Adaptive Noise Cancellation in Sinusoidal Signal using Wiener Filter

A Thesis report

submitted towards the partial fulfillment of the requirements of the degree of

Master of Engineering
In
Electronic Instrumentation and Control Engineering

submitted by

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Under the supervision of

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THAPAR UNIVERSITY, PATIALA- 147004

JULY 2010

DEDICATED

TO

MY PARENTS

CERTIFICATE

I hereby certify that the work which is being presented in the thesis entitled, **"Adaptive Noise Cancellation of Sinusoidal Signal using Wiener Filter "** in partial fulfillment of the requirements for the award of degree of Master of Engineering in Electronic Instrumentation and Control Engineering submitted in Electrical and Instrumentation Engineering Department of Thapar University, Patiala, is an authentic record of my own work carried out under the supervision of Ms. Gagandeep Kaur and refers other researcher's works which are duly listed in the reference section.

The matter embodied in this report has not been submitted anywhere for the award of any degree.

Date: 15/7/2010

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It is certified that the above statement made by the student is correct to the best of our knowledge and belief.

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ABSTRACT

This Project involves the study of the principles of Adaptive Noise Cancellation and its Application. Adaptive noise Cancellation is an alternative technique of estimating signals corrupted by additive noise or interference. Its advantage lies in that, with no apriori estimates of signal or noise, levels of noise rejection are attainable that would be difficult or impossible to achieve by other signal processing methods of removing noise. ANC needs two inputs - a primary input containing the corrupted signal and a reference input containing noise correlated in some unknown way with the primary noise. The reference input is adaptively filtered and subtracted from the primary input to obtain the signal estimate.

Adaptive filtering before subtraction allows the treatment of inputs that are deterministic or stochastic, stationary or time-variable.

The effect of uncorrelated noises in primary and reference inputs and presence of signal components in the reference input on the ANC performance is investigated. It is shown that in the absence of uncorrelated noises and when the reference is free of signal; noise in the primary input can be essentially eliminated without signal distortion.

Computer simulations for all cases are carried out using Matlab software and experimental results are presented that illustrate the usefulness of Adaptive Noise Canceling Technique.

ORGANIZATION OF THESIS

1. The first chapter gives the introduction about the objective of this work, followed by background which describes previous work done on this subject in a very brief manner.
2. The second chapter is the review of literature about the developments in the subject.
3. The third chapter covers basics of the noise and types of noise.
4. The fourth chapter describes about the filter used for noise cancellation.This chapter deals with brief overview of weiner filter.
5. The fifth chapter discusses implementation and testing part of thesis.
6. The sixth chapter contains the results, conclusions and discusses the future prospects of ANC.

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ABBREVIATION

ANC	Adaptive Noise Cancellation
MSE	Mean Square Error
SNR	Signal to Noise Ratio
LMS	Least Mean Square
ALE	Adaptive Line Enhancer
FIR	Finite Impulse Response
TDMA	Time Division Multiple Access
VLSI	Very Large Scale Integrated circuits
IIR	Infinite Impulse Response
DSP	Digital Signal Processing
DFT	Discrete Fourier Transform

CHAPTER-1

INTRODUCTION

1.1 Overview

Real world signals usually contain departures from the ideal signal that would be produced by the model of the signal production process. Such departures are referred to as noise. Noise arises as a result of unmodelled processes going on in the production and capture of the real signal. It is not part of the ideal signal and may be caused by a wide range of sources, e.g. variations in the detector sensitivity, environmental variations, the discrete nature of radiation, transmission or quantization errors, etc. The characteristics of noise depend on its source, as does the operator which best reduces its effects.

In a noisy environment speech communication is greatly affected by the presence of background acoustic noise e.g. noise produced by vehicle engine. Consequently, there is an utmost requirement to ensure negligible noise components in the recorded speech signal.

One possible way to satisfy such a requirement to obtain a better recording of the desired signal is the use of a simple noise canceller depicted in Fig 1.1

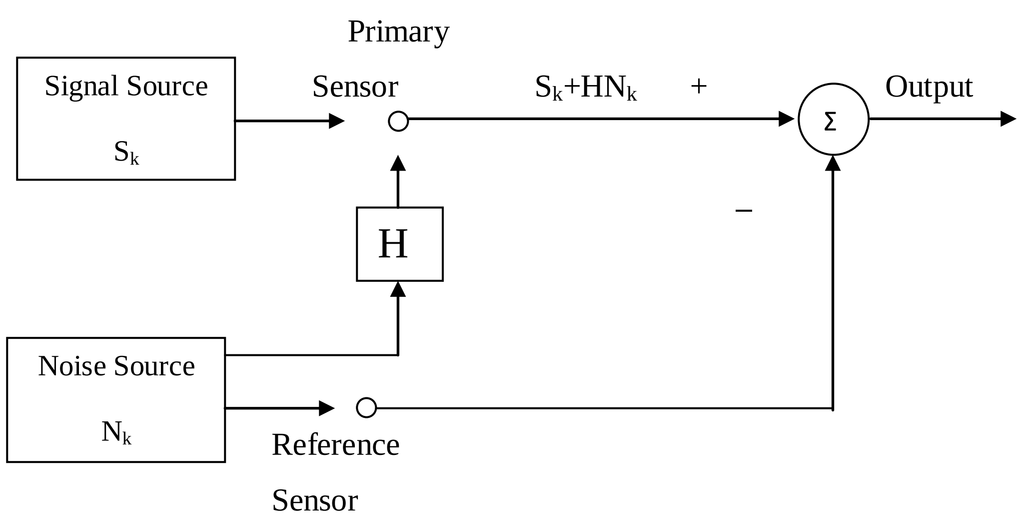

Fig 1.1 Block Diagram of Noise Canceller

However, such a approach to subtract the reference noise signal directly from the primary signal is bound to fail because the noise signal at the reference sensor is not exactly the same as the delayed and/or filtered version of noise at the primary sensor. In some cases, this may even lead to an increase in the average power of the noise output.

However, when proper provisions are enforced and the subtraction operation is controlled by an adaptive process, superior noise cancellation performance is obtained as compared to the previous approach. Consider the situation when we use an adaptive filer as illustrated in Fig 1.2.

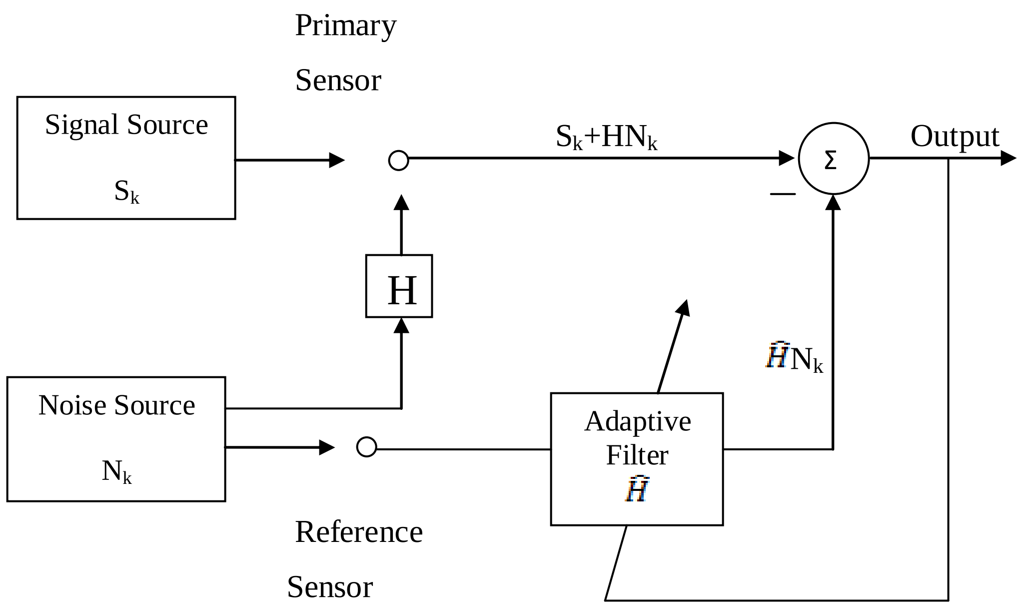

Fig 1.2 Adaptive Noise Canceller

In this setup, the signal path from the noise source is passed to the primary sensor as an unknown FIR channel H. The adaptive filter to the noise recorded at the reference sensor, and then an adaptive algorithm is used to train the adaptive filter to match or estimate the characteristics of the unknown channel H.

If the estimated characteristics of the unknown channel have negligible differences as compared to the actual characteristics, the noise components in the corrupted signal can be cancelled to obtain the desired signal.

1.2 Operations of Adaptive Noise Cancellation

The principle of adaptive noise cancellation is to obtain an estimate of the noise signal and subtract it from the corrupted signal.

An adaptive noise canceller is a dual-input, closed-loop adaptive feedback system as depicts in Fig 1.3. On the input side a primary sensor and a reference sensor is employed.

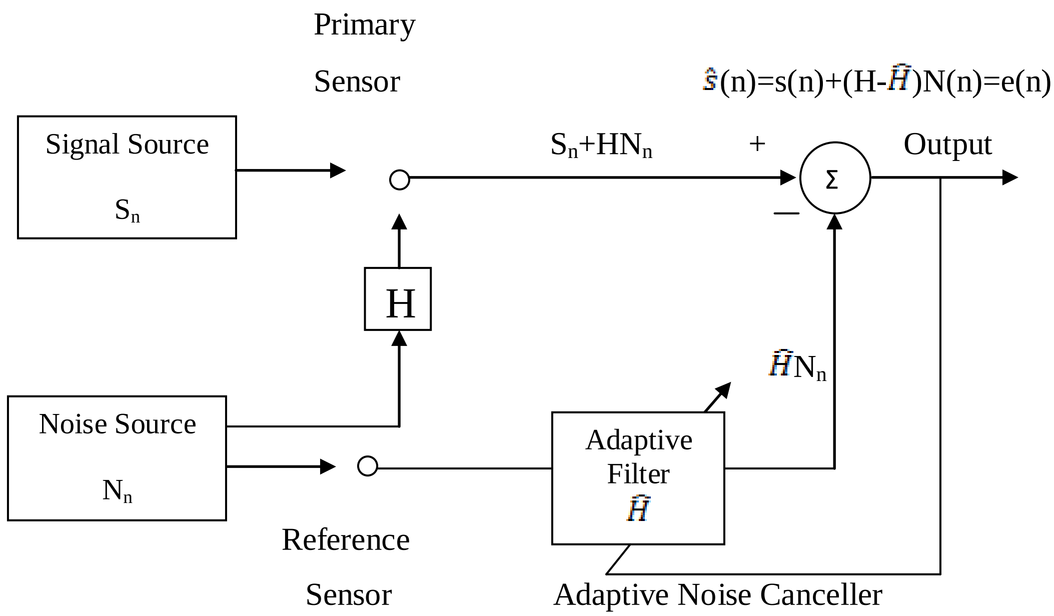

Fig 1.3 Block Diagram of Adaptive Noise Canceller

As illustrated clearly in fig 1.3, the primary sensor not only records the signal from the desired signal source, it also picks up a delayed and/or filtered version of noise signals originating from the noise source. That is:

Recorded signal at primary sensor = S(n) + HN(n)

(i) Let V(n) = HN(n) represent the noise signals at the primary sensor and assume that desired signal and the noise signal are uncorrelated with each other such that

$$E[S(n)V(n-m)] = 0 \qquad \text{for all } m$$

(ii) The noise signal N(n) recorded at the reference sensor is uncorrelated with the signal S(n) i.e.

$$E[S(n)N(n-m)] = 0 \qquad \text{for all } m$$

But it is correlated with the delayed and filtered version noise V(n) or HN(n) at the primary sensor output in an unknown way such that,

$$E[V(n)N(n-m)] = P(m) \qquad \text{for all } m$$

where p(m) is the unknown cross-correlation for lag m.

(iii) The adaptive filter processes the noise signal to produce $\widehat{H}$N(n) where $\widehat{H}$ is the estimated tap vector for H. This filter output is then subtracted from the primary sensor output to obtain the estimated desired signal.

$$\hat{S}(n) = S(n) + HN(n) - \widehat{H}N(n) = S(n) + (H - \widehat{H})N(n) = e(n)$$

The estimated output is in turn used as the error signal to adjust the tap weights of the adaptive filter such that the control loop around the operations of filtering and subtraction is thereby closed.

(iv) From above equation, the essential noise component is $(H\text{-}\widehat{H})$N(n). This term can be minimized if $H \approx \widehat{H}$, which in turn leads to maximization of the system output signal-to-noise (SNR) ratio.

(v) The effectiveness of this adaptive noise cancellation system depends on the following important factors or assumptions:

- The signal and noise at the output of the primary sensor are uncorrelated.
- The noise signal recorded at the reference sensor is highly correlated with the noise component in the primary sensor output.
- The desired signal component in the primary sensor output is undetectable at the reference sensor.

1.3 Practical Applications of Adaptive Noise Cancellation

Adaptive noise cancellation can be usefully applied in situations where it is required to cancel an interfering noise from a given signal that is a mixture of the desired signal an interference noise. Two useful applications of the adaptive noise cancellation operation are presented in the following section.

1.3.1 Noise Control in Narrow Ducts

The operation of an adaptive noise canceller is for a noise controlling purpose in narrow ducts such as exhaust pipes and ventilation systems, as illustrated in Fig 1.4

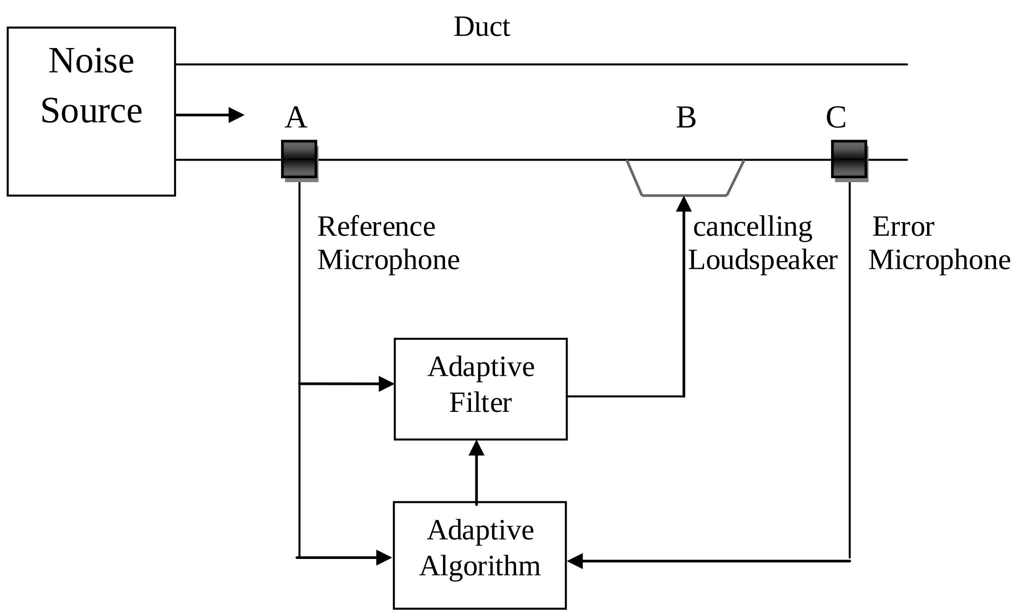

Fig 1.4 Block Diagram of Noise Cancellation in a Narrow Duct

The acoustics noise traveling along the duct is picked up by a microphone at position A. The adaptive noise filter will process this reference/noise signal, such that its output, after conversion to acoustics wave through the loudspeaker is equal to the negative value of the duct noise at position B, therefore canceling it. An error microphone is located slightly further at position C to pick up any residual noise and use it as the error signal for adjusting the tap weights of the adaptive filter.

Associating this application with the setup in fig 1.3, we observed the following similarities:

- The duct noise is the noise source and is picked up by the reference microphone at position A.
- The primary input picked up at position B is a filtered and delayed version of the noise signal recorded at the reference microphone.
- The adaptive filters output is an estimation of the filtered and delayed version of the noise signal at Position B.
- The desired output of this system at and after position B is zero.
- The error signal refers to any other unwanted components that remain after the canceling operation at position B. This error signal is used to adjust the tap weights of the adaptive filter.

1.3.2 Adaptive Noise Control in Jet Aircraft

The engine of a jet aircraft can produce noise at a level over 140 decibels. With normal human speech at a level of 30-40 decibels, speech communication of the pilots in the aircraft can hardly take place. The adaptive nature of the adaptive noise cancellation operating condition sustain in the similar situation, particularly when the noise signal level of the aircraft engine varies at different flight requirements. The concept of the noise cancellation operation in a jet aircraft is illustrated in Fig 1.5.Although the actual implementation is complicated enough for requirement of multiple reference sensors and estimation for time-variant channels.

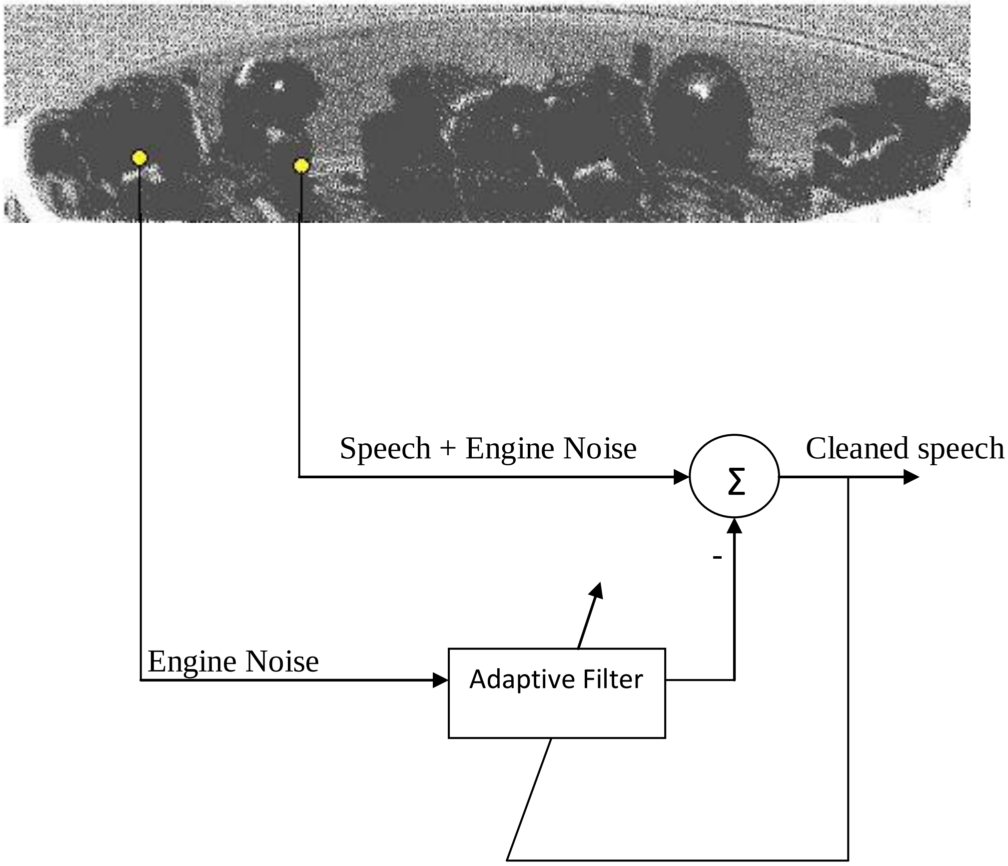

Fig 1.5 Block Diagram of Adaptive Noise Control System in a Jet Aircraft

1.4 Objective

This study mainly deals with the various aspects of Adaptive Noise Cancellation and its usage in different applications. The major objectives of this thesis can be listed as follow:

- This Project involves the study of the principle of Adaptive Noise Cancellation and its Applications.
- Analyze the effect of uncorrelated noises in primary and reference inputs, as well as presence of signal components in the reference input on the ANC performance.
- Computer simulations for all cases are carried out using Matlab software and experimental results are presented that illustrate the usefulness of Adaptive Noise Canceling Technique.

1.5 Background

The Least Mean Square adaptive algorithm, which was first proposed in 1960 by its originators - Bernard Widrow and Ted Hoff, is the most widely used adaptive filtering algorithm. This wide spectrum of applications of the LMS algorithm can be attributed to its simplicity i.e. low computational complexity and robustness/reliability to signal statistics. Unlike other adaptive algorithms, it does not require complex computation like measurements of the pertinent correlation functions and matrix inversion. In fact, it is the simplicity of the LMS algorithm that has made it the standard against which other adaptive filtering algorithms are benchmarked.

To elaborate further, when the filter input is white, i.e. its power spectrum is flat across the whole range of frequencies; the LMS algorithm converges very fast. When the input signal is highly auto correlated or colored, the performance of the LMS algorithm in terms of convergence rate, deteriorates as compared to the white input.

It all started in 1965 when John Kelly and Ben Logan from Bell Telephone Laboratories conceived the idea of the use of an adaptive transversal filter for echo cancellation, with the speech signal itself utilized in performing the adaptation.

In the same year, a self-tuning filter or adaptive line enhancer was originated by Bernard Widrow and his co-workers at Stanford University. The first version of this device was built to cancel 60 Hz interference at the output of an electrocardiographic amplifier and recorder.

These two major works, although intended for different applications, were later generalized as the Adaptive Noise Canceller scheme as discussed in a paper by Widrow et al in 1975. This scheme refers to situations where it is required to cancel an interfering signal or noise from a given signal which is a mixture of the desired signal and interfering signal.

Chapter-2

Literature Review

Xin Wu et.al has presented an application of adaptive filter in sidelobe suppression for radar pulse compression. Traditionally, windowing techniques are employed to reduce the sidelobe levels in the compressed waveform, at the expense of slightly reduced SNR and broaden main pulse width. The proposed adaptive filters use the ideal compressed waveform as reference response for training.Two simple adaptive filter algorithms: least mean square and recursive least square has used. The results indicated that sidelobe may be significantly reduced and main pulse remains narrow. [6]

Kutluyıl Do˘gançay et.al has proposed that in some applications of adaptive filtering such as active noise reduction, and network and acoustic echo cancellation, the adaptive filter may be required to have a large number of coefficients in order to model the unknown physical medium with sufficient accuracy. The computational complexity of adaptation algorithms is proportional to the number of filter coefficients. This implies that, for long adaptive filters, the adaptation task can become prohibitively expensive, ruling out cost-effective implementation on digital signal processors. The purpose of partial coefficient updates is to reduce the omputational complexity of an adaptive filter by adapting a block of the filter coefficients rather than the entire filter at every iteration. In this paper, a selective-partial-update normalized least-mean-square algorithm has developed, and analyzes its stability using the traditional independence assumptions and error-energy bounds. Selective partial updating is also extended to the affine projection algorithm by introducing multiple constraints. The new algorithms appear to have good convergence performance as attested to by computer simulations with real speech signals. [7]

David S. Leeds has described an application of adaptive noise cancellation in the form of an adaptive multiple notch filter, to remove transmitter burst envelope noise that may be induced in high gain audio circuits of a wireless handset device.The periodicity of TDMA type systems where the transmitter burst envelope is stationary exploited. Since samples of the transmitter burst envelope are correlated to the additive noise that corrupts the sampled speech, therefore use this as a reference input to the ANC and also obtain the reference input by delaying the primary input to de-correlate the speech. The system was simulated using GSM transmit burst model to demonstrate the noise power reduction as a function of adaptation. Preliminary tests using the GSM transmitter burst model indicate at least -40 dB of noise reduction after $^1/_2$ second of convergence. The spectral noise characteristics after system convergence were analyzed. [8]

Mat lkram Yusof et.al analysed two types of noise cancellation algorithms i.e the least mean square and the recursive least squares algorithm and tries to outlines their strengths and their weakness. These algorithms were implemented in a semi hardware fashion, using a microphone, two speakers and a sound blaster, sound card and the data from this hardware is processed via software. This semi hardware approach allows to determine the practically and effectiveness of these two algorithms in handling real life situations. The results are encouraging as they are similar to the theoretical results. It also proves that the algorithms do work and that are capable of solving real life problems. [9]

Chi-Chou Kao has presented the new methods to cancel echo especially for the short path eg.car and eliminate noise for speech enhancement. An adaptive filter based on the delayed error least mean square algorithm was used to cancel echo. The external noise is eliminated and the clean speech is estimated by using the Kalman filter and the spectral subtraction technique. To be suitable for use in consumer electronics, a high speed and flexible VLSI architecture of the adaptive filter for canceling echo can also be disigned.The architecture has hardware utilization efficiency of 100%, therefore the filter can easily be scaled without reducing the throughput rate. The 0.6μm Complementary Metal-Oxide Semiconductor standard cells technology had been used to implement the chip. [10]

Karen Egiazarian et.al has proposed an adaptive system, which provides engine noise cancellation for hands-free cellular phones is developed. The system employs a cascade of three secondorder adaptive notch/bandpass filters based on Gray-Markel lattice structure. This structure defines the high stability of the adaptive system. A Newton type algorithm was used for updating the filter coefficients that determines fast adaptation. One of significant advantages of the proposed system is its low computational complexity. The presented adaptive system for engine noise cancellation could improve considerably the speech intelligibility of hands-free cellular phones. [11]

Fatma Rouissi et.al has presented the work to address impulsive noise cancellation for digital broad band power line communication scheme. This paper presents the details of impulsive noise model based on its stabtical properties and defined broad- band technique. By adding a noise power estimator a new adaptive noise canceller based on Maisuo algorithm was proposed. The simulation results shows that the new proposed adaptive technique permits an improvement, but also in reducing processing time and so implementation complexity of the noise cancelIer. [12]

Ying-Wen Bai et.al proposed a design of an embedded digital stethoscope that uses the adaptive noise cancellation filter and the Type I Chebyshev IIR bandpass filter to reduce the noise of the heart sound. We integrate a traditional stethoscope, two microphones, an amplifier, an analog to digital conversion, a DSP board, and embedded board. First, the system acquits the heart sound, amplify, digitize, and input into the DSP board for noise reduction by using of the adaptive noise cancellation and the IIR bandpass filter. Then, the preprocessed heart sound signals are send into the embedded board for the Liquid Crystal Diode displaying and the interface to Personal Computer. Overall, we design the digital filter, interface circuit, displaying driver, graphical user interface the prototype system integration of the hardware and software modules shows the stable operation with a range of adjustments. [14]

Jafar Ramadhan Mohammed has given the general idea that the background noise is usually an important factor that affects speech recognition performance and many other applications. In their paper the background noise or wideband noise and sinusoidal noise can be significantly suppressed using the proposed adaptive noise cancellation scheme based on adaptive line enhancer and Normalized Least Mean Square filters. The proposed scheme is comprised of two stages. The first stage uses an ALE filters, which are used to reduce sinusoidal noise from the primary and reference input signals, whereas the wideband noise is reduced using Normalized LMS adaptive filter in the second stage. To demonstrate the effectiveness of the proposed scheme, it is compared to the traditional adaptive noise cancellation scheme. The good performance of the proposed scheme has been verified via computer simulations in noisy and reverberant environment. [15]

Eduard Bertran has proposed that the analog adaptive filters are an important subset of adaptive-filter theory and practice. They are preferable at high speeds when low power consumption, small integrated area, and moderate linearity are required. In this paper, an analog adaptive-disturbance canceller is presented. The canceller uses the analog least mean square algorithm, and its structure is similar to a linear combiner. The operation of the proposed canceller is based on the decomposition of the disturbances into the in-phase and quadrature components by means of a Hilbert transformer, which is used as an analog LMS for the cancellation of each component. Finally, some experimental results, which are obtained from a low-cost discrete-component realization of the proposed canceller, are presented. The proposed structure is also suitable for very large-scale integration designs. [16]

Soroor Behbahani has presented the new generation of medical treatment supported by computerized processes. Signals recorded from the human body had provided the valuable information about the biological activities of the body organs. The organs' characteristic topologies with temporal and spectral, properties can be correlated with a normal or pathological function. In response to dynamic changes in the behavior of those organs, the signals exhibit timevarying, non-stationary responses. The signals are always contaminated by a drift and interference caused by several bioelectric phenomena, or by various types of noise, such as intrinsic noise from the recorder and noise from electrode-skin contact. The concept of adaptive filters for noise cancellation and analysis ECG signals has been utilized here. [17]

Lin Bai et.al has proposed that the adaptive noise cancellation being used widely to reduce noise from a noisy speech sound. However the least-mean-square algorithm and its variants, such as the normalized NLMS, the modified M-LMS and the constrained stability CS-LMS algorithms do not perform well in ANC since the desired speech signal has a bad effect on the convergence rate and steady state misadjustment of these algorithms. Thus, we propose a new adaptive algorithm that further relaxes the constraint in the CS-LMS algorithm. The new algorithm attempts to minimize the estimation error of the a posteriori error and the estimation is obtained using the concept of Taylor's expansion. The analysis and simulation results show that the proposed new algorithm outperforms the NLMS and CS-LMS algorithms. [22]

Jiashu Zhang et.al stated that the LMS adaptive noise cancellers are often used to recover signal corrupted by additive noise. A major drawback of conventional LMS algorithms is that the excess mean-square errors increase linearly with the desired signal power. This results in degraded performance when the desired signal exhibits large power fluctuations. In this paper, a normalized difference LMS algorithm is proposed to deal with the situation when the desired signal is strong, e.g., speech signals. Simulations were carried out using real speech signal with different noise power levels in both stationary and nonstationary noise environments.Results demonstrate the superiority of the proposed NLMS algorithm over conventional LMS algorithms in achieving much smaller steady-state excess mean square errors. [18]

Ji-Zhen Liu et.al has proposed that along with the increasing requests of the control level for power plant operation, accurate state parameters are needed for the advanced control, diagnosis and optimization algorithm. But the signal of the state parameter is obscured by all kinds of noises in thermal system and difficult to analyze. To solve this problem, a novel least-mean-square algorithm is used for characteristic extracting in the adaptive noise cancellation problem. An improved LMS algorithm based on sigmoid function was presented. The simulation result shows that a superior performance of the new algorithm in stationary environment and an equivalent performance in nonstationary environment. [19]

Yaghoub Mollaei has presented that the adaptive filter is one of the most important areas in digital signal processing. This paper seeks to use this area to remove noise from noise corrupted audio signals. An adaptive FIR filter with normalized LMS algorithm is designed to cancel the noise. [20]

Lingkun MA et.al stated that the subband adaptive filtering has the better performance in convergence and computing efficiency, it has been widely used in many signal processing fields, but the aliasing in-band from decimated in subband impair the system performance greatly. In the paper, based on the theory of signal orthogonal decomposition, used self-contained sinusoid basis, a novel subband signal adaptive noise cancellation method is presented, where the analysis filters implemented by DFT have discrete ideal performance. Because there has no aliasing inband after decimation, so the performance of cancellation is increased. The simulation results indicated that the system had higher convergence speed and SNR gain comparing with full band adaptive noise cancellation system, especially when the reference signal is colored noise. [21]

CHAPTER–3

NOISE

Noise can be defined as any unwanted signals, random or deterministic, which interfere with the faithful reproduction of the desired signal in a system. Stated another way any interfering signal, which is usually noticed as random fluctuations in voltage or current tending to obscure and mask the desired signals, is known as noise. These unwanted signals arise from a variety of sources and can be classified as man-made or naturally occurring. Noise is normally specified as a spectral density in rms volts or amps per root Hertz, V Hz or A Hz.

Some degree of noise is always present in any electronic device that transmits or receives a "signal." For televisions this signal is the broadcast data transmitted over cable or received at the antenna. In our daily life noise of course refers to loud, disagreeable sound without any musical aspirations. In the early days of radio communication the word noise was introduced to describe "any unwanted electrical signal within a communication system that interferes with the sound being communicated", which is thus audible as "noise" on a headphone. In the context of physical experiment the word noise is refers to "any unintentional fluctuations that appear on top of signals to be measured". Any quantity can exhibit the random fluctuations which may be termed as noise. In the radio and microwave region we deal with electro-magnetic fluctuations caused by the thermal or spontaneous emission of low-energetic photons. But noise can also refer to unintentional fluctuations in other quantity, like the traffic flow on a highway, or the rhythm of water droplets on a roof.

3.1 Types of Noise

3.1.1 White Noise

White noise is a random signal or process with a flat power spectral density, so it is a noise in which the frequency and power spectrum is constant and independent of frequency. Its name comes from a similarity to white light, which has equal quantities of all colors .It would have infinite energy at infinite frequencies. White noise always becomes pinkish at high frequencies. The signal power for a constant bandwidth centered at frequency f_0 does not change if f_0 is varied. In practical systems noise is thus never truly white; this means that the noise spectral density is relatively constant up to a certain cutoff frequency, but decreases beyond this cutoff frequency, to keep the variance finite. In practical systems the cutoff frequency is generally large, and the noise spectral density below cutoff is constant.Steady rainfall or radio static on an unused channel approximates a white noise characteristic. White noise comes in two types

(i) Thermal noise

(ii) Shot noise

3.1.1.1 Thermal Noise

Thermal noise is sometimes referred to as Johnson noise after its discoverer. It is generated by thermal agitation of electrons in a conductor. A conductor is heated, it will become noisy. Electrons are never at rest; they are always in motion. Heat disrupts the electrons' response to an applied potential. It adds a random component to their motion. Thermal noise only stops at absolute zero. Like shot noise, thermal noise is spectrally flat or has a uniform power density, but thermal noise is independent of current flow.

At frequencies below 100 MHz, thermal noise can be calculated using Nyquist's relation:

$$E_{th} = \sqrt{4KTRB}$$

Or

$$I_{th} = \sqrt{\frac{4KTB}{R}}$$

Where:

Eth = Thermal noise voltage in Volts rms

I_{th} = Thermal noise current in Amps rms

K = Boltzmann's constant (1.38×10^{-23})

T = Absolute temperature (Kelvin)

R = Resistance in ohms

B = Noise bandwidth in Hertz ($f_{max} - f_{min}$)

The noise from a resistor is proportional to its resistance and temperature. It is important not to operate resistors at elevated temperatures in high gain input stages. Lowering resistance values also reduces thermal noise.

3.1.1.2 Shot Noise

Shot noise normally occurs when

- The variations in the electrical current produced by electrons emitted from a cathode.
- The variations in the light intensity produced by photons hitting a photosensitive element.

The name shot noise is short for Schottky noise. It is also referred to as quantum noise. It is caused by random fluctuations in the motion of charge carriers in a conductor. Current flow is electrons, the charged particles that move in accordance with an applied potential. When the electrons encounter a barrier, potential energy builds until they have enough energy to cross that barrier. When they have enough potential energy, it is abruptly transformed into kinetic energy as they cross the barrier. As each electron randomly crosses a potential barrier, such as a pn junction in a semiconductor, energy is stored and released as the electron encounters and then shoots across the barrier. The aggregate effect of all of the electrons shooting across the barrier is the shot noise.

PN junction diode is an example that has potential barrier. When the electrons and holes cross the barrier, shot noise is produced. For example, a diode, a transistor, and vacuum tube all produces shot noise. On the other hand, a resistor normally does not produce Shot noise since there is no potential barrier built within a resistor. Current flowing through a resistor will not exhibit any fluctuations. However, current flowing through a diode produces small fluctuations.

Some characteristics of shot noise:

i. Shot noise is always associated with current flow. It stops when the current flow stops.
ii. Shot noise is independent of temperature.
iii. Shot noise is spectrally flat or has a uniform power density, meaning that when plotted versus frequency it has a constant value.

iv. Shot noise is present in any conductor - not just a semiconductor. Barriers in conductors can be as simple as imperfections or impurities in the metal. The level of shot noise, however, is very small due to the enormous numbers of electrons moving in the conductor, and the relative size of the potential barriers. Shot noise in semiconductors is much more pronounced.

The rms shot noise current is equal to:

$$I_{sh} = \sqrt{}\,(2qI_{dc}\ )\ 4qI_0)\ B$$

Where:

q = Electron charge (1.6 x 10^{-19} coulombs)

I_{dc} = Average forward dc current in A

I_0 = Reverse saturation current in A

B = Bandwidth in Hz

If the pn junction is forward biased, I_0 is zero, and the second term disappears. Using Ohm's law and the dynamic resistance of a junction,

$$r_d = \frac{KT}{qI_{dc}}$$

The rms shot noise voltage is equal to:

$$E_{sh} = KT\sqrt{\frac{2B}{qI_{dc}}}$$

Where:

K = Boltzmann's constant (1.38 x 10^{-23} Joules /$^\circ$K)

q = Electron charge (1.6 x 10^{-19} coulombs)

T = Temperature in ^{0}K

I_{dc} = Average dc current in A

B = Bandwidth in Hz

3.1.2 Atmospheric Noise

Atmospheric noise is radio noise caused by natural atmospheric processes, primarily lightning discharges in thunderstorms.

3.1.3 Extraterrestrial Noise

Space is the source of mostly broadband noise which can be considered as plane electromagnetic waves. Cosmic radiation has to be accounted for if either the main lobe or the sidelobes of the receiving antenna are directed towards space. The noise sources are both thermal and non-thermal emission from the Sun, the Moon, the Cassiopeia and planets and from elsewhere in our galaxy and other galaxies. If the emission is of thermal origin its contribution to noise power can be described through the spectral brightness, which is the power density per unit solid angle per unit area per Hertz. At radio-frequencies the spectral brightness B_f is given by the Rayleigh-Jeans law

$$B_f = \frac{2KT_c}{\lambda^2} \quad \text{in} \quad \left[\frac{\text{Watt}}{m^2.\text{sr}.\text{Hertz}}\right]$$

Where

Tc = the brightness temperature (Tc is always less or equal to the physical temperature),

λ = the wavelength and

k = Bolzmann's constant

The actual noise power received within a narrow frequency range depends on the direction of the main lobe and the side lobes of the receiving antenna and on the effective area of the antenna. Thus in general the spectral brightness of an extended source is a function of the direction relative to the antenna coordinates. For discrete sources such as the Sun which lie within the main lobe of the antenna and subtend a solid angle Ω_s that is much smaller than the antenna main-beam solid angle, the spectral power density becomes

$$P = \frac{2KT_c}{\lambda^2}\Omega_s \quad w / m^2 \text{ Hz}$$

Further use of the spectral brightness will be made, when the total noise power percepted by an antenna will be evaluated in detail.

In the general case B_f varies as λ^n where n is known as the spectral index. Thus for the thermal emission of a black body n = -2. For non-thermal emission can still be used but the brightness temperature T_c is no longer related to the thermal emission but is an equivalent brightness temperature, in addition the spectral index has to be specified.

Background Radiation: The entire Universe is saturated with what is known as microwave background radiation, a remnant of the Big Bang. After the Big Bang, the formation of matter, space and time out of virtually nothing, the prevailing temperatures were at first almost inconceivably high. However, as the Universe expanded the temperature sank to approximately -270^0C. The expansion of space lengthened the wavelength of the electromagnetic radiation until it entered the microwave range. Today, this radiation can be measured which is reaching us evenly from all directions of space, thus the term “background radiation”. It would “heat up” any colder object to the space temperature of minus 270 degrees Celsius.

3.1.4 Flicker Noise or 1/f noise

1/f noise is found in many natural phenomena such as nuclear radiation and electron flow through a conductor. All systems contain some form of white noise, but many practical systems are also plagued by additional low-frequency noise components. When this low-frequency noise has the common form in which the noise spectral density increases as the inverse frequency one speaks about 1/f noise. The relative importance of 1/f noise is best specified via the transition frequency, white noise dominates for frequencies above transition frequency, 1/f noise dominates below transition frequency. The physical origin of 1/f noise in the electronic conduction mechanism in semiconductor devices generally lies in impurities in the semiconductor material and imperfection in the production process. 1/f noise is generally more prominent in devices that are small and contain lots of surface like MOSFETs, FETs, and bulky resistors.

Some characteristics of flicker noise:

i. It increases as the frequency decreases, hence the name 1/f.

ii. It is associated with a dc current in electronic devices.

Flicker noise is found in carbon composition resistors, where it is often referred to as excess noise because it appears in addition to the thermal noise that is there. Other types of resistors also exhibit flicker noise to varying degrees, with wire wound showing the least. Since flicker noise is proportional to the dc current in the device, if the current is kept low enough, thermal noise will predominate and the type of resistor used will not change the noise in the circuit.

3.1.5 Burst Noise

Burst noise, also called popcorn noise, is related to imperfections in semiconductor material and heavy ion implants. It is characterized by discrete high-frequency pulses. The pulse rates may vary, but the amplitudes remain constant at several times the thermal noise amplitude. Burst noise makes a popping sound at rates below 100 Hz when played through a speaker, it sounds like popcorn popping, hence the name. Low burst noise is achieved by using clean device processing, and therefore is beyond the control of the designer.

3.1.6 Avalanche Noise

Avalanche noise is created when a pn junction is operated in the reverse breakdown mode. Under the influence of a strong reverse electric field within the junction's depletion region, electrons have enough kinetic energy that, when they collide with the atoms of the crystal lattice, additional electron-hole pairs are formed. These collisions are purely random and produce random current pulses similar to shot noise, but much more intense. When electrons and holes in the depletion region of a reversed-biased junction acquire enough energy to cause the avalanche effect, a random series of large noise spikes will be generated. The magnitude of the noise is difficult to predict due to its dependence on the materials. The zener breakdown in a pn junction causes avalanche noise; therefore the best way of eliminating avalanche noise is to redesign a circuit without using zener diodes.

CHAPTER-4

FILTER

The communication of a signal of interest, by other unwanted, signals or noise is a problem often encountered in all the applications of signal transmissions. Where the signal and noise occupy fixed and separate frequency bands, conventional linear filters with fixed coefficients are normally used to extract the signal. However, there are many instances when it is necessary for the filter characteristics to be variable, adapted to changing signal characteristics or to be altered intelligently. In such cases, the coefficient of the filter must vary and can not be specified in advance. Such is the case where there is a spectral overlap between the signal and noise or band occupied by the noise is unknown or varies with time.

4.1 Adaptive Filter

Adaptive filters are digital filters with an impulse response or transfer function that can be adjusted or changed over time to match desired system characteristics. Unlike fixed filters, which have a fixed impulse response, adaptive filters do not require complete a priori knowledge of the statistics of the signals to be filtered. Adaptive filters require little or no a priori knowledge and moreover, have the capability of adaptively tracking the signal under non-stationary circumstances. For an adaptive filter operating in a stationary environment, the error-performance surface has a constant shape as well as orientation. When the adaptive filter operates in a non-stationary environment, the bottom of the error-performance surface continually moves, while the orientation and curvature of the surface may be changing. Therefore, when the inputs are non-stationary, the adaptive filter of not only seeks continously the bottom of the error performance surface, but also track it.

An adaptive filter is essentially a digital filter with self-adjusting characteristics. It adapts, automatically, to changes in its input signals. An adaptive filter consists of two parts: one is a digital filter with adjustable coefficients and another is an adaptive algorithm which is used to adjust or modify the coefficients of the filter. Many adaptive algorithms can be viewed as approximations of the discrete wiener filter.

4.2 Wiener Filter

A Wiener filter is a digital filter, which is designed to minimize the mean square difference between the filtered output and some desired signal. It is sometimes called a minimum mean square error filter. Two signals x_k and y_k are applied simultaneously to the filter. Typically, y_k consists of a component that is correlated with x_k. The wiener filter produces an optimal estimate of the part of y_k that is correlated with x_k which is then subtracted from y_k to yield e_k.

Assuming an FIR filter structure with N coefficients or weights, the error e_k, between the wiener filter output and the primary signal y_k, is given by

$$\begin{aligned} e_k &= y_k - \hat{n}_k \\ &= y_k - W^T X_k \\ &= y_k - \sum_{i=0}^{N-1} w(i)\, x_{k-i} \end{aligned}$$

Where w(i), i = 0,1,2…., are the adjustable filter coefficients or weights and $x_k(i)$ is the input of the filter. Similarly X_k and W, the input signal vector and weight vector, respectively are given by

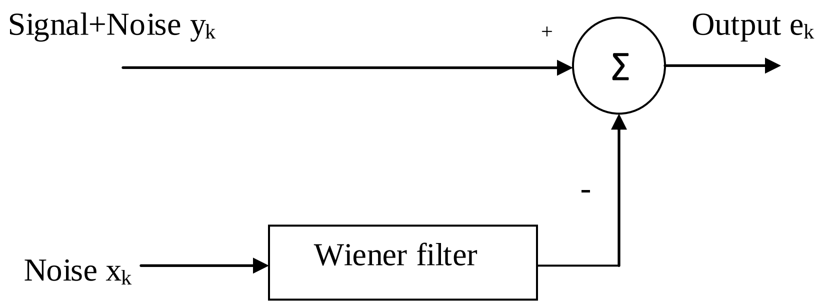

Fig.4.1 Block Diagram of the Basic Wiener Filter

$$X_k = \begin{bmatrix} x_k \\ x_{k-1} \\ \vdots \\ x_{k-(N-1)} \end{bmatrix} \quad \text{and} \quad W = \begin{bmatrix} w(0) \\ w(1) \\ \vdots \\ w(N-1) \end{bmatrix}$$

The square of the error is given as

$$e_k^2 = y_k^2 - 2y_k X_k^T W + W^T X_k X_k^T W$$

The mean square error j, is obtained by taking the expectations of both sides of above equation, assuming that the input vector X_k and the signal y_k are jointly stationary

$$J = E[e_k^2]$$

$$= E[y_k^2] - 2E[y_k X_k^T W] + E[W^T X_k X_k^T W]$$

$$= \sigma^2 + 2P^T W + W^T R W$$

Where E[ ] symbolizes expectation, $\sigma^2 = E[y_k^2]$ is the variance of y_k, $P= E[y_k x_k]$ is the N length cross-correlation vector and $R=E[X_k X_k^T]$ is the N×N autocorrelation matrix.

(i) A plot of the MSE against the filter coefficient W is bowl shaped with a unique bottom or performance surface. The gradient of the performance surface is given by

$$\nabla = \frac{dJ}{dW}$$

$$= -2P+2RW$$

Each set of coefficient, W(i) (i=0,1,2,3,…..N-1), corresponds to a point on the surface. At the minimum point of the surface, the gradient is zero and the filter weight vector has its optimum value, W_{opt}

$$W_{opt} = R^{-1}P$$

W_{opt} = $R^{-1}P$ is known as the Wiener-Hopf equation. The task in adaptive filtering is to adjust the filter weights w(0), w(1),…… using a suitable algorithm to find the optimum point on the performance surface.

(ii) Weiner-hopf Equation by the use of Mean Square Error Equation

The MSE is given by

$$\text{MSE} = J = \sigma^2 + 2P^TW + W^TRW$$

The gradient∇, of the MSE is obtained by differentaiting the MSE with respect to the weight vector W and setting the result to zero.

$$\nabla = \frac{dJ}{dW}$$

$$= \frac{d\sigma^2}{dW} + \frac{d(P^TW)}{dW} + \frac{d(W^TRW)}{dW} \quad .....(4.1)$$

Now,

$$\frac{d\sigma^2}{dW} = 0$$

$$\frac{d(2P^TW)}{dW} = -2P$$

$$\frac{d(W^TRW)}{dW} = 2RW$$

Using these results and setting ∇ = 0, equation (4.1) becomes

$$\nabla = \frac{dJ}{dW} = -2P + 2RW = 0$$

The optimum coefficient vector is then given by

$$W_{opt} = R^{-1}P \quad ......(4.2)$$

Instead of computing W_{opt} in one go as suggested by above equation, in the LMS the coefficients are adjusted from sample to sample in such a way as to minimize the MSE.

The LMS is based on the steepest descent algorithm where the weight vector is updated from sample to sample as follows

$$W_{k+1} = W_k - \mu\nabla_k$$

Where W_k and ∇_k are the weight and the true gradient vectors, respectively at the k_{th} sampling instant, μ controls the stability and rate of convergence.

The steepest descent algorithm in above equation still requires the knowledge of R and P, since ∇_k is obtained by calculating ∇. The LMS algorithm is a practical method of obtaining estimates of the filter weights W_k in real time without the matrix inversion in equation (4.2) or the direct computation of the autocorrelation and cross-correlation. The widrow-hopf LMS algorithm for updating the weights from sample to samle is given by

$$W_{k+1} = W_k - 2\mu e_k X_k$$

Where

$$e_k = y_k - W_k^T X_k$$

Clearly, the LMS algorithm above does not require the priori knowledge of the correlations R and P, but intead uses their instantaneous estimates. The weights obtained by the LMS algorithm are only estimates, but these estimates improve gradually with time as the weights are adjusted and the filter learns the characterstics of the signals. Evantually, the weights converge and the condition for convergence is

$$0 < \mu > \frac{1}{\lambda_{max}}$$

Where λ_{max} is the maximum eigenvalue of the input data covariance matrix. In practice, W_k never reaches the theoretical optimum or the wiener solution, but fluctuates about it.

4.3 Least-Mean-Squares LMS Algorithm

If exact measurements of the gradient vector at each iteration are known and the step-size parameter μ is suitably chosen, then the tap-weight vector computed by using the method of steepest-descent will converge to the optimum Wiener solution. In reality, however, exact measurements of the gradient vector are not possible, and it must be estimated from the available data. In other words, the tap-weight vector is updated in accordance with an algorithm that adapts to the incoming data.

One of these algorithm is the least mean square algorithm. A significant feature of LMS is its simplicity it does not require measurements of the pertinent correlation functions.Also it require matrix inversion.

Gradient vector, $\nabla(n) = -2p + 2Rw(n)$

To find this, estimate the correlation matrix R and cross-correlation matrix P by instantaneous estimates i.e.

$$R'(n) = u(n)\, u^H(n)$$
$$P'(n) = u(n)\, d^*(n)$$

Correspondingly, the instantaneous estimate of the gradient-vector is

$$\nabla'(n) = -2\, u(n)\, d^*(n) + 2\, u(n)\, u^H(n) w(n)$$

The estimate is unbiased. It is the expected value which is equal to the true value of the gradient vector. Substituting this estimate in the steepest-descent algorithm, we get a new recursive relation for updating the tap-weight vector:

$$w'(n+1) = w'(n) + \mu u(n)[\, d^*(n) - u^H(n)\, w'(n)] \qquad \ldots(4.3)$$

Equivalently the LMS update equation can be written in the form of a pair of relations:

$$e(n) = d(n) - u^H(n)\, w'(n) \qquad \ldots.(4.4)$$
$$w'(n+1) = w'(n) + \mu u(n)\, e^*(n) \qquad \ldots.(4.5)$$

The equation (4) defines the estimation error e(n), the computation of which is based on the current estimate of the tap-weight vector w′(n). The term μu(n) e^*(n) in equation(4.3) represents the correction that is applied to the current estimate of the tap-weight vector. The iterative procedure is started with the initial guess w′(0), a convenient choice being the null vector w′(0) = 0.

The algorithm described by the equation (4.3) or equivalently by the equations (4.4) and (4.5), is the complex form of the adaptive least mean square algorithm. It is also known as the stochastic-gradient algorithm.

The instantaneous estimates of R and P have relatively large variances. It may therefore seem that the LMS algorithm is incapable of good performance. The LMS algorithm being recursive in nature, effectively averages these estimates, in some sense, during the course of adaptation.

Ideally, the minimum mean-squared error j_{min} is realized when the coefficient vector w(n) of the transversal filter approaches the optimum value w_0.The steepest descent algorithm does realize this idealized condition as the number of iterations, n approaches infinity, because it uses exact measurements of the gradient vector at each iteration. On the other hand, LMS relies on a noisy estimate of the gradient vector, with the result that the tap-weight vector only approaches the optimum value after a large number of iterations and then executes small fluctuations about w_0 . Consequentl use of LMS results in a mean-squared error j(∞) after a large no. of iterations.

CHAPTER 5

Adaptive Noise Cancellation

Adaptive filters have the ability to adjust their impulse response to filter out the correlated signal in the input. It requires the knowledge of the signal and noise characteristics. Adaptive filters have the capability of adaptively tracking the signal under non-stationary conditions.

Noise Cancellation is a variation of optimal filtering that involves producing an estimate of the noise by

1. Filtering the reference input and then
2. Subtracting this noise estimate from the primary input containing both signal and noise.

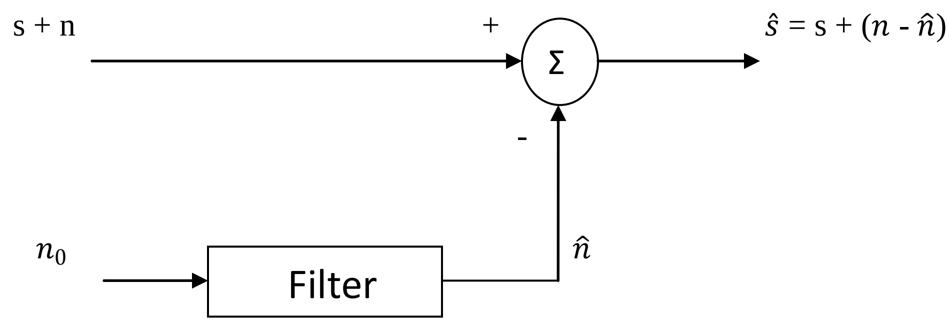

Fig 5.1 Block Diagram of Noice Cancellation

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

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

The error signal to be used depends on the application. The criteria to be used may be the minimization of the mean square error, the temporal average of the least squares error etc. Different algorithms are used for each of the minimization criteria e.g. the Least Mean Squares algorithm, the Recursive Least Squares algorithm etc. To understand the concept of adaptive noise cancellation, the minimum mean-square error criterion is used. The steady-state performance of adaptive filters based on the minimum mean-square error criterion closely approximates that of fixed Wiener filters. Hence, Wiener filter theory provides a convenient method of mathematically analyzing statistical noise canceling problems. In this work the adaptive filter performance is studied after it has converged to the optimal solution in terms of unconstrained Wiener filters and uses the LMS adaptive algorithm which is based on the Weiner approach.

5.1 Principle of Adaptive noise Cancellation

An Adaptive Noise Canceller has two inputs viz. primary and reference. The primary input receives a signal ‘s’ from the signal source that is corrupted by the presence of noise ‘n’ uncorrelated with the signal as shown in the fig 5.2.

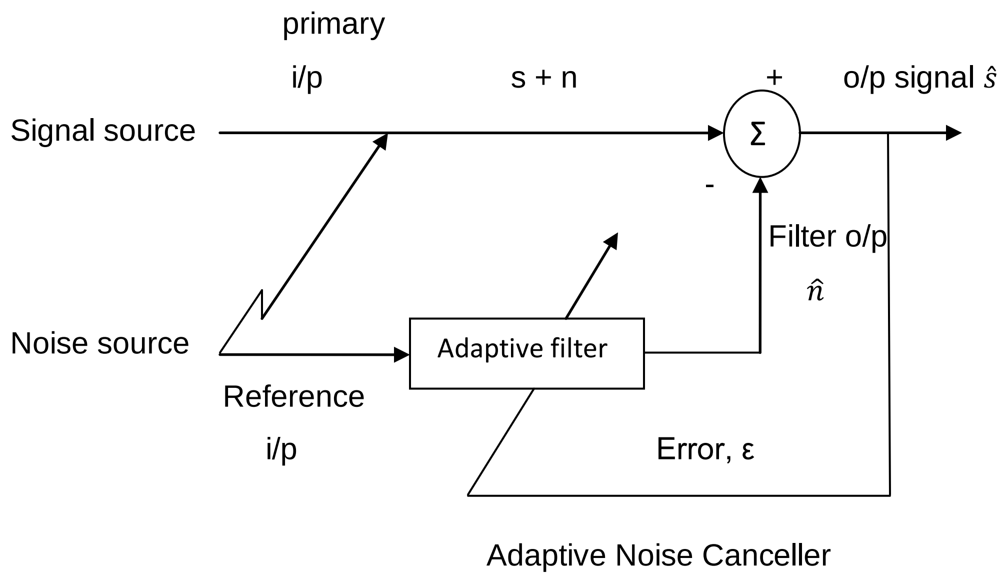

Fig 5.2 Block Diagram of Adaptive Noise Canceller

The reference input receives a noise n_0 uncorrelated with the signal but correlated in some way with the noise 'n'. The noise n_0 passes through a filter to produce an output $\hat{n}$ that is a close estimate of primary input noise. This noise estimate is subtracted from the corrupted signal to produce an estimate of the signal at the ANC system output.

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

Assume that s,n_0, n_1 and y are statistically stationary and have zero means. The signal s is uncorrelated with n_0 and n_1, and n_1 is correlated with n_0.

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

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

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

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

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

By adjusting the adaptive filter towards the optimum position, the remnant noise power and hence the total output power is minimized. If the estimate $\hat{n}$ is the exact replica of n, the output power will contain only the signal power. Thus, when the filter is adjusted to minimize the output noise power $E[\hat{s}^2]$, the remnant noise power $E[(n - \hat{n})^2]$ which may still be in s, is also minimized. The desired signal power is unaffected by this since s is uncorrelated with n.

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

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

Since

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

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

5.1.1 Basic LMS Algorithm

The computational procedure for the LMS algorithm is given as

1. Initially, set each weight W_k (i), where i= 0, 1,., N-1, to an arbitrary fixed value such as 0.
2. Compute filter output

$$\hat{n}_k = \sum_{i=0}^{N-1} w_k(i)x_{k-i}$$

3. Compute the error estimate

$$e_k = y_k - \hat{n}_k$$

4. Update the next filter weights

$$w_{k+1}(i) = w_k(i) + 2\mu e_k x_{k-i}$$

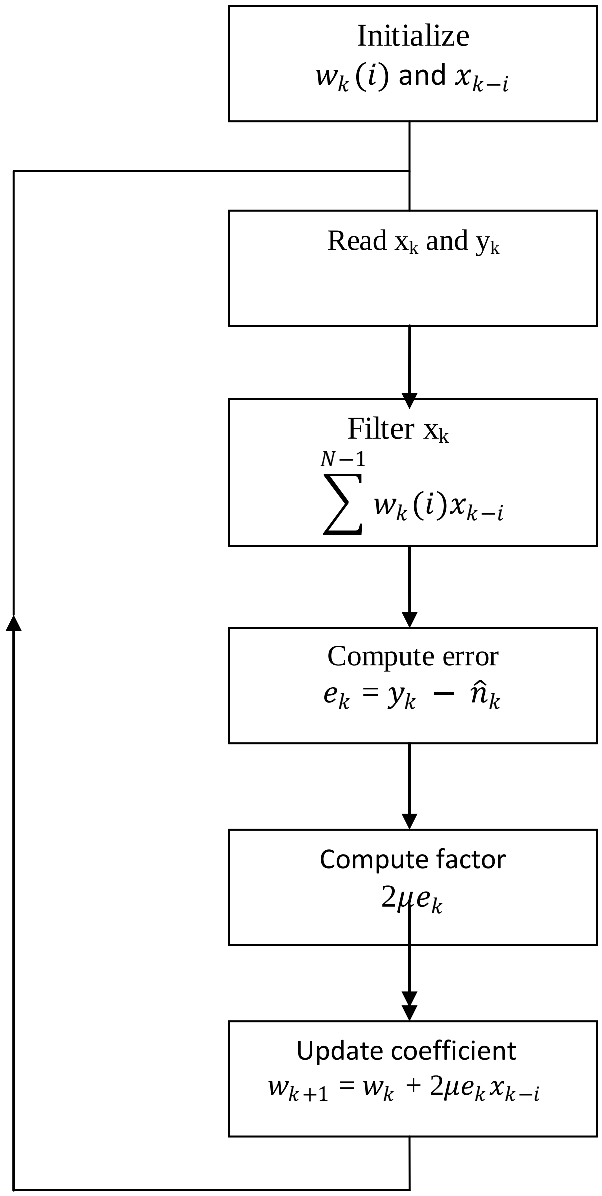

Fig 5.3 Flowchart for the LMS Adaptive Filter

5.2 Effect of Uncorrelated Noise in Primary and Reference Inputs

The adaptive noise canceller works on the principle of correlation cancellation i.e. the ANC output contains the primary input signals with the component whose correlated estimate is available at the reference input, removed. Thus the ANC is capable of removing only that noise which is correlated with the reference input.Presence of uncorrelated noises in both primary and reference inputs degrades the performance of the adaptive noise canceller. Thus it is important to study the effect of these uncorrelated noises.

5.2.1 Uncorrelated Noise in Primary Input

A single channel adaptive noise canceller with an uncorrelated noise m_0 present in the primary input is shown in fig 5.4. The primary input thus consists of a signal and two noises m_0 and n.

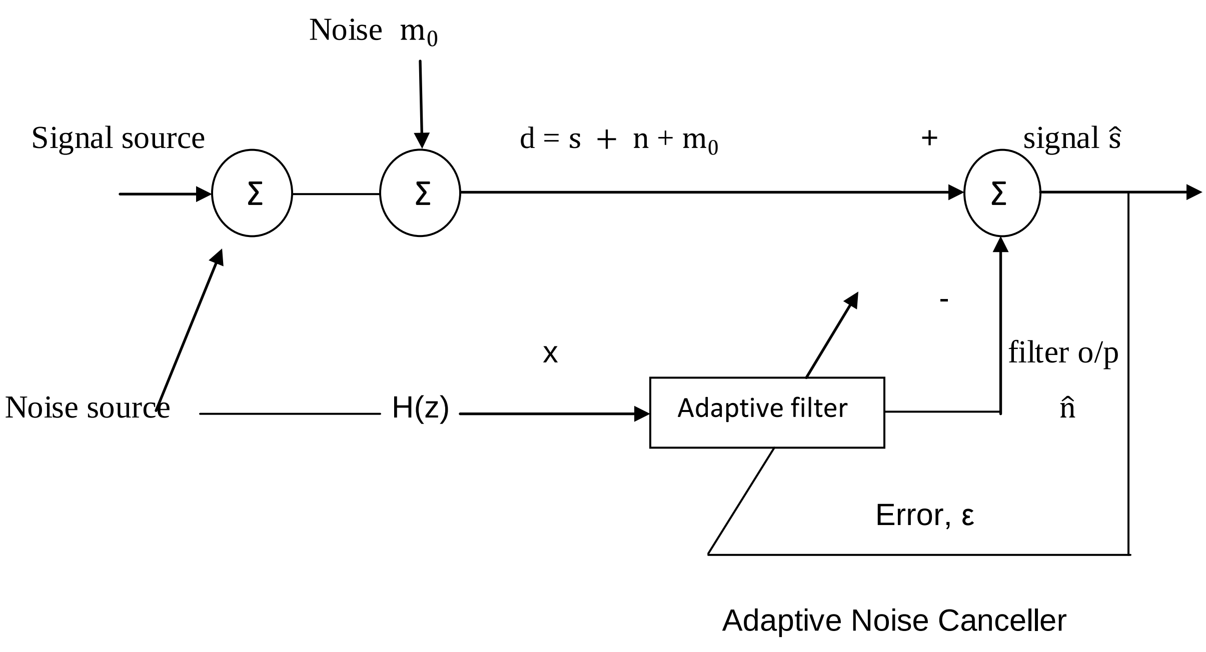

Fig 5.4 Block Diagram of ANC with Uncorrelated Noise in Primary Input

The reference input consists of n* h(j), where h(j) is the impulse response of the channel whose transfer function is H(z). The noises n and n* h(j) have a common origin and hence are correlated with each other but are uncorrelated with s. The desired response d is thus $s + m_0 + n$.

Assuming that the adaptive process has converged to the minimum mean square solution, the adaptive filter is now equivalent to a Wiener filter. The optimal unconstrained transfer function of the adaptive filter is given by

$$W^*(z) = \frac{\delta_{xd}(z)}{\delta_{xx}(z)}$$

The spectrum of the filters input $\delta_{xx}(z)$ can be expressed as

$$\delta_{xx}(z) = \delta_{nn}\ |H(z)|^2$$

where $\delta_{nn}(z)$ is the power spectrum of the noise n.The cross power spectrum between filter's input and the desired response depends only on the mutually correlated primary and reference components and is given as

$$\delta_{xd}\ (z) = \delta_{nn}(z)H(z^{-1})$$

The Wiener function is thus

$$W^*(z) = \frac{\delta_{nn}\ (z)H(Z^{-1})}{\delta_{nn}\ (z)|H(z)|^2} = \frac{1}{H(z)}$$

Note that $W^*(z)$ is independent of the primary signal spectrum $\delta_{ss}(z)$ and the primary uncorrelated noise spectrum $\delta_{m_0m_0}(z)$. This result is intuitively satisfying since it equalizes the effect of the channel transfer function H(z) producing an exact estimate of the noise n. Thus the correlated noise n is perfectly nulled out at the noise canceller output. However the primary uncorrelated noise m_0 remains un-cancelled and propagates directly to the output.

5.2.2 Uncorrelated Noise in the Reference Input

An adaptive noise canceller with an uncorrelated noise m_1 in the reference input is shown in figure 5.5. The adaptive filter input x is now $m_1 + n^* h(j)$.

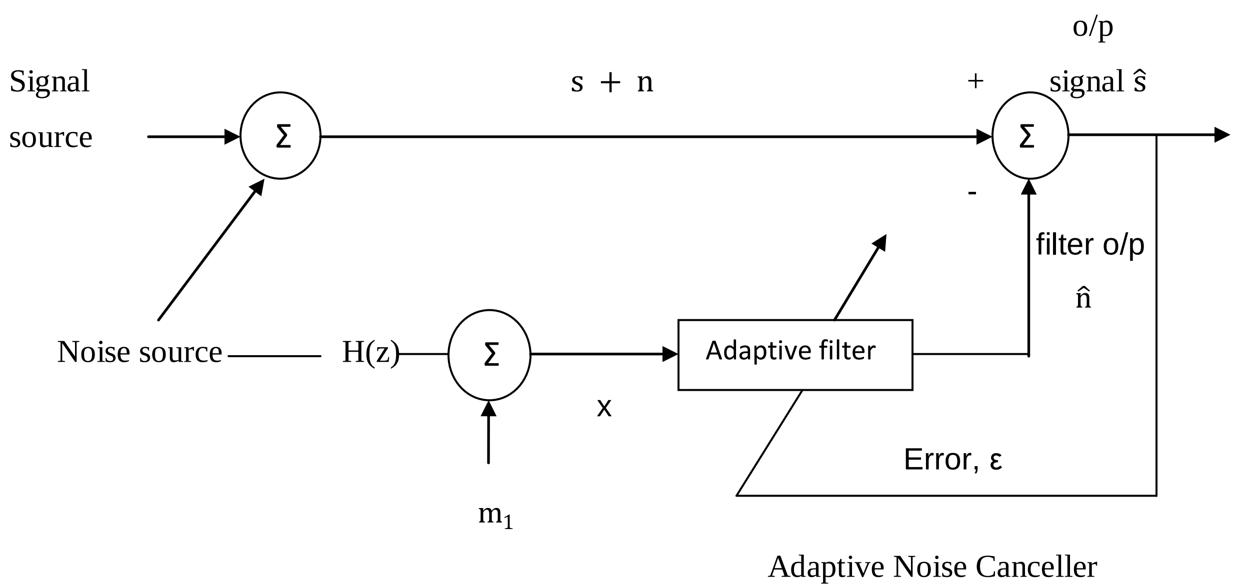

Fig 5.5 Block Diagram of ANC with Uncorrelated Noise in Reference Input

The filters input spectrum is thus

$$\delta_{xx}(z) = \delta_{m_1 m_1}(z) + \delta_{nn}(z)\,|H(z)|^2$$

The Wiener transfer function now becomes

$$W^*(z) = \frac{\delta_{nn}(z)H(z^{-1})}{\delta_{m_1 m_1}(z) + \delta_{nn}(z)\,|H(z)|^2}$$

It is clear that the filter transfer function now cannot equalize the effect of the channel and the filter output is only an approximate estimate of primary noise n.

5.2.3 Effect of Primary and Reference Uncorrelated Noises on ANC Performance

The performance of the single channel noise canceller in the presence of uncorrelated noises m_0 in primary input and m_1 in reference input simultaneously, can be evaluated in terms of the ratio of the signal to noise density ratio at the output $\rho_{out}(z)$, to the signal to noise density ratio at the primary input $\rho_{pri}(z)$ Factoring out the signal power spectrum yields

$$\frac{\rho_{out}(z)}{\rho_{pri}(z)} = \frac{\text{primary noise spectrum}}{\text{output noise spectrum}}$$

$$= \frac{\delta_{nn}(z) + \delta_{m_0 m_0}(z)}{\delta_{n_{out}}(z)}$$

The canceller's output noise power spectrum $\delta_{n_{out}}(z)$ is a sum of three components:

1. Due to propagation of m_0 directly to the output.
2. Due to propagation of m_1 to the output through the transfer function, - $W^*(z)$.
3. Due to propagation of n to the output through the transfer function, 1- $H(z)\,W^*(z)$.

The output noise spectrum is thus

$$\delta_{n_{out}}(z) = \delta_{m_0 m_0}(z) + \delta_{m_1 m_1}(z)\left|W^*(z)\right|^2 + \delta_{nn}(z)\left|1\text{-}H(z)W^*(z)\right|^2$$

The ratios of the spectra of the uncorrelated to the spectra of the correlated noises at the primary and reference as

$$R_{prin}(z) = \frac{\delta_{m_0 m_o}(z)}{\delta_{nn}(z)}$$

and

$$R_{refn}\,(z) = \frac{\delta_{m_1 m_1}(z)}{\delta_{nn}\,(z)\,|H(z)|^2}$$

respectively

The output noise spectrum can be expressed accordingly as

$$\delta_{n_{out}}\,(z) = \delta_{m_0 m_0}(z) + \frac{\delta_{m_1 m_1}(z)}{|H(z)|^2\,|R_{refn}\,(Z)+1|^2} + \delta_{nn}(z)\left|1 - \frac{1}{R_{refn}\,(z)+1}\right|^2$$

$$= \delta_{nn}\,(z)\,R_{prin}\,(z) + \delta_{nn}\,(z)\frac{R_{refn}\,(z)}{R_{refn}\,(z)+1}$$

The ratio of output to the primary input noise power spectra can now be written as

$$\frac{\rho_{out}\,(z)}{\rho_{pri}\,(z)} = \frac{(R_{prin}\,(z)+1)(R_{refn}\,(z)+1)}{R_{prin}\,(z) + R_{prin}\,(z)\,R_{refn}\,(z) + R_{refn}\,(z)}$$

This expression is a general representation of the ideal noise canceller performance in the presence of correlated and uncorrelated noises. It allows one to estimate the level of noise reduction to be expected with an ideal noise canceling system. It is apparent from the above equation that the ability of a noise canceling system to reduce noise is limited by the uncorrelated-to-correlated noise density ratios at the primary and reference inputs. The smaller are R_{prin} (z) and R_{refn} (z) the greater will be the ratio of signal-to-noise density ratios at the output and the primary input i.e. ρ_{out} (z)/ ρ_{pri} (z) and the more effective the action of the canceller.The desirability of low levels of uncorrelated noise in both primary and reference inputs is thus emphasized.

5.3 Effect of Signal Components in the Reference Input

Low-level signal components are often present in the reference input and the adaptive noise canceller is a correlation canceller: The implementation of signal components in the reference input will put some cancellation of the signal also. This also causes degradation of the ANC system performance.The reference input is usually obtained from points in the noise filed where the signal strength is small.So it becomes essential to investigate whether the signal distortion due to reference signal components outweigh the improvement in the signal-to noise ratio provided by the ANC.

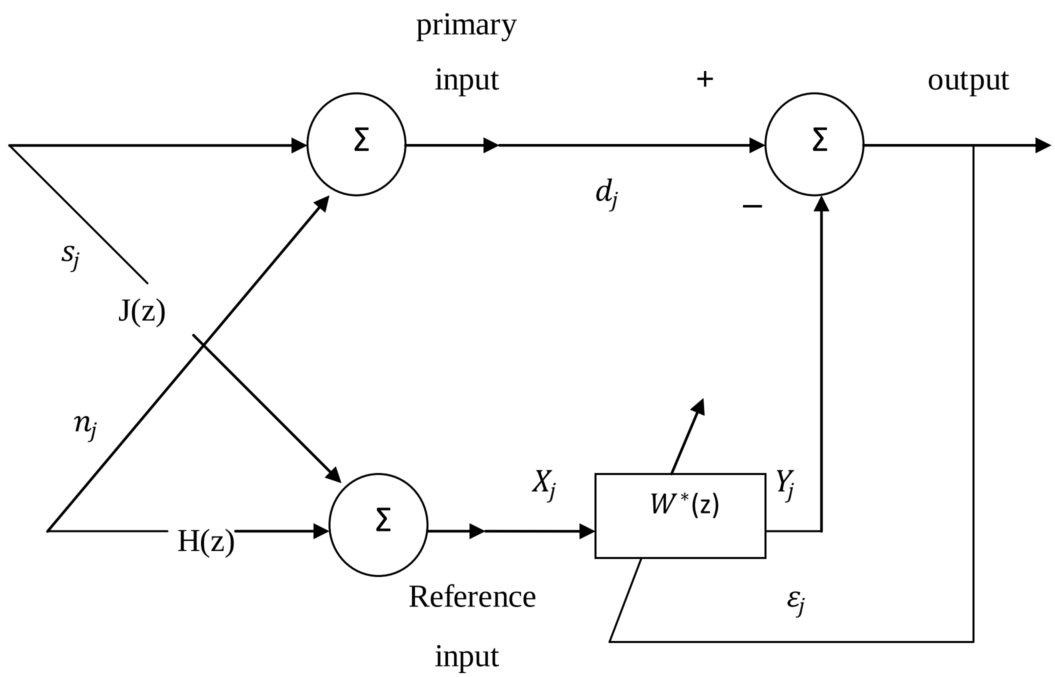

Fig 5.6 Block Diagram of ANC with Signal Components in Reference Input

The figure 5.6 shows an adaptive noise canceller that contains signal components in the reference input.The signal then propagate through a channel with transfer function J(z). If the spectra of the signal and noise are given by $\delta_{ss}(z)$ and $\delta_{nn}(z)$ respectively, the signal-to- noise density ratio at the primary input is

$$\rho_{pri}(z) = \frac{\delta_{ss}(z)}{\delta_{nn}(z)}$$

The spectrum of the signal component in the reference input is

$$\delta_{ssref}(z) = \delta_{ss}(z)\,|J(z)|^2$$

and that of the noise component is

$$\delta_{nnref}(z) = \delta_{nn}(z)\;|H(z)|^2$$

Therefore, the signal-to-noise density ratio at the reference input is thus

$$\rho_{ref}(z) = \frac{\delta_{ss}(z)\,|J(z)|^2}{\delta_{nn}(z)\;|H(z)|^2}$$

The spectrum of the reference input x can be written as

$$\delta_{xx}(z) = \delta_{ss}(z)\;|J(z)|^2 + \delta_{nn}(z)\;|H(z)|^2$$

and the cross spectrum between the reference input x and the primary input d is given by

$$\delta_{xd}(z) = \delta_{ss}(z)\,J(Z^{-1}) + \delta_{nn}(z)H(Z^{-1})$$

When the adaptive process converged, the unconstrained Weiner filter transfer function will be given by

$$W^*(z) = \frac{\delta_{ss}(z)\,J(Z^{-1}) + \delta_{nn}(z)H(Z^{-1})}{\delta_{ss}(z)\;|J(z)|^2 + \delta_{nn}(z)\;|H(z)|^2}$$

The expressions for the output signal-to-noise density ratio and the signal distortion are then compared to check the effects of signal distortion and if they are significant enough to render the improvement in SNR.

5.3.1 Signal Distortion

When signal components are present in the reference input then signal distortion will occur. The extent of signal distortion depends on the amount of signal propagated through the adaptive filter. The transfer function of the propagation path through the filter is

$$- J(z)\, W^{*}(z) = - J(z)\, \frac{\delta_{ss}(z)\, J(Z^{-1}) + \delta_{nn}(z) H(Z^{-1})}{\delta_{ss}(z)\, |J(z)|^{2} + \delta_{nn}(z)\, |H(z)|^{2}}$$

When |J(z)| is small i.e. signal components coupled to the reference input are small, this function is expressed as

$$- J(z)\, W^{*}(z) \cong - \frac{J(z)}{H(z)}$$

The spectrum of the signal component propagated to the noise canceller output through the adaptive filter is approximately

$$\delta_{ss}(z) \left| \frac{J(z)}{H(z)} \right|^{2}$$

While defining the signal distortion D(z) as the ratio of the spectrum of the signal components in the output propagated through the adaptive filter to the spectrum of signal components in the primary input, we get

$$D(z) = \frac{\delta_{ss}(z) \left| J(z) W^{*}(z) \right|^{2}}{\delta_{ss}(z)}$$

$$D(z) = \left| J(z) W^{*}(z) \right|^{2}$$

When J(z) is small, this reduces to

$$D(z) \cong \left| J(z) / H(z) \right|^2$$

From the expressions for SNR at the primary and reference inputs,

$$D(z) \cong \frac{\rho_{ref}(z)}{\rho_{pri}(z)}$$

This result shows that the relative strengths of signal-to-noise density ratios at the primary and reference inputs govern the level of signal distortion. Higher the SNR at the reference input i.e. the larger the amount of signal components present in the reference, the higher is the distortion. A low distortion results form high signal-to-noise density ratio at the primary input and low signal-to-noise density ratio at the reference input.

5.3.2 Output Signal-to-Noise Density Ratio

Here the signal propagates to the noise canceller output via the transfer function 1- J(z)W*(z), while the noise propagates through the transfer function 1- H(z) W*(z). The spectrum of the signal component in the output is thus

$$\delta_{ssout}(z) = \delta_{ss}(z) \left| 1 - J(z)W^*(z) \right|$$

$$\delta_{ssout}(z) = \delta_{ss}(z) \left| \frac{[H(z) - J(z)]\delta_{nn}(z)H(z^{-1})}{\delta_{ss}(z)\left|J(z)\right|^2 + \delta_{nn}(z)\left|H(z)\right|^2} \right|^2$$

and that of noise component is similarly given by

$$\delta_{nnout}(z) = \delta_{nn}(z) \left| 1 - H(z)W^*(z) \right|$$

$$= \delta_{nn}(z) \left| \frac{[J(z) - H(z)]\delta_{ss}(z)J(z^{-1})}{\delta_{ss}(z)|J(z)|^2 + \delta_{nn}(z)|H(z)|^2} \right|^2$$

The output signal-to-noise density ratio is thus

$$\rho_{out}(z) = \frac{\delta_{ss}(z)}{\delta_{nn}(z)} \left| \frac{\delta_{nn}(z)H(z^{-1})}{\delta_{ss}(z)J(z^{-1})} \right|^2$$

$$= \frac{\delta_{nn}(z)|H(z)|^2}{\delta_{ss}(z)|J(z)|^2}$$

From the expression for signal-to-noise density ratio at reference input, we conclude that

$$\rho_{out}(z) = \frac{1}{\rho_{ref}(z)}$$

Hence the signal-to-noise density ratio at the noise canceller output is simply the reciprocal at all frequencies of the signal-to-noise density ratio at the reference input, i.e. the lower the signal components in the reference, the higher is the signal-to-noise density ratio in the output.

5.3.3 Output Noise

When J(z) is small, the expression for output noise spectra reduces to

$$\delta_{nnout}(z) \cong \delta_{nn}(z) \left| \frac{\delta_{ss}(z)J(z^{-1})}{\delta_{nn}(z)H(z^{-1})} \right|^2$$

In terms of signal-to-noise density ratios at reference and primary inputs,

$$\delta_{nnout}(z) \cong \delta_{nn}(z) |\rho_{ref}(z)| \, |\rho_{pri}(z)|$$

The dependence of output noise on these three factors is explained as under

1. First factor: $\delta_{nn}(z)$ implies that the output noise spectrum depends on the input noise spectrum, which is obvious.

2. The second factor: implies that, if the signal-to-noise density ratio at the reference input is low, the output noise will be low, i.e. the smaller the signal components in the reference input, the more perfectly the noise will be cancelled.

3. The third factor: implies that if the signal-to-noise density ratio in the primary input is low, the filter will be trained most effectively to cancel the noise rather than the signal and consequently output noise will be low.

5.4 Use of ANC without a Reference Signal

Where signal is narrowband and noise is broadband, or signal is broadband and noise is narrowband than a delayed version of the input signal can be used as the reference input.

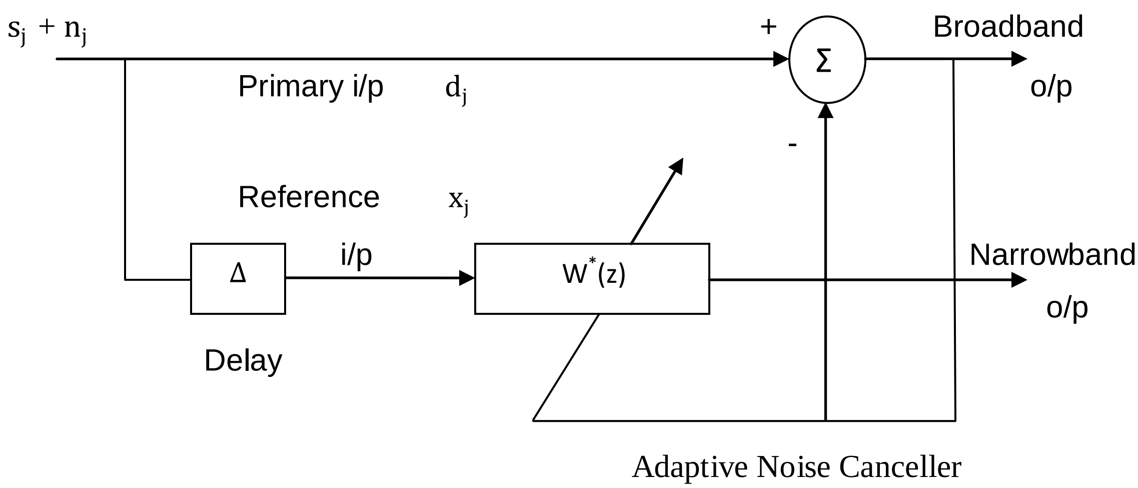

Fig 5.7 Block Diagram of ANC without Reference Input

This is because a broadband signal is not correlated to previous sample values unlike a narrowband signal. Here only need to insure that the delay introduced should be greater than the decorrelation-time of the broadband signal and less than the decorrelation-time of the narrowband signal i.e

$$\tau_d(\text{BB}) < \text{delay} < \tau_d(\text{NB})$$

This concept can be applied to a number of problems listed below:

1. Canceling periodic interference without an external reference source.
2. Adaptive self-tuning filter.
3. Adaptive Line Enhancer.

5.5 Application

An application of ANC is provided for basic understanding bias or low-frequency drift canceling using adaptive noise canceller has been considered:

The use of a bias weight in an adaptive filter to cancel low-frequency drift in the primary input is a special case of notch filtering with the notch at zero frequency. A bias weight is incorporated to cancel dc level or bias and hence is fed with a reference input set to a constant value of one. The value of the weight is updated to match the dc level to be cancelled. Because there is no need to match the phase of the signal, only one weight is needed.

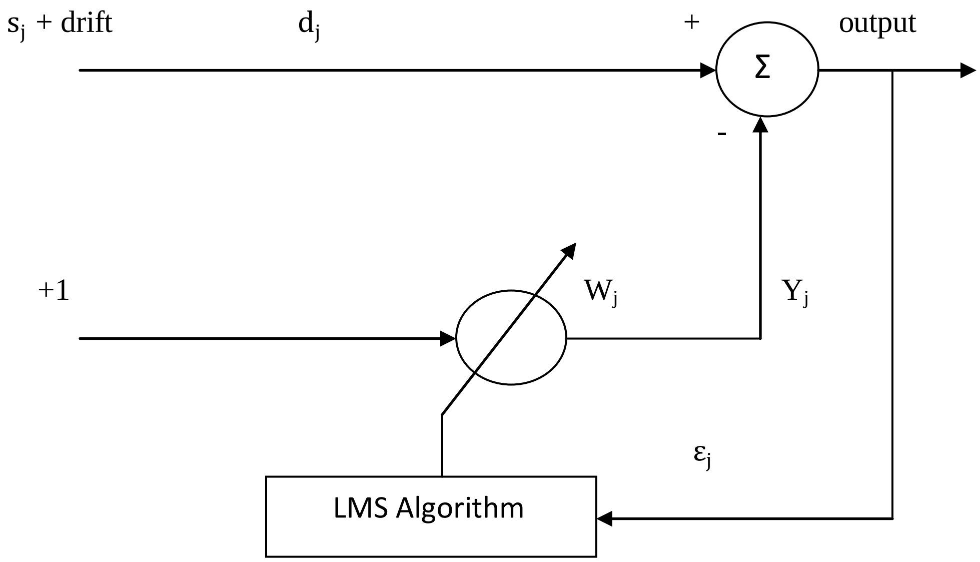

Fig 5.8 Block Diagram of ANC as Bias/Low-Frequency Drift Canceller

The transfer function from the primary input to the noise canceller output is now derived. The expression of the output of the adaptive filter Y_j is given by

$$Y_j = W_j \ , 1= W_j$$

The bias weight w is updated according to the LMS update equation

$$W_{j+1} = W_j + 2\mu(\epsilon_j,1)$$
$$Y_{j+1} = Y_j + 2\mu(d_j\text{-}y_j)$$
$$= (1\text{-}2\mu)\ y_j + 2\mu d_j$$

Taking the z-transform of both the sides yields the steady-state solution:

$$Y(z) = \frac{2\mu}{z-(1-2\mu)} D(z)$$

Z-transform of the error signal is

$$E(z) = D(z) - Y(z)$$
$$= \frac{z-1}{z-(1-2\mu)} D(z)$$

The transfer function is now

$$H(z) = \frac{E(z)}{D(z)}$$
$$= \frac{z-1}{z-(1-2\mu)}$$

This shows that the bias-weight filter is a high pass filter with a zero on the unit circle at zero frequency and a pole on the real axis at a distance 2μ to the left of the zero. The smaller the μ, the closer is the location of the pole and the zero, and hence the notch is recisely at zero frequency i.e. only dc level is removed. The single-weight noise canceller acting as a high-pass filter is capable of removing not only a constant bias but also slowly varying drift in the primary input. If the bias level drifts and this drift is slow enough, the bias weight adjusts adaptively to track and cancel the drift. Using a bias weight along with the normal weights in an ANC can accomplish bias or drift removal simultaneously with cancellation of periodic or stochastic interference.

CHAPTER-6

RESULT AND DISCUSSION

6.1 Matlab Software

MATrix LABoratory is a programming language for technical computing. This software is used for a wide variety of scientific and engineering calculations, especially for automatic control and signal, image processing, it has extensive graphical capabilities. Matlab allows easy matrix manipulation, plotting of functions and data, implementation of algorithms, creation of user interfaces, and interfacing with programs in other languages. Matlab is built around the Matlab language, sometimes called M-code or simply M.

In this thesis, all the algorithms and possible implementations of the adaptive noise canceller as discussed in the previous chapters is be simulated using MATLAB.

The results are divided into sections according to the four implementations of the adaptive noise canceller discussed in Chapter5.

Model 1 - Adaptive Noise Canceller

Model 2 - Adaptive Noise Canceller with uncorrelated noise in primary and reference input.

Model 3 - Adaptive Noise Canceller with signal components in reference inputs.

Model 4 - Adaptive Noise Canceller of bias/drift removal.

6.1.1 Model 1 - Adaptive Noise Canceller

The simulated models are set to the following parameters:

(i) Number of Iterations = 200

(ii) Order of filter =16

(iii) Adaptation Step Size Parameter

LMS Step Size: m = 0.04

(iv) Cut of frequency W_n = [0.1 0.5]

(v) Input Signals: White, Normally distributed, zero mean, unit variance.

(vi) Additive Noises: Input sensors noises are simulated as white signals.

It has been assumed these additive noises are uncorrelated with the other signals in the adaptive noise canceller.

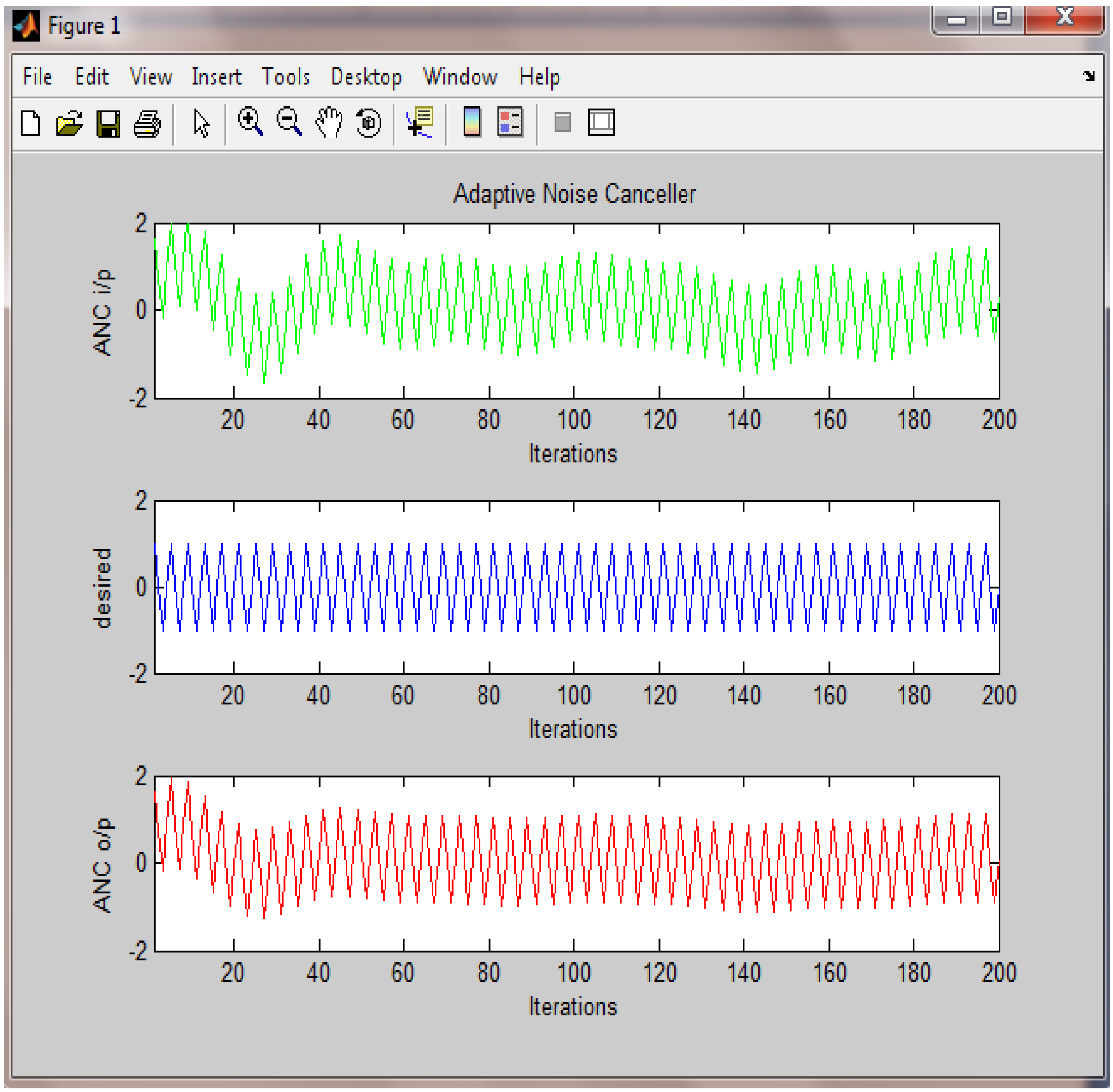

Fig.6.1 Adaptive Noise Canceller

As observed from the above graph, the distortions in the output waveform get reduced to a large extent as compared to the desired waveform. So wiener filter proves to be as an efficient filter.

6.1.2 Model 2 - Adaptive Noise Canceller with Uncorrelated Noise in Primary and Reference Input.

The simulated models are set to the following parameters:

(i) Number of Iterations = 500

(ii) Order of filter =16

(iii) Adaptation Step Size Parameter

LMS Step Size: m = 0.04

(iv) Cut of frequency W_n = [0.1 0.5]

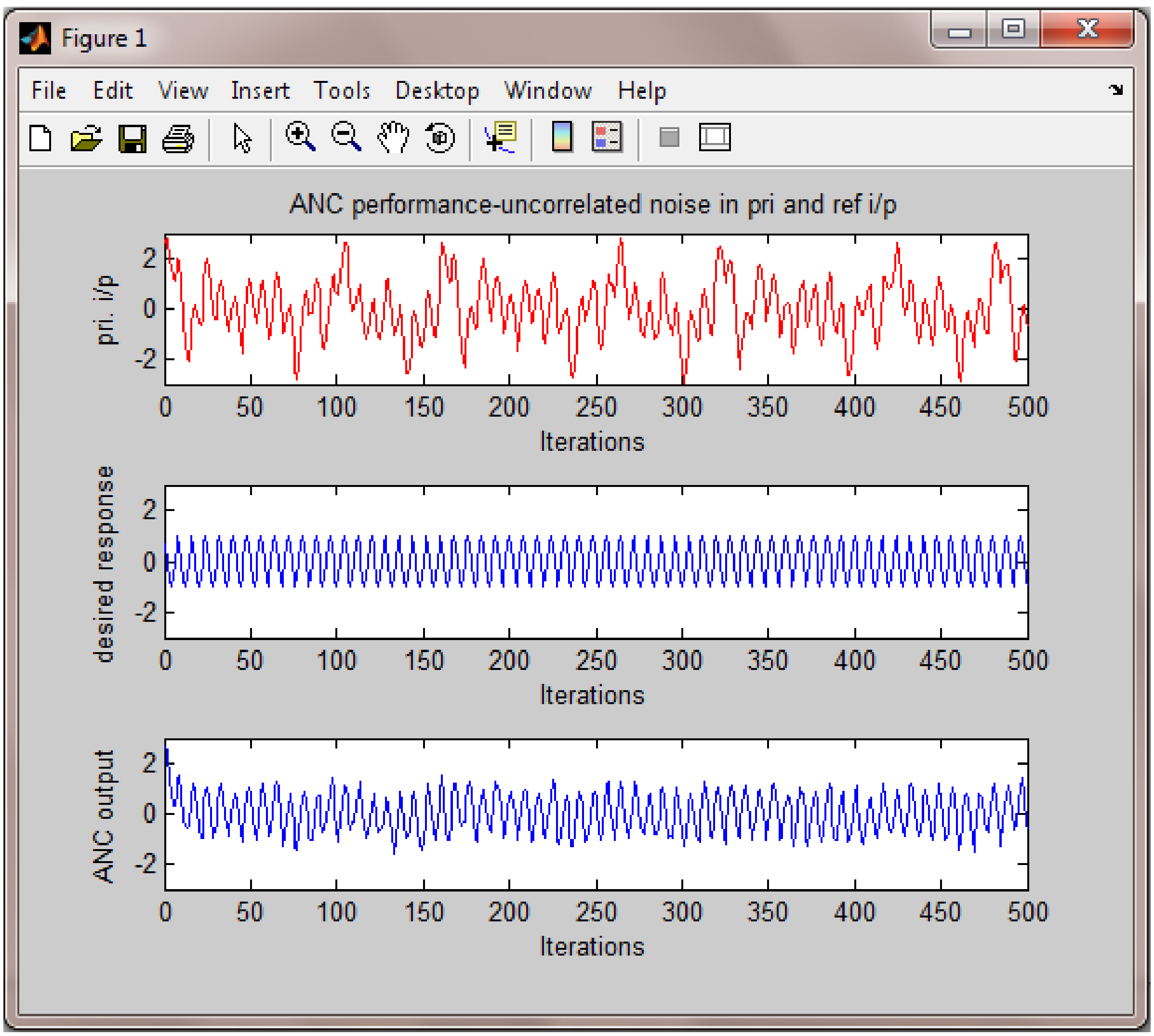

Fig.6.2 ANC with Uncorrelated Noise in Primary and Reference Input

An adaptive noise canceller performance in the presence of correlated and uncorrelated noises is shown in fig 6.2. As discussed in the previous chapter, the ability of a noise canceling system to reduce the noise is limited by the uncorrelated-to-correlated noise density ratios at the primary and reference inputs. Smaller the ratios of the spectra of the uncorrelated to the spectra of the correlated noises at the primary and reference, the greater the ratio of signal-to-noise density at the output and the primary input and the more effective action of the canceller. The desirability of low levels of uncorrelated noise in both primary and reference inputs is thus emphasized.

6.1.3 Model 3 - Adaptive Noise Canceller with Signal Components in Reference Inputs.

The simulated models are set to the following parameters:

(i) Number of Iterations = 1000

(ii) Order of filter =16

(iii) Adaptation Step Size Parameter

LMS Step Size: m = 0.05

(iv) Cut of frequency W_n = [0.1 0.5]

The effect of the signal components in reference inputs on adaptive noise canceller is shown in the graph. When signal components are present in the reference input, some signal distortion will occur and the extent of signal distortion will depend on the amount of signal propagated through the adaptive filter.

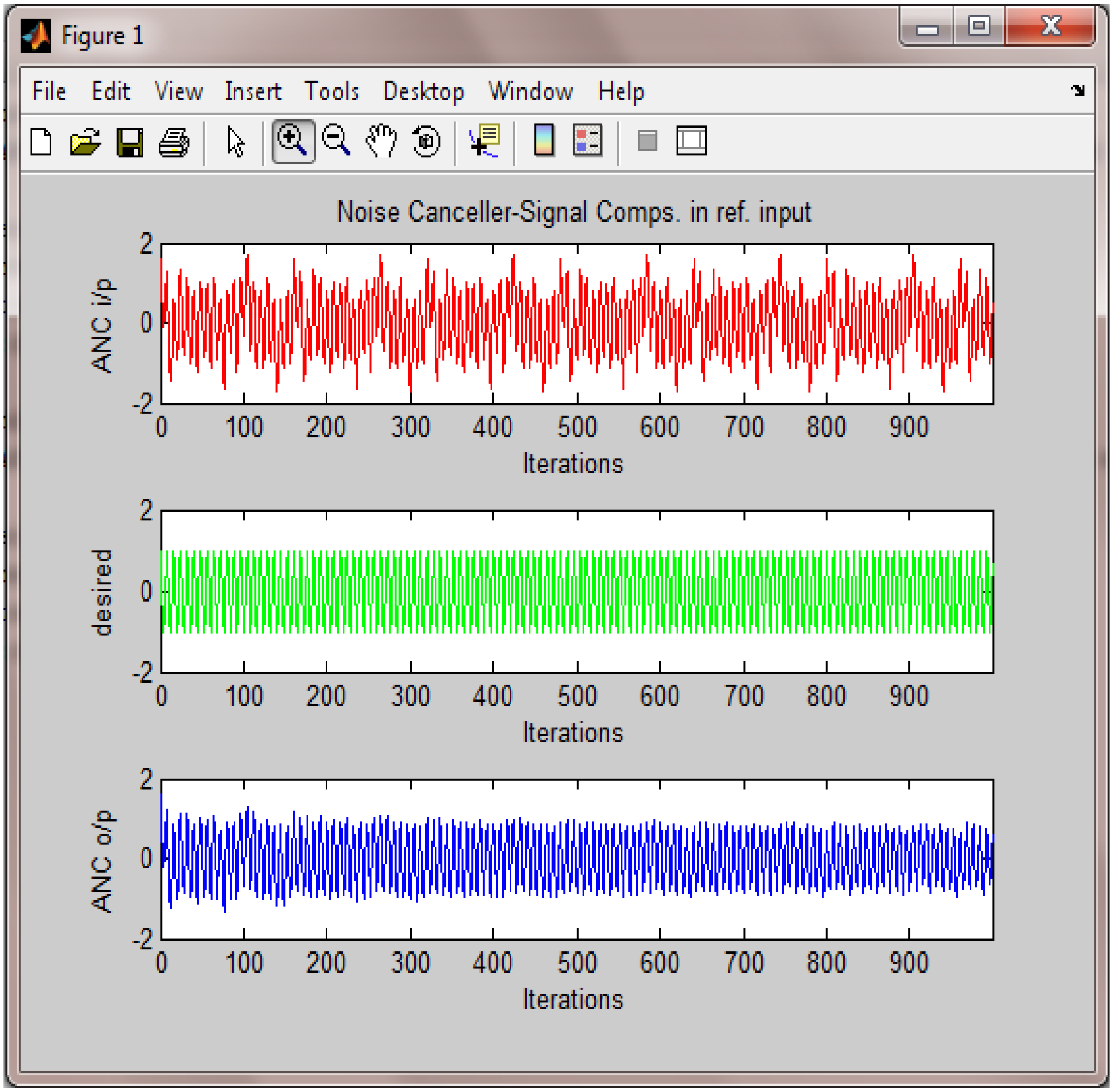

Fig.6.3 Adaptive Noise Canceller with Signal Components in Reference Inputs

6.1.4 Model 4 - Adaptive Noise Canceller of Bias/Drift Removal

The simulated models are set to the following parameters:

(i) Number of Iterations =1024

(ii) Order of filter =16

(iii) Adaptation Step Size Parameter

LMS Step Size: m = 0.05

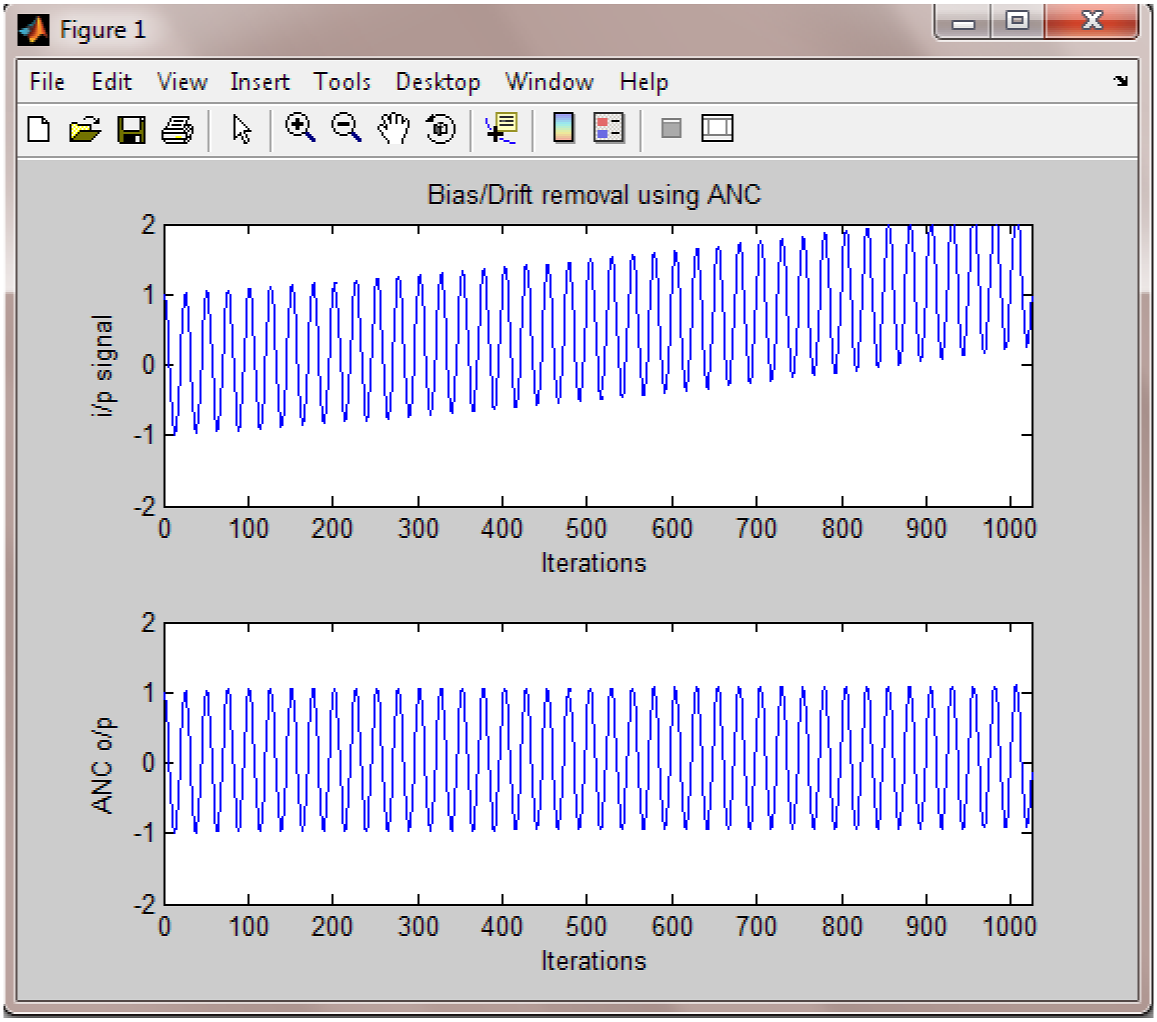

Fig.6.4 Adaptive Noise Canceller of Bias/Drift Removal

It is clear from the above graph the distortions in the output waveform get reduced to a large extent. The single-weight noise canceller acting as a high-pass filter is capable of removing not only a constant bias but also the slowly varying drifts in the primary input. If the bias level drifts and this drift is slow enough, the bias weight adjusts adaptively to track and cancel the drift. Using a bias weight along with the normal weights in an ANC can accomplish bias or drift removal simultaneously with cancellation of periodic or stochastic interference.

Conclusion

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

Scope for Further Work

In this project, only the Least-Mean-Squares Algorithm has been used. Other adaptive algorithms can be studied and their suitability for application to Adaptive Noise Cancellation can be compared. Other algorithms that can be used include Recursive Least Squares, Normalized LMS, Variable Step-size algorithm etc. Moreover, this project does not consider the effect of finite-length filters and the causal approximation. The effects due to these practical constraints can be studied.

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