency.

4.2 Proposed System Model

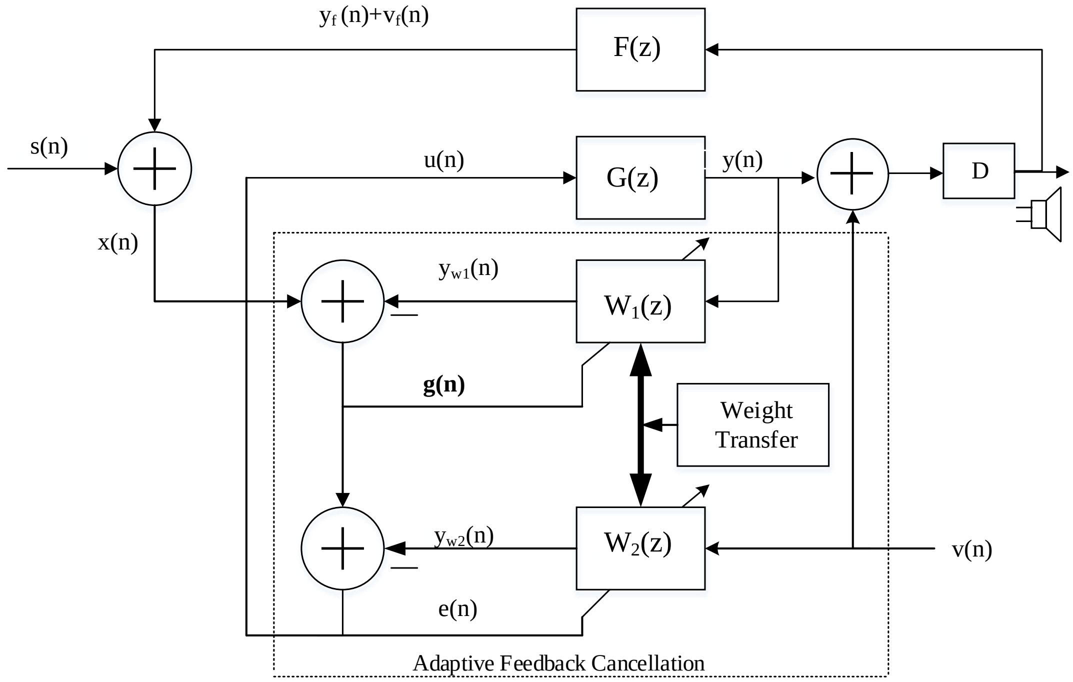

Figure 4.1 Block diagram of the proposed method for continuous AFC in hearing aids

The block diagram of the new method is shown in figure. 4.1. This method employs two adaptive filters $W_1(z)$ and $W_2(z)$ working in tandem. The important difference, however, is that the delay is inserted at the output of the hearing aid. Traditionally such type of delay is used to solve the correlation problem in the AFC filter [9]. In our approach, the objective of the appended delay is twofold:

1) to provide (some) decorrelation, as well as
2) to help designing an efficient strategy for weight transfer between the two adaptive filters as explained below.

The adaptive filter $W_1(z)$ is excited by $y(n)$ and is expected to provide a neutralization signal for the feedback component y_f(n). The second adaptive filter $W_2(z)$ is excited by the feedback component $v_f(n)$ due to the added probe signal $v(n)$. It is assumed that $v(n)$ is a low level white signal and is uncorrelated with the input signal $s(n)$ and hence with the output signal $y(n)$. The signal picked up by the input microphone, x(n) is now given as

$$x(n) = s(n) + y_f(n) + v_f(n) \quad (4.5)$$

Where $v_f(n) = f(n) * v(n-D)$ is the acoustic feedback component due to probe signal $v(n-D)$ where D is an appropriately selected delay. The error signal for $W_1(z)$, $g(n)$, is computed as

$$g(n) = x(n) - y_{w1}(\mathrm{n}) = s(n) + [y_f(\mathrm{n}) - y_{w1}(\mathrm{n})] + v_f(n) \text{ --------- } (4.6)$$

which is also used as the desired response for $W_2(z)$, and hence the error signal for $W_2(z)$, $e(n) = g(n) - y_{w2}(\mathrm{n})$, is given as

$$e(n) = s(n) + [y_f(\mathrm{n}) - y_{w1}(\mathrm{n})] + [v_f(n) - y_{w2}(n)] \text{ -------------- } (4.7)$$

A delay based technique has been employed which has been largely applied in the field of acoustic echo cancelation [14]

A measure of the filter convergence is the deviation or the system mismatch. The normalized squared deviation (NSD) of the adaptive filter $W_1(z)$ and $W_2(z)$ can be respectively estimated as:

$$\Delta\widetilde{W_1}(n) = 10log\left\{\frac{\|\tilde{f}(n) - \boldsymbol{w}_{1F}(n)\|^2}{\|\tilde{f}(n)\|^2}\right\} \text{ ------------------------------ } (4.8)$$

$$\Delta\widetilde{W_2}(n) = 10log\left\{\frac{\|\tilde{f}(n) - \boldsymbol{w}_{2F}(n)\|^2}{\|\tilde{f}(n)\|^2}\right\} \text{ ------------------------------ } (4.9)$$

It is worth mentioning that both adaptive filters are continuously adapted and hence, $W_1(z)$ would tend to a biased solution and $W_2(z)$ would slowly fine tune to a better estimate. Now the following weight transfer strategy has been employed such that both filters give good estimate of $F(z)$.

4.3 Proposed Weight-Transfer Strategy

The normalized squared deviation (NSD) of the adaptive filter $W_1(z)$ from the feedback path $F(z)$ can be computed as:

$\Delta W_1(n) = 10\log\left\{\frac{\|\boldsymbol{f}-\boldsymbol{w}_1(n)\|^2}{\|f\|^2}\right\}$ (dB) where $\boldsymbol{f}$ and $\boldsymbol{w}_1(n)$ are the coefficient vectors for $F(z)$ and $W_1(z)$ respectively and $\|.\|$ is the Euclidean norm. The NSD for $W_2(z)$, $\Delta W_2(n)$ can be calculated analogously [13]. The coefficients of $W_1(z)$ and $W_2(z)$ can be exchanged as:

$$if \Delta W_2(n) < \Delta W_1(n)\ then\ \boldsymbol{w}_1(n) \leftarrow \boldsymbol{w}_2(n).$$
$$if \Delta W_1(n) < \Delta W_2(n)\ then\ \boldsymbol{w}_2(n) \leftarrow \boldsymbol{w}_1(n).$$

However in order to develop an efficient weight transfer scheme, an appropriate delay is inserted at the output of the hearing aid; this increases the effective path to be identified by the AFC filters $W_1(z)$ and $W_2(z)$. Thus both the adaptive filters $W_1(z)$ and $W_2(z)$ are considered with extended-length coefficient vectors as being given as:

$$\boldsymbol{w}_1(n) = \begin{bmatrix}\boldsymbol{w}_{1z}(n)\\ \boldsymbol{w}_{1f}(n)\end{bmatrix}\ and\ \boldsymbol{w}_2(n) = \begin{bmatrix}\boldsymbol{w}_{2z}(n)\\ \boldsymbol{w}_{2f}(n)\end{bmatrix} \text{--------------------} \quad (4.10)$$

where $\boldsymbol{w}_{1z}(n) = [w_{1z,0}(n), w_{1z,1}(n), \cdots, w_{1z,D-1}(n)]^T$ and $\boldsymbol{w}_{2z}(n)$ represent the part used to model the delay (and would eventually converge to zeros), and both $\boldsymbol{w}_{1f}(n)$ and $\boldsymbol{w}_{2f}(n)$ model $F(z)$. Now convergence of the two adaptive adaptive filters $W_1(z)$ and $W_2(z)$ can be monitored on the basis of norm of extension coefficients modeling the appended delay as

$$\rho_1(n) = \|\boldsymbol{w}_{1z}(n)\|^2 \text{ and } \rho_2(n) = \|\boldsymbol{w}_{2z}(n)\|^2 \text{-------------------} \quad (4.11)$$

The power estimates for the error signals in (4.6) and (4.7) can be respectively expressed as

$$P_g(n) = P_{\{s+(y_f-y_{w1})\}}(n) + P_{v_f}(n) \text{ --------------------------} \quad (4.12)$$
$$P_e(n) = P_{\{s+(y_f-y_{w1})\}}(n) + P_{(v_{f-y_{w2}})}(n) \text{------------------------} \quad (4.13)$$

These power estimates can be recursively computed using lowpass estimator of type

$$P_q(n) = \lambda P_q(n-1) + (1-\lambda)q^2(n) \text{ --------------------------} \quad (4.14)$$

Where λ is the forgetting factor ($0.9 < \lambda < 1$) and $q(n)$ is the signal of interest. At the start up $(n = 0), P_g(n) \approx P_e(n)$. However, $W_1(z)$ converges faster as compared with $W_2(z)$ ($W_2(z)$ being excited by a low level probe noise $v(n)$), and hence $P_g(n) < P_e(n)$ for $n > 0$. Finally as $n \to \infty$, $W_2(z)$ converges too and hence $P_e(n) \approx P_g(n)$.

Both $\boldsymbol{w}_{1z}(n)$ and $\boldsymbol{w}_{2z}(n)$ are initialized with the values obtained by considering the cutoff frequency and tap weight length. Cut off frequency can be obtained with the help of sampling frequency which is a known value. The values of $\boldsymbol{w}_{1f}(n)$ and $\boldsymbol{w}_{2f}(n)$ may be initialized by null vectors of appropriate orders. The convergence of $W_1(z)$ is faster than $W_2(z)$ and initially $\rho_1(n) < \rho_2(n)$, and hence weights from $W_1(z)$ are copied to $W_2(z)$ as $\boldsymbol{w}_{1f}(n) \to \boldsymbol{w}_{2f}(n)$.

4.4 Significance of Weight Transfer

Simulation results obtained based on the proposed strategy outperforms that of conventional one. Since $W_1(z)$ is excited by $y(n)$ which is an amplified version of$s(n)$, and hence convergence of $W_1(z)$ is very fast but it might have been converged to a biased solution. On the other hand, $W_2(z)$, though converging slowly being excited by a low level probe signal $v(n)$, would give a good steady state estimate of the acoustic feedback path. In order to make sure that both $W_1(z)$ and $W_2(z)$ would give good estimate of $F(z)$, the misconvergence of $W_1(z)$ must be avoided and the initial convergence of $W_2(z)$ must be improved. For this purpose, their weights have been exchanged by a weight transfer strategy.

4.5 Proposed Adaptation Algorithm

The output of the adaptive filter $W_1(z)$ is given as

$$y_{w1}(n) = \boldsymbol{w}_1^T(n)\,\boldsymbol{y}(n) \quad (4.16)$$

where $\boldsymbol{w}_1(n) = [w_{1,0}(n), w_{1,1}(n), \cdots, w_{1,L-1}(n)]^T$is the tapweight vector for $W_1(z)$, $L_1 = D + L$ is the tap-weight length of $W_1(z)$, and $\boldsymbol{y}(n) = [y(n-1), y(n-2), \cdots, y(n-L_1)]^T$ is the signal vector comprising L_1 recent samples of $y(n)$. It is worth mentioning that there is inherent one-sample delay which is not shown in figure 4.1 just for the sake of simplicity. The coefficient vector for $W_1(z)$, $\boldsymbol{w}_1(n)$, is updated using the NLMS algorithm as

$$\boldsymbol{w}_1(n+1) = \boldsymbol{w}_1(n) + \frac{\mu_1(n)}{\boldsymbol{y}^T(n)\boldsymbol{y}(n)+\delta_1} g(n)\boldsymbol{y}(n) \quad (4.17)$$

where δ_1 is another positive constant to avoid division by zero, and $\mu_1(n)$ is a time varying step-size parameters being computed as

$$\mu_1(n) = \begin{cases} \frac{\hat{N}_{D_1}(n)}{P_g(n)}; & \frac{\hat{N}_{D_1}(n)}{P_g(n)} > \mu_{1_{min}} \\ \mu_{1_{min}}; & otherwise \end{cases} \quad (4.18)$$

Where $\mu_{1_{min}}$ is the minimum value of the step-size parameter $\mu_1(n)$, and $\hat{N}_{D_1}(n)$ is being computed as

$$\hat{N}_{D_1}(n) = \lambda \hat{N}_{D_1}(n-1) + (1-\lambda)\frac{(\boldsymbol{w}_{1z}^T(n)\boldsymbol{w}_{1z}(n)\boldsymbol{y}^T(n)\boldsymbol{y}(n))}{D} \quad (4.19)$$

The output of the extended-length adaptive filter $W_2(z)$, $y_{w2}(n)$,
is given as

$$y_{w2}(n) = \boldsymbol{w}_2^T(n)\boldsymbol{v}(n) \quad (4.20)$$

where $\boldsymbol{w}_2(n) = [w_{2,0}(n), w_{2,1}(n), \cdots, w_{2,L_2-1}(n)]^T$ is the tap-weight vector for $W_2(z)$, $L_2 = D + L$ is the tap-weight length of $W_2(z)$, and $\boldsymbol{v}(n) = [v(n), v(n-1), \cdots, v(n-L_2+1)]^T$ is a signal vector for the probe signal $v(n)$. The coefficient vector for $W_2(z)$, $w_2(n)$, is updated using the NLMS algorithm as

$$\boldsymbol{w}_2(n+1) = \boldsymbol{w}_2(n) + \frac{\mu_2(n)}{\boldsymbol{v}^T(n)\boldsymbol{v}(n)+\delta_2} e(n)\boldsymbol{v}(n) \quad (4.21)$$

where δ_2 is another positive constant to avoid division by zero, and $\mu_2(n)$ is a time varying step-size parameters being computed as

$$\mu_2(n) = \begin{cases} \frac{\widehat{N}_{D_2}(n)}{P_e(n)}; & \frac{\widehat{N}_{D_2}(n)}{P_e(n)} > \mu_{2_{min}} \\ \mu_{2_{min}}; & otherwise \end{cases} \text{------------------------} (4.22)$$

where $\mu_{2_{min}}$ is the minimum value of the step-size parameter $\mu_2(n)$, and $\widehat{N}_{D_2}(n)$ is being computed as

$$\widehat{N}_{D_2}(n) = \lambda \widehat{N}_{D_2}(n-1) + (1-\lambda) \frac{\left(\boldsymbol{w}_{2z}^T(n)\boldsymbol{w}_{2z}(n)\boldsymbol{v}^T(n)\boldsymbol{v}(n)\right)}{D} \text{------------} (4.23)$$

CHAPTER FIVE: RESULTS AND ANALYSIS

This section presents the details on computer simulations carried out to verify the effectiveness of the delay based dual adaptive filtering employed in acoustic feedback suppression. Various methods and algorithms are considered in the simulation study and the corresponding simulation parameters are determined by the successive trials over the specified theoretical limits. The simulation tool used is MATLAB. Sampling frequency considered during the simulation is $F_s = 8000\ Hz$. All adaptive filters are assumed to be FIR filters of tap weight length 32 i.e. $(\sum_{i=0}^{32} K_i\, Z^{-i})$. The forward path representing the hearing aid processing unit, is assumed to be in the form of $G(z) = \sum_{i=0}^{10} K_i z^{-\Delta}$ where K and Δ represent the gain and delay of the system respectively. In the result presented below $\Delta = 10$ and the gain is chosen as $K = 3$. The Normalized Squared Deviation (NSD) of the filters $W_1(z)$ and $W_2(z)$ are used as a performance measure as:

$$\Delta\widetilde{W_1}(n) = 10log\left\{\frac{\|\tilde{f}(n) - \mathbf{w}_{1F}(n)\|^2}{\|\tilde{f}(n)\|^2}\right\} \text{------------------------} \quad (5.1)$$

$$\Delta\widetilde{W_2}(n) = 10log\left\{\frac{\|\tilde{f}(n) - \mathbf{w}_{2F}(n)\|^2}{\|\tilde{f}(n)\|^2}\right\} \text{------------------------} \quad (5.2)$$

Various Literatures such as [13] suggest to initialize the weight vectors by either all 1's or 0's. In this thesis work, however, the initial weights of the adaptive filters are chosen such that the convergence time gets reduced. Instead of initializing the initial weights by either all 1's or by null vectors, the new strategy employs a different approach to select the initial guess. These initial weights are obtained by considering the tap weight length and cutoff frequency of the filter that is half of the sampling frequency since sampling frequency is the known value.

5.1 Simulation Parameters

Table 5. 1: Different Parameters used in Simulation

S. No.	Parameter	Value
1.	Step Size Parameter μ (conventional NLMS method)	1×10^{-9}
2.	Small Positive Constant δ (conventional NLMS method)	1×10^{-6}
3.	Step Size Parameter $\mu_{1_{min}}$(modified NLMS method)	1×10^{-9}
4.	Step Size Parameter $\mu_{2_{min}}$(modified NLMS method)	1×10^{-9}
5.	Small Positive Constant δ_1 (conventional NLMS method)	1×10^{-8}
6.	Small Positive Constant δ_2 (conventional NLMS method)	2.5×10^{-3}
7.	SNR_{probe}	$-15\ dB$
8.	Gain of Filter $G(z)$ i.e. k	3
9.	Adaptive Filter's Tap Weight Length	32
10.	Forgetting Factor λ	0.97

Different simulation parametes has been chosen to carry out the computer simulations. Adjusting the step size parameter in case of both the methods, conventional NLMS and modified NLMS is very difficult. A number of trails has been performed to obtain the value of these parameters that works well. Selecting this parameter too high will lead to the convergence of the adaptive filter's weight to a biased solution whereas selecting it too low will yield to the increment in the convergence time. So obtaining the optimal value of μ is a challenging task. Small positive constants δ, δ_1 and δ_2 are used to avoid the division by zero error during the computation process. Signal to Noise Ratio of the probe signal is set at a low value of $-15\ dB$ so that it does not affect the system's performance. Gain of filter is chosen such that satisfactory result is obtained at the output of the hearing aid processing unit. Increasing tap weight length improves the filter's performance, however it leads to the increase in the overall complexity of the system. So, appropriate tap weight length of the adaptive filters is selected as 32. The weighting factor λ is chosen as 0.97. It is also known as forgetting factor since it emphasizes the recent data and tends to forget the past.

5.2 Sample Signals, Feedback and Resulting Output

Figure 5.1 shows the amplitudes of the various signals used in computer simulations. It includes a music signal and four other speech signal of varying nature including male and female audio signals. The amplitude of corresponding signals is plotted against the number of samples.

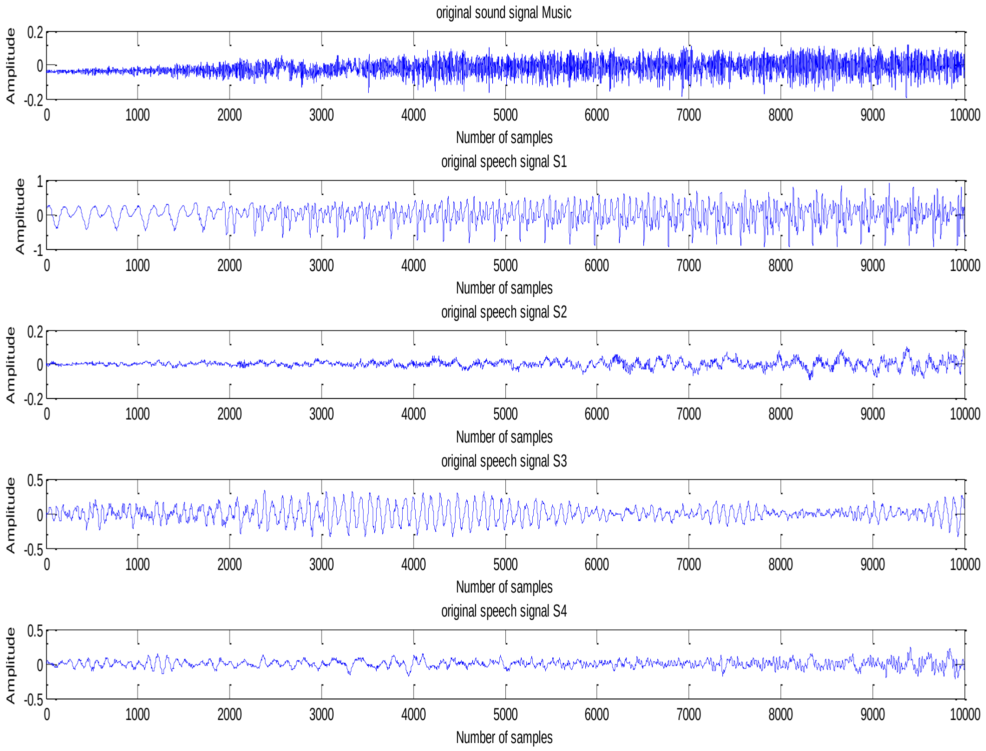

Figure 5.1 Plots for various signals used in computer simulations

The amplitude of the feedback modeled by $F(z)$ is shown in figure 5.2. It includes the feedback signals for a music signal and four other speech signals S1, S2, S3 and S4 respectively. Different speech signals with varying characteristics of male and female are considered as input signals.

The plots for the amplitude of the output signals obtained after employing the conventional single adaptive filter based NLMS algorithm and dual adaptive filter based modified NLMS algorithm is show in the above figures 5.3 and 5.4. The amplification on the input signal can be noted from the amplitude levels shown on y-axis. It is difficult to see any difference between the amplified signals of two methods, however, a close observation reveals that the new method is better able to replicate the input signal. In fact we hear some 'musical' noise in the case of conventional and previous methods, whereas the proposed method produces no such musical noise.

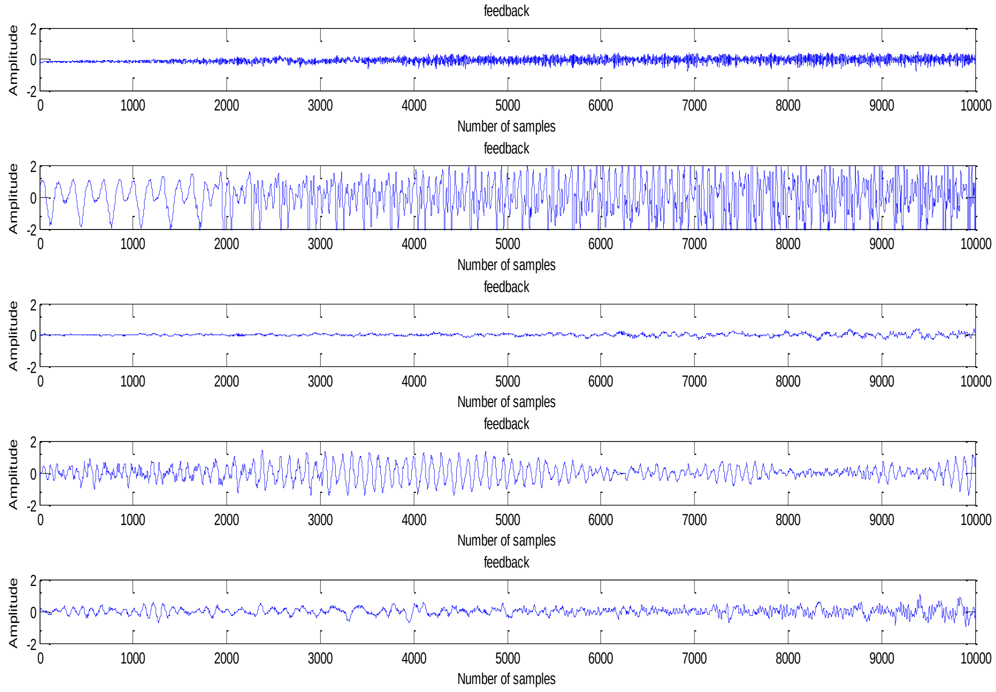

Figure 5.2 Plots for the feedback signals

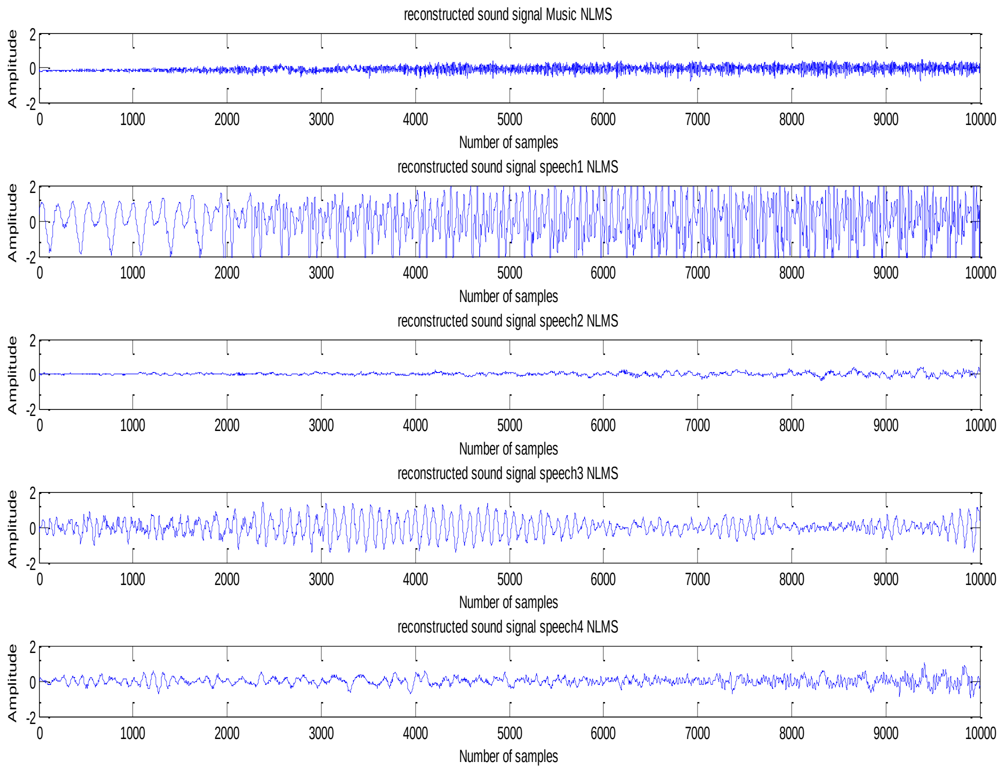

Figure 5.3 Plots for the output signals with conventional NLMS algorithm

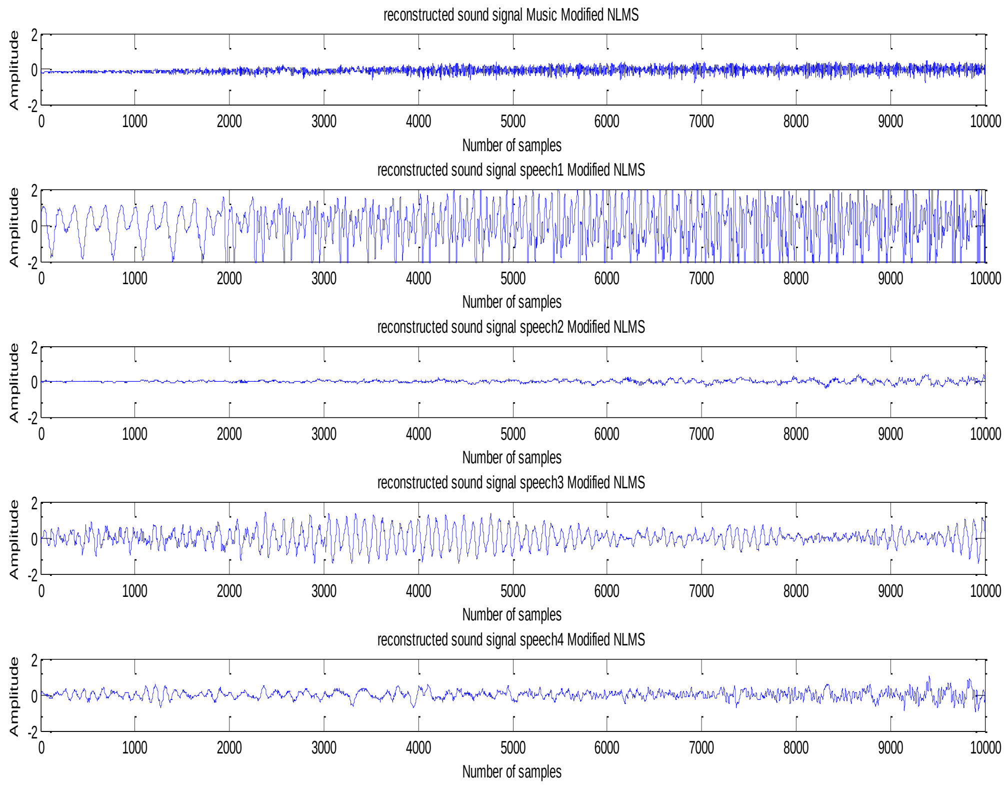

Figure 5.4 Plots for the output signals with modified NLMS algorithm

5.3 Magnitude Responses

Figures 5.5 and 5.6 are the magnitude response plot for the hearing aid processing unit $G(z)$ and the feedback path $F(z)$. The magnitude values are plotted against normalized frequency. It is seen that the response plot is of low pass filter type.

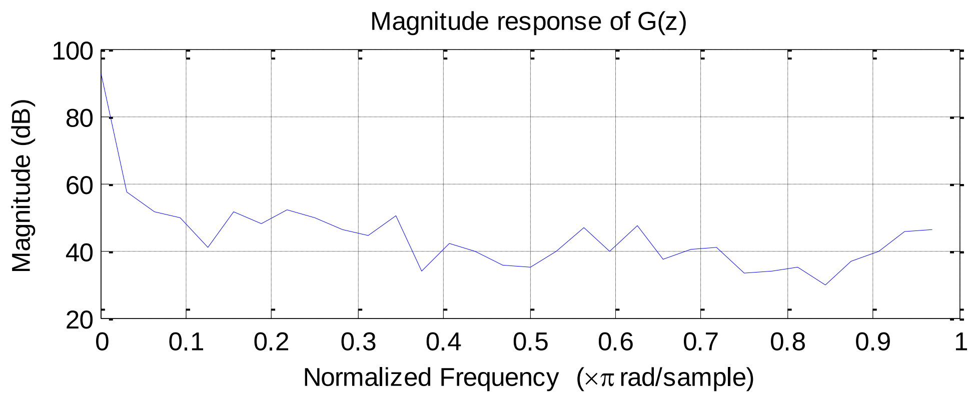

Figure 5.5 Magnitude response of hearing aid processing unit G(z)

Figures 5.7 and 5.8 depicts the magnitude response plots for the first adaptive filter and the second adaptive filter respectively. The filters used are of low pass types. It is also verified from the magnitude response plots of the various filter systems.

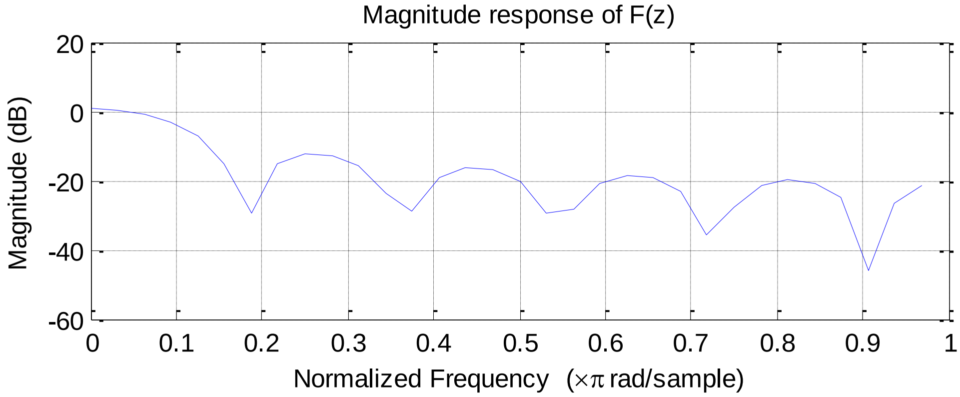

Figure 5.6 Magnitude response of feedback path F(z)

If the length of adaptive filters is increased, the response becomes much smooth thereby reducing the harmonics in the magnitude response, whereas if the length of adaptive filters is decreased then the number of harmonics goes on increasing. These plots are for the tap weight length 32.

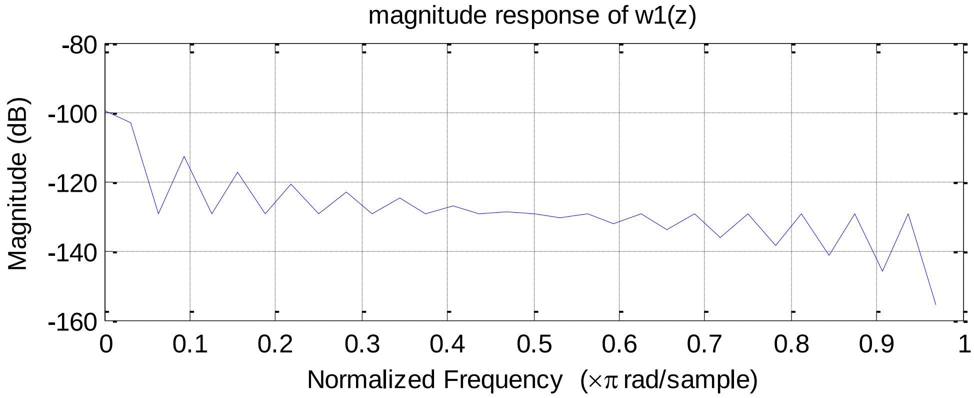

Figure 5.7 Magnitude response of first adaptive filter

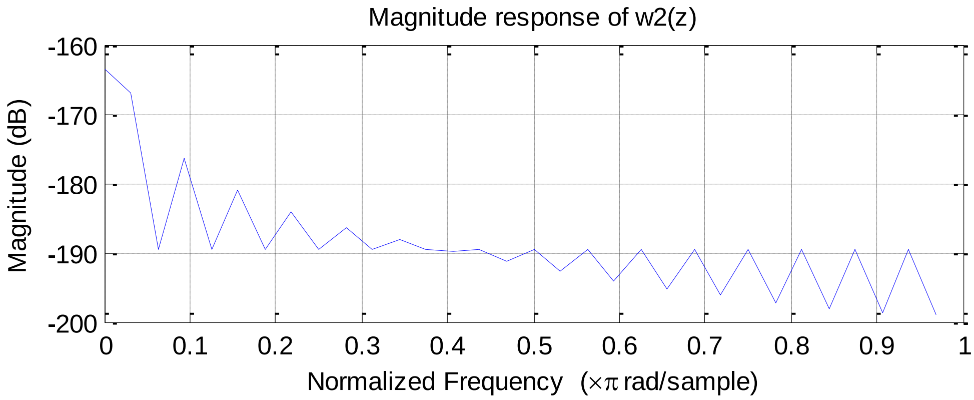

Figure 5.8 Magnitude response of second adaptive filter

5.4 Resulting Error $\Delta S(\mathbf{n})$

Figure 5.9 shows error in reconstruction of the desired input at the hearing aid, being computed as;

$$\Delta s(n) = |s(n) - u(n)|$$

It is obvious that for a perfect reconstruction of the desired input at the hearing aid, we must have $\Delta S \to 0$. From the figure, it is seen that the proposed method gives a very fast convergence speed in reproducing the desired signal at the input of the hearing aid processing unit. It is worth mentioning that level of added probe signal is so low that it does not affect the hearing experience. The resulting error is drastically reduced in case of dual adaptive acoustic feedback controlling scheme using the modified NLMS algorithm.

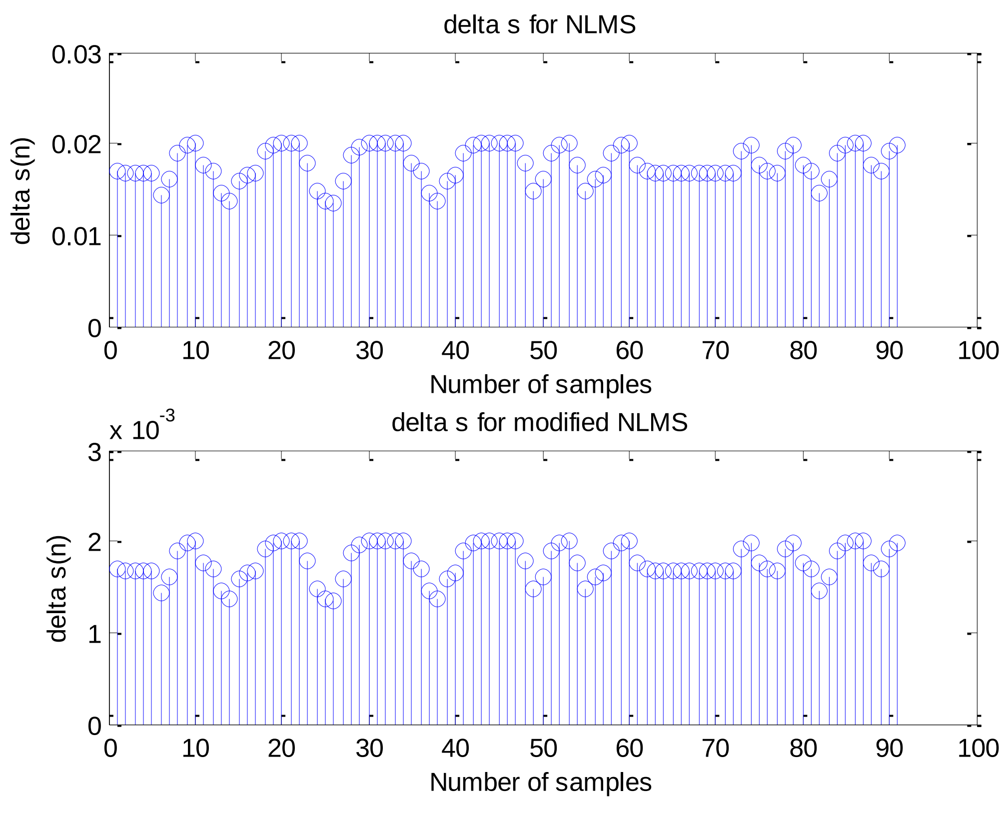

Figure 5.9 Error plots in reconstruction of the desired signal ΔS(n)

5.5 Normalized Squared Deviation

It is necessary to evaluate the deviation between estimated feedback path and the feedback that is actually appearing. Normalized Squared Deviation (NSD) is chosen as a parameter that characterizes the deviation. Smaller the NSD better is the performance of the system. Corresponding plot for NSD versus number of samples is shown in figure 5.10. Figure shows that the NSD values has been drastically reduced in case of dual adaptive NLMS algorithm. Average of the two NSD values corresponding to the two adaptive filters is chosen in case of dual method since the weight transfer strategy is employed among them. This small quantity signifies that the estimated feedback component best matches the actual feedback appearing at the feedback path of digital hearing aids. Actually when $\Delta\widetilde{W_2}(n) < \Delta\widetilde{W_1}(n)$, $\boldsymbol{w}_1(n)$ is replaced by $\boldsymbol{w}_2(n)$ and when $\widetilde{W_1}(n) < \Delta\widetilde{W_2}(n)$, $\boldsymbol{w}_2(n)$ is replaced by $\boldsymbol{w}_1(n)$.

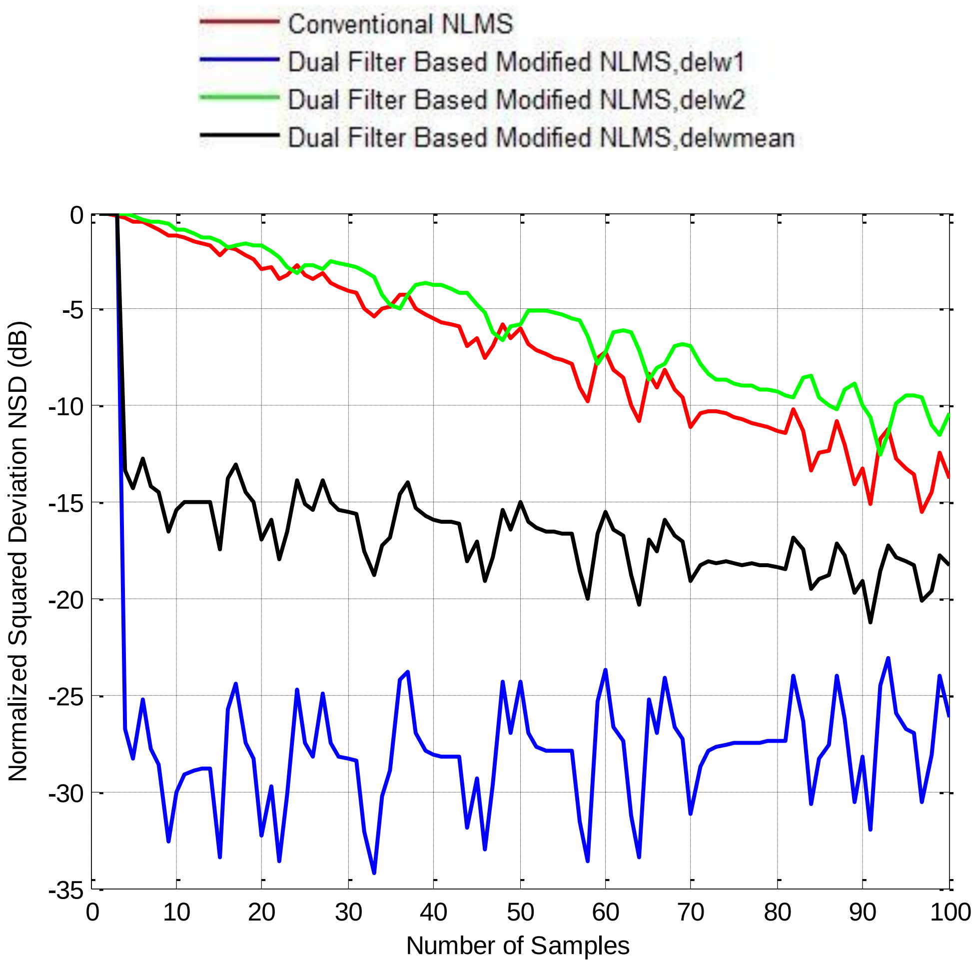

Figure 5.10 Normalized Squared Deviation (NSD) for various cases

5.6 Misalignment

It is also called the relative modeling error. In this thesis work it is calculated as $\Delta S(n) = 10log\left\{\frac{\|s(n)-\mathrm{u}(n)\|^2}{\|s(n)\|^2}\right\}$ where $s(n)$ is the desired signal and $u(n)$ is the input signal to the hearing aid processing unit. Figure 5.11 shows that the value of misalignment for dual adaptive filter based modified NLMS is much less than that of single adaptive filter based conventional method. From the figure it is seen that initially there is a transient but after some samples, the steady state value is attained. Both the methods resulted in steady state results but in case of conventional method error present is large.

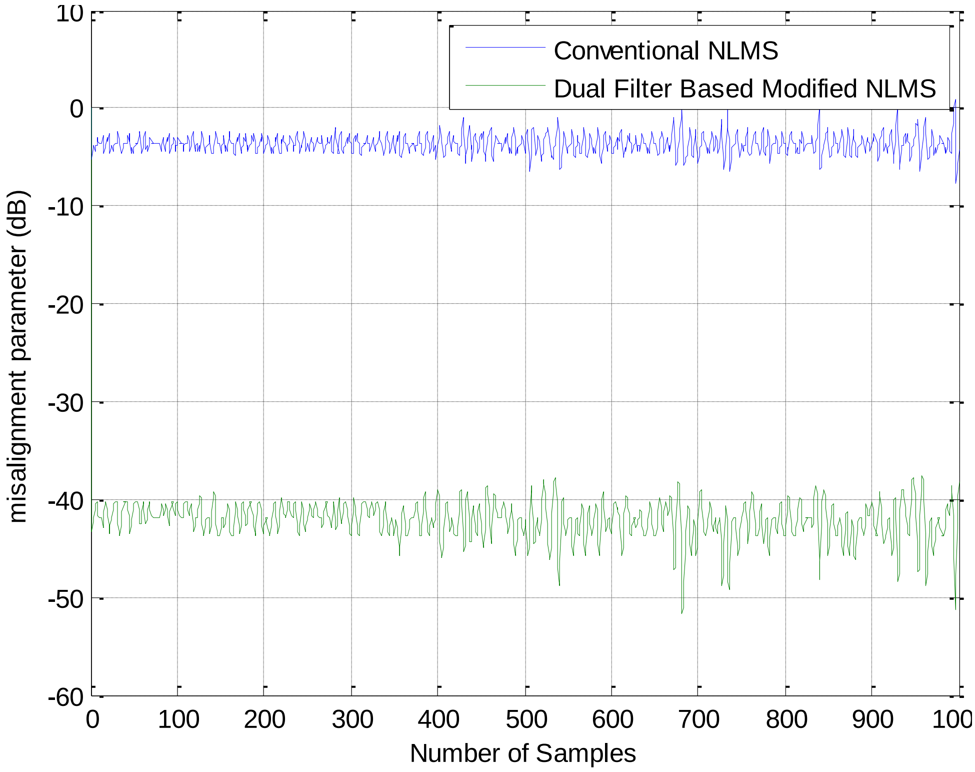

Figure 5.11 Response of misalignment parameter

5.7 Residual Error Reduction Parameter R

Due to the effect of added probe noise there is the presence of residual noise and it is preferable to keep it as low as possible. To access the effect of added noise, residual error reduction parameter R is calculated as:

$$R(n) = 10log\left\{\frac{\sum_{i=0}^{n} u(i)^2}{\sum_{i=0}^{n} s(i)^2}\right\}$$

where $u(i)$ and $s(i)$ are the error and desired signal of the i^{th} sample respectively.

Small values of R depict better noise reduction capability of the system. Initially the value of R is large for conventional NLMS system as shown in figure 5.12. However as the number of samples goes on increasing, the value of R gets reduced for modified method for few samples. After some samples there is no significant difference in the R values among the two methods since the delay employed is much less.

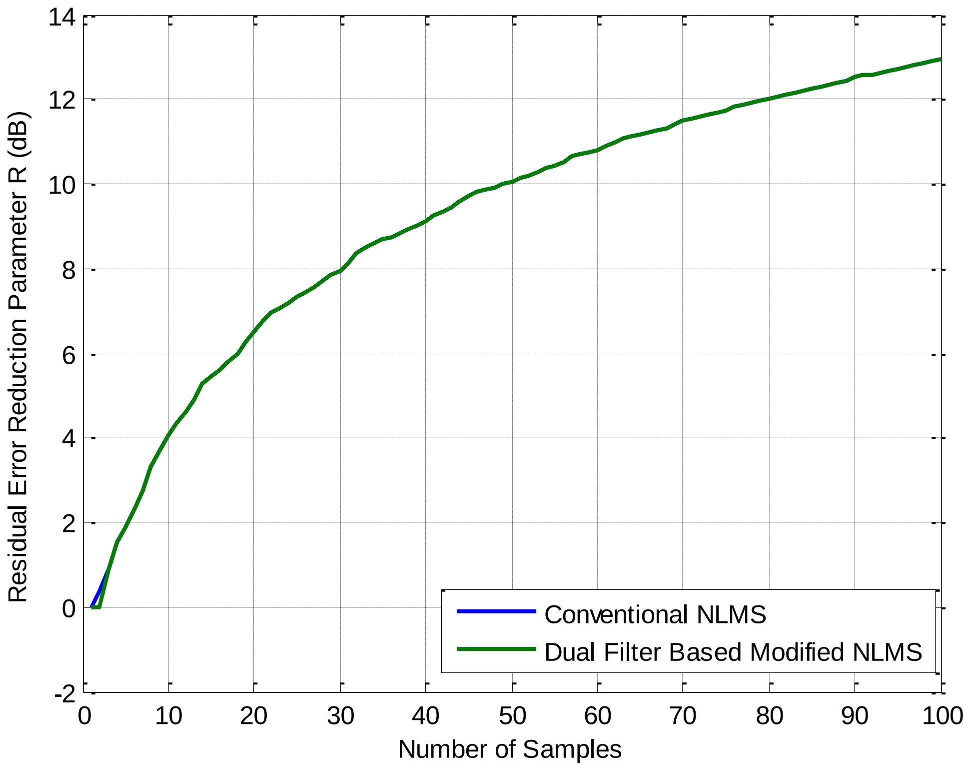

Figure 5.12 Response of residual error reduction parameter

When the value of delay is varied there is a significant difference in the resulting R. The simulation result obtained after varying the delay is depicted in figure 5.13. First two sample delays are used and then it is doubled thereafter. Initially some oscillation is occurred. After the filter came into effect the value of error reduction parameter is decreased while the delay is increased. This signifies that the insertion of delay improves the performance. This is due to the fact that the correlation between the input signal and the response signal gets minimized when the delay is increased. However increasing delay too high would lead to the extension of the adaptive filter which implies increased memory and complexity requirements: thus a tradeoff situation is occurred. In this thesis delay of 8 samples is taken into consideration to carry out the simulations.

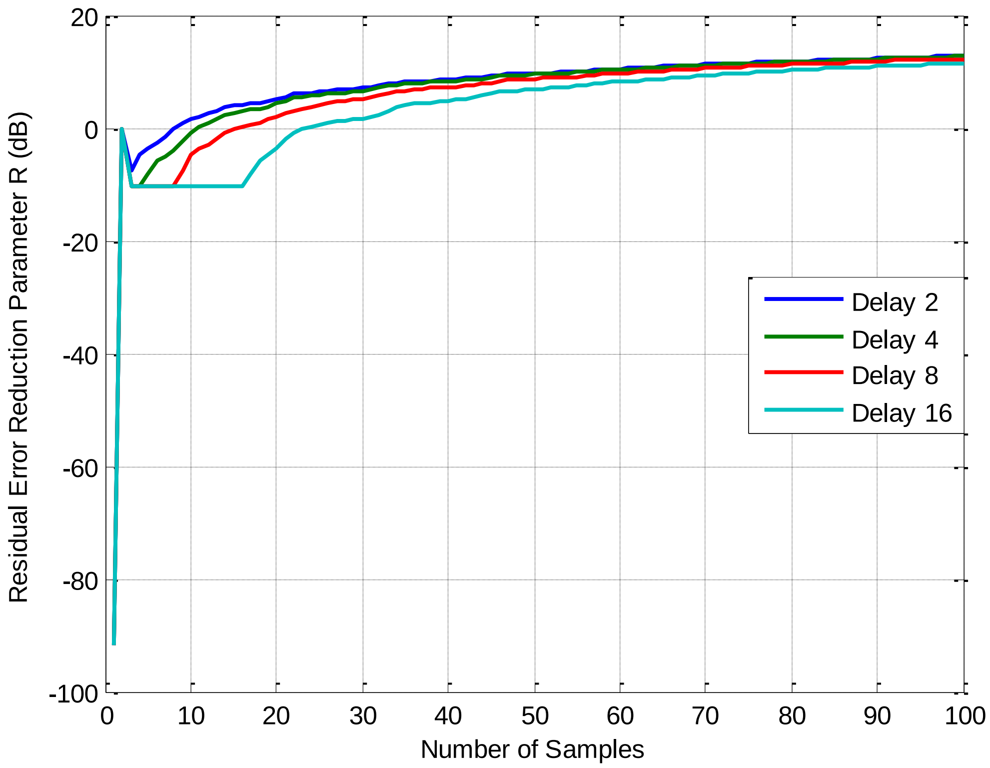

Figure 5.13 Residual Error Reduction parameter versus different delays

CHAPTER SIX: EPILOGUE

6.1 Conclusion

Acoustic feedback suppression is a key task of digital hearing aids which commonly uses least mean square (LMS) or normalized LMS (NLMS) adaptive algorithm to cancel acoustic feedback signal. To improve the performance of continuous AFC digital hearing aids, a new strategy based on dual adaptive filtering has been proposed in this thesis. This method adapts the filter weights and transfers the weights among the two adaptive filters which are working in tandem. The error signal of the first adaptive filter is used as a desired response for the second adaptive filter being excited by a low level constant probe signal. Initially at start up, first adaptive filter gives a fast convergence, however due to the correlation between input and desired response, the filter weights converge to a biased solution. To reduce this effect an appropriate delay is inserted at the output of the hearing aid. The obtained results show that the proposed method gives fast convergence speed and better steady-state results as compared with the conventional methods. The proposed method, being comprised of two adaptive filters, has an increased hardware complexity as compared with the conventional method. This increased complexity is the price paid for an improved performance.

6.2 Limitations and Future Work

In this thesis a new approach for continuous AFC in the hearing aids has been presented. The results obtained are quite promising, however, a detailed investigation is required for the added stable gain (ASG), maximum stable gain (MSG) and comparison with other methods. MSG is defined as the maximum gain without instability assuming a flat response of the hearing-aid process. ASG is defined as the additional gain that is possible by using the feedback canceller. In situations where the amplitude of the input signal is decaying/varying, the level of the probe signal must also be time varying so that a constant SNR is achieved. This is the limitation of this thesis. Threshold based efficient weight transfer strategy can be employed for much better performance. These are the tasks of future work.

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