DESIGNING AN ALGORITHM USING ACTIVE NOISE CANCELLATION FOR DEVELOPMENT OF A HEADPHONE IN HEAVY NOISE INDUSTRY

A thesis submitted in partial fulfilment of the

requirements for the degree of

Bachelor of Technology

In

Electronics and Instrumentation Engineering

By

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Department of Electronics and Communication Engineering
National Institute of Technology, Rourkela

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Under the guidance of

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CERTIFICATE

This is to certify that the thesis entitled **"DESIGNING AN ALGORITHM USING ACTIVE NOISE CANCELLATION FOR DEVELOPMENT OF A HEADPHONE IN HEAVY NOISE INDUSTRY"** submitted by Sahil Pahuja (108EI034) in partial fulfilment of the requirements for the award of the Degree of BACHELOR OF TECHNOLOGY in Electronics and Instrumentation Engineering at National Institute of Technology, Rourkela (Deemed University) is an authentic work carried out by him under my supervision and guidance.

Date: 14th May, 2012

Prof Sarat Kumar Patra
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DECLARATION

I hereby declare that the project work entitled **"DESIGNING AN ALGORITHM USING ACTIVE NOISE CANCELLATION FOR DEVELOPMENT OF A HEADPHONE IN HEAVY NOISE INDUSTRY"** is a record of my original work done under Prof. Sarat Kumar Patra, Professor, National Institute of Technology, Rourkela. Throughout this documentation wherever contributions of others are involved, every endeavour was made to acknowledge this clearly with due reference to literature. This work is being submitted in the partial fulfilment of the requirements for the degree of Bachelor of Technology in Electronics and Instrumentation Engineering at National Institute of Technology, Rourkela for the academic session 2008 – 2012.

Date: 14th May 2012
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CONTENTS

ABSTRACT

Noise pollution is a very big problem prevailing in the environment these days. The workers working in heavy noise industry gets affected by the high level of noise present in the industries. The results may be as adverse as permanent hearing loss or even heart-attack. Here, I have tried to implement a few algorithms which can be used to develop a headphone which will cancel the noise from the environment. I have introduced various Active Noise Cancellation techniques or algorithms. I have discussed the LMS algorithm, the Filtered-x LMS algorithm, FLANN Filter and Particle Swarm Optimization (PSO) Algorithm. I have shown their behaviour in presence of linear as well as non-linear noise environment and discussed the application of each under various circumstances. Finally, I have shown the simulation result and performance of each technique under various circumstances.

LIST OF FIGURES

Chapter

ONE

INTRODUCTION

1.1 NOISE

Any unwanted signal that interferes with the communication or measurement of an information carrying signal is termed as noise. Noise is present in various form or percentage in almost all environments.

For example, in a digital cellular mobile telephone system, there may be several varieties of noise that could degrade the quality of communication, such as acoustic background noise, electromagnetic radio-frequency noise, co-channel radio interference, radio-channel distortion, outage and signal processing noise. Noise can cause various transmission errors and may even disrupt a communication process and hence noise processing is an important and integral part of modern signal processing systems.

On the basis of the range of frequency present, noise can be broadly categorised into Broadband Noise and Narrowband Noise:

- Broadband - the energy is distributed equally across all frequency bands. E.g. low-frequency sound of a jet plane
- Narrowband - most energy is concentrated around specific frequencies. E.g. caused by rotating machinery.

1.2 NOISE REDUCTION

The consequences of exposing people to noise from various sources may vary from short term effects such as sleep disturbance to long term effects such as permanent hearing loss. To reduce the noise from source reaching our year involves various methods which can be categorised into

- Passive Noise Control

  Passive Noise control is a method in which the noise from the source is not allowed to reach the ear of the person. This is done by blocking the path of the noise using absorbing materials or by reflecting the noise in some other direction. Thermocol or polystyrene, clothes and wood are some examples of the materials which absorb the noise and reduce the adverse effects occurring from it.

- Active Noise Control

  Active Noise Control is a very effective electronic method to reduce the effect of the noise in an environment. It is basically generation of anti-noise, equal in magnitude and opposite in phase with the noise. The anti-noise and the noise are destructively interfered to remove the effects of noise from the path of the noise.

While passive and active noise cancellation may be applied separately, they are often combined to attain maximum effectiveness in noise cancellation.

Chapter

TWO

ACTIVE NOISE CANCELLATION

Active Noise Cancellation or active noise control involves the electro-acoustic generation of a sound field to cancel an unwanted existing sound filed. Active Noise Control is the more often used term.

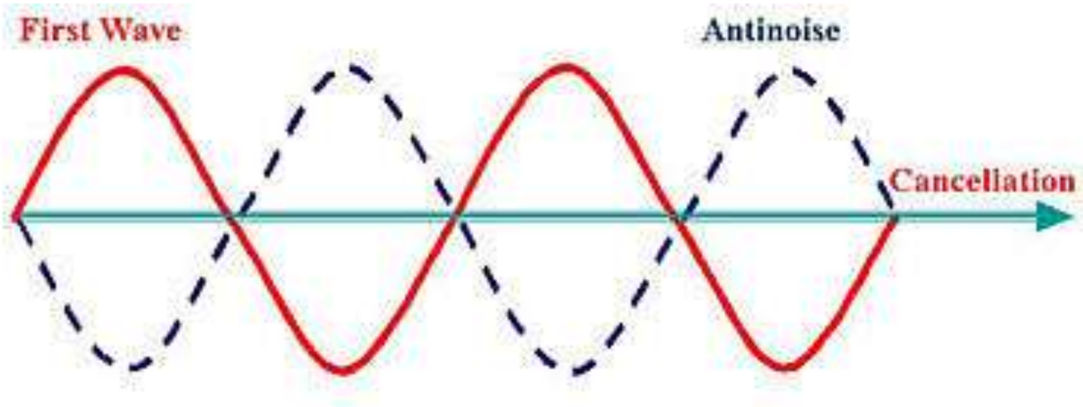

Fig. 2.1 Active Noise Cancellation

A very basic single channel active noise control system consists of:

- A reference microphone sensor- to sample the disturbance to be cancelled.
- An electronic control system to process the input signal and then generate the control signal. This is basically an adaptive filter
- A loudspeaker driven by the control signal to generate the anti-noise
- An error microphone to provide feedback to the controller so that it can adjust itself to minimise the resulting sound output.

The system thus described is known as an “Adaptive System” as it can adapt itself according to the change in the reference signal which is feedback to the controller through the error microphone.

2.1 Basic Structure of Active Noise control systems

Modern active sound control systems consist of a control source used to introduce a controlling signal into the acoustic system. This disturbance reduces the unwanted noise originating from the primary sources by adding to it a signal of same magnitude but opposite in phase. The control signals that drive the control actuators are generated by an electronic controller, which uses as inputs, the feedback error from the error microphone.

Active noise control systems are mostly used in the low frequency range, usually below 500-600 Hz. At higher frequencies, passive control measures generally become more cost effective.

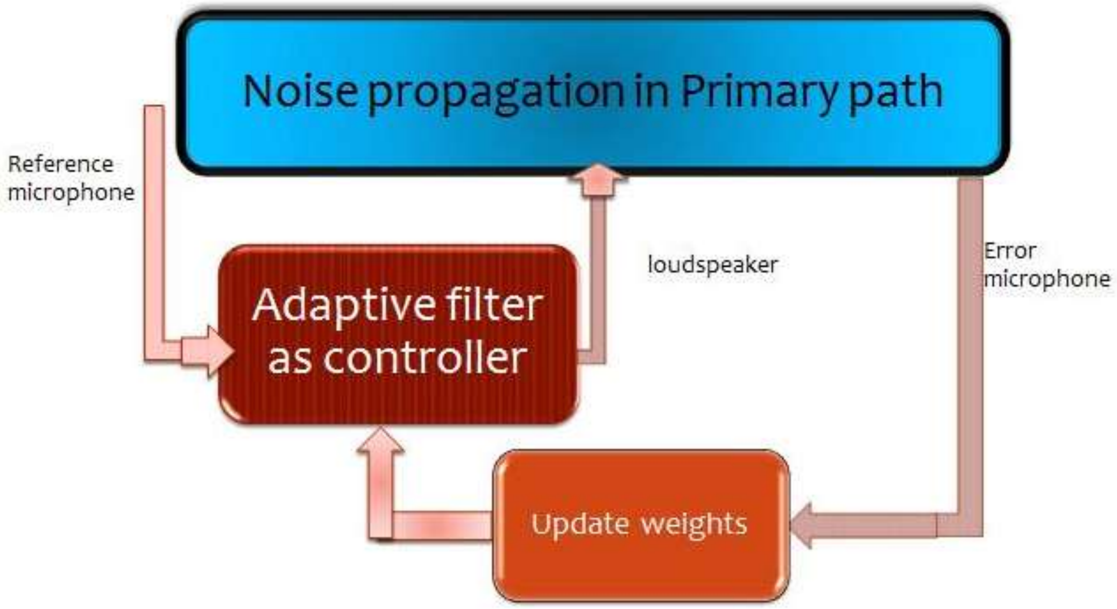

Fig 2.2 Active Noise Control System with Adaptive Filter

Two major types of active noise control system will be considered here:

- Adaptive filtering - the coefficients are updated adaptively to reduce the error output, and
- Waveform synthesis- a type of feed-forward control that is suited only to periodic noise.

2.2 Adaptive Control

An adaptive controller is a controller that can change its nature in response to changes in the process and the disturbances occurring dynamically. An adaptive controller is a controller with adjustable parameter and a mechanism for adjusting the parameters.

The adaptive control mechanism includes a digital filter with dynamically changing coefficients as per the requirement and with the changes in the environment.

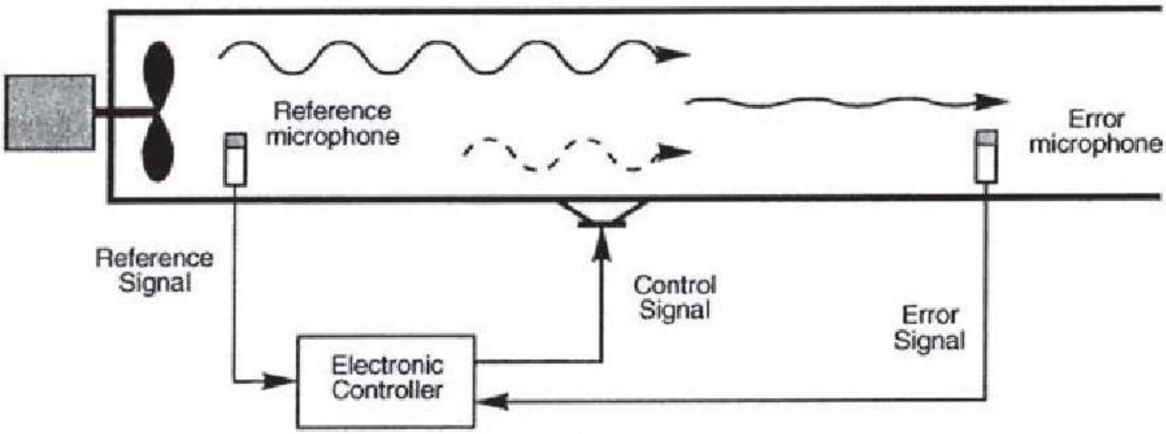

Fig. 2.3 ANC system block diagram with single channel

2.3 Digital Filter

The heart of the control system is a digital filter with specific properties, which synthesizes the anti-noise. The two main requirements of the digital filter we have used here is: (i) FIR Filter (ii) Adaptive Filter

2.3.1 Adaptive Filter

The term 'adaptive' signifies that that the filter weights are not fixed, rather these are adjustable according to the variation in external environment. The weights are randomly initialized and according to an adaptive algorithm the controller updates its weights so as to minimize the residual noise at the listener side. The significances of an adaptive filter can be summarized as

Filter parameters such as bandwidth and resonant frequency change with time.
The coefficients vary with time and are adjusted automatically by an adaptive algorithm.

Coefficient Adaptation

- The purpose of determining the coefficients of the filter model is to maximize the statistical correlation between the reference signal and the coefficients.
- This in turn is done by minimizing the correlation between the error signal and the filter state as is relevant to the coefficients.
- When the adaptive filter is working, the error signal decreases in magnitude, and this slows down the movement of the coefficients. The filter is observed to be converging to a solution.

2.3.2 FIR Adaptive Filter

- The controller filter may take a number of forms, the most common of which is the Finite Impulse Response (FIR) filter. An FIR filter may be represented as shown in the Figure below. Here, z-1 represents a delay of one (input) sample and wi represents filter weight i.

- FIR filters are ideally suited to tonal noise problems, i.e. noise with harmonics, where the reference signal is a few sinusoids and where the control signal does not in any way corrupt the reference signal.

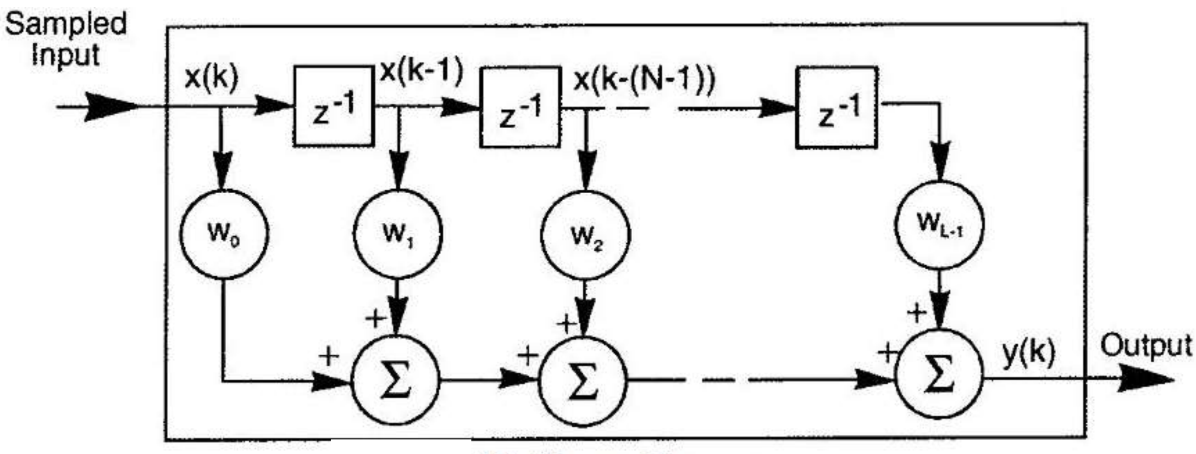

Fig. 2.4 FIR filter architecture

When there are resonances in the system or if there is some noise feedback from the control source to the reference sensor, resulting in the corruption of the reference signal, the FIR filter is not the best choice and then the Infinite Impulse Response (IIR) filter is often chosen for its ability to directly model the poles in the system resulting from such effects.

The main advantage of the IIR filter is that it uses fewer weight coefficients than required by an FIR filter for a complex system, thus reducing computational load. But this advantage comes at the cost of instability, slower convergence and also the possibility of convergence to a local minimum in the error surface increases instead of a global minimum.

The three parameters that affect the performance of a digital filter in an active noise cancelling system are: the type of filter, the filter weight values and the number of weights. The adaptation algorithm of the controller is responsible for tuning the adaptive filter so that the resulting control signal minimises the error signal received by the controller. We shall read about various algorithms depending upon if the noise in the environment is linearly varying or non-linearly varying.

Chapter

THREE

ANC ALGORITHMS

&

TECHNIQUES

3.1 Least Mean Square Algorithm (LMS)

The Least Mean Square (LMS) algorithm was introduced by Widrow and Hoff in 1959. It uses a gradient-based method of steepest decent and is the simplest technique used for updating the coefficients of an adaptive filter. It adopts iterative procedure that makes successive corrections to the weights of the filter in the direction of the negative of the gradient vector which gradually leads to the minimum mean square error.

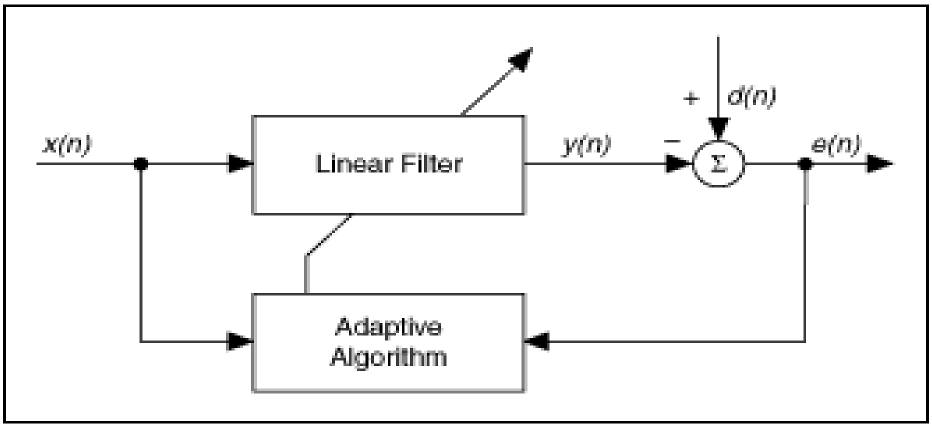

Fig. 3.1 Architecture of a system with LMS algorithm implementation

where x(n) : input signal to the linear filter

y(n) : corresponding output signal

d(n) : noise entering the path

e(n) : error signal that denotes the difference between d(n) & y(n).

The LMS algorithm performs the underneath operations to update the coefficients of an adaptive FIR filter:

- Calculate the output signal y(n) from the FIR filter.

$$y(n) = \vec{u}^{T}(n) \cdot \vec{w}(n)$$

Where, $\vec{u}(n)$ is filter input vector

and $\vec{u}(n) = [x(n)x(n-1)\ldots x(n-N+1)]^{T}$

$\vec{w}(n)$: filter coefficients vector

$\vec{w}(n)$ and $\vec{w}(n) = [w_0(n)\; w_1(n) \ldots w_{N-1}(n)]^{T}$

- Calculates the error signal e(n) by using :

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

- Updates the filter coefficients by using the update equation:

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

where μ is the step size of the adaptive filter

w(n) : filter coefficients vector

u(n) : filter input vector

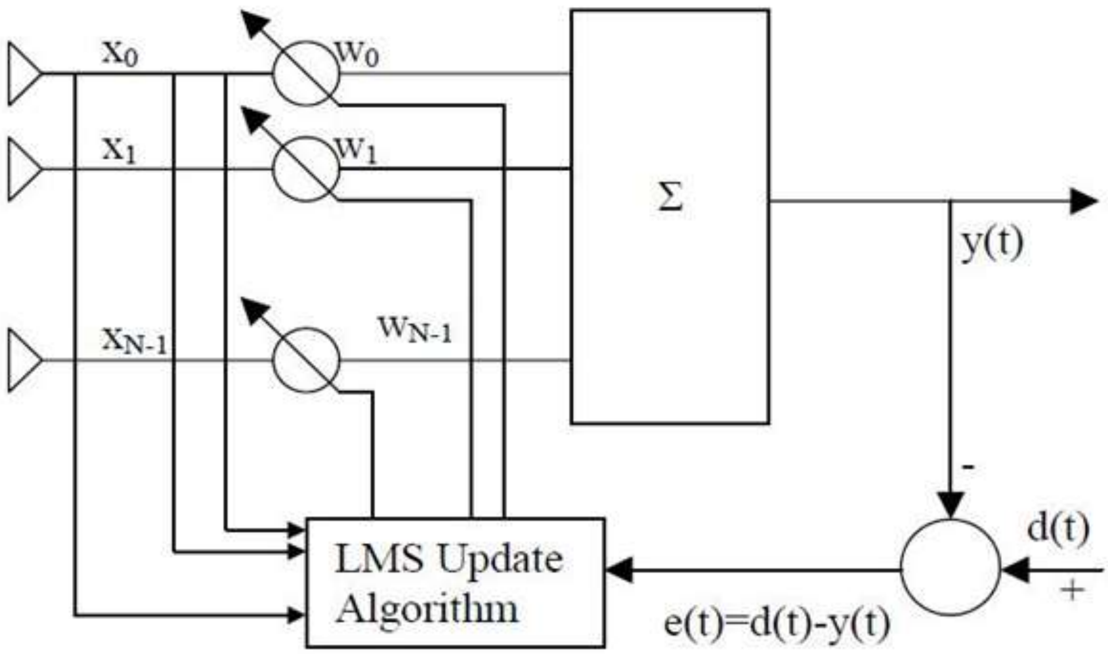

Fig. 3.2 Block Diagram of ANC system using LMS Algorithm

μ in other words is the convergence factor of the filter i.e. if μ is chosen to be very small the rate of convergence reduces. While a larger value μ will lead to faster convergence but will reduce the stability of the system around the minimum value.

The LMS algorithm is the most widely used adaptive algorithm because of its simplicity and its reasonable performance. It has a stable and robust performance in various noise environments but it may not have equally fast convergence speed compared to other complicated adaptive algorithms. There are several upgraded versions of the LMS algorithm that deal with the shortcomings of its basic form.

3.2 Filtered-x LMS Algorithm

The filtered–X LMS algorithm is one of the most popular adaptive control algorithm used in active noise control systems. There are several reasons for this algorithm's popularity. It is well-suited to both broadband and narrowband control tasks, with a structure that can be adjusted according to the problem at hand. Most importantly it behaves robustly when there are physical modelling errors and numerical effects caused by finite-precision calculations. This algorithm is relatively simple to set up and tune in a real-world environment.

It is called the "filtered-x" algorithm because it requires a filtered version of the reference signal as input, with the filter having the same impulse response as the cancellation path i.e. it include the effects of the acoustic cancellation path. During implementation of LMS algorithm in the ANC system the secondary path (from the loudspeaker to the error microphone) needs to be identified so that during updating weights the reference signal must be filtered through the secondary path in order to nullify the effect. The complexity of the system increases as it needs to identify the secondary path.

The block diagram of an ANC system using the FXLMS algorithm is illustrated in the figure where $P(z)$ is the transfer function of the primary path from the noise source to the error microphones, $S(z)$ is the transfer function of secondary path and $\overline{S}(z)$ is its estimate. The adaptive filter $W(z)$ generates the anti-noise, $y(n)$ which cancels the primary noise $d(n)$ present in the primary path. The secondary loudspeakers generate the anti-noise and $e(n)$ is the residual noise picked up by the error microphone.

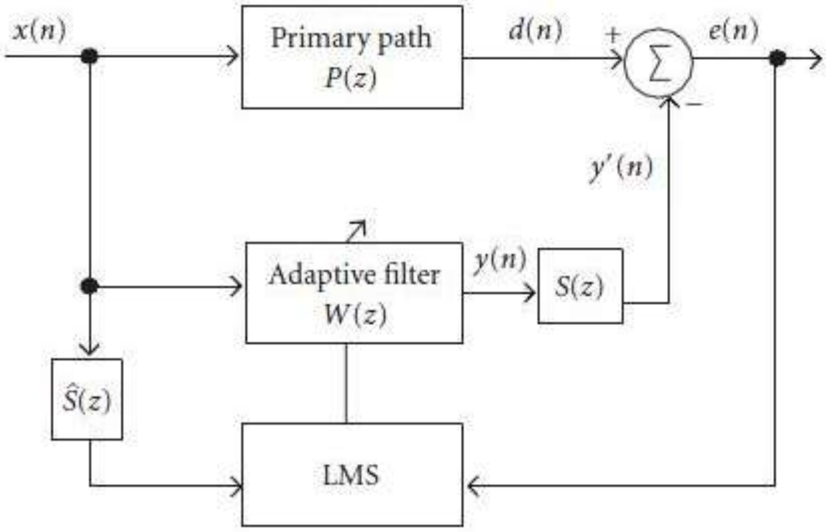

Fig. 3.3 Block Diagram of ANC system with the FXLMS algorithm

In the figure, $S(z)$ which is the secondary path between $e(n)$ and $y(n)$, includes the secondary loudspeakers, error microphones, and acoustic path between the loudspeakers and the error microphones. The estimate compensates for the secondary-path effects. The output of the adaptive filter can be represented as

$$y(n) = \mathrm{w}^t(n)\mathbf{x}(n)$$

where $\mathbf{w}(n) = [w0(n)\ w1(n) \cdots wL-1(n)]T$ is the coefficient vector of the adaptive filter $W(z)$ and $\mathbf{x}(n) = [x(n)\ x(n-1) \cdots x(n-L+1)]T$ is the $L\times1$ reference signal vector.

The signal $y(n)$ is filtered through the secondary path $S(z)$ and is subtracted from the primary noise $d(n)$ to generate the residual error $e(n)$. The equations for simulation are given by

$$d(n) = p(n)*x(n)$$

$$y'(n) = s(n)*y(n)$$

$$e(n) = d(n) - y'(n) = d(n) - s(n)*[\mathrm{w}^t(n)\mathbf{x}(n)]$$

where $*$ represents the convolution operator,

$p(n)$ is the primary path response

$s(n)$ is the secondary path response

All these operations are carried out by the system internally and the signals picked up in real-time ANC are the reference signal $x(n)$ and the residual error $e(n)$.

The weight update equation for the adaptive filter is

$$\mathbf{w}(n+1) = \mathbf{w}(n) + \mu e(n)\mathbf{x}'(n)$$

μ: step size

This is the standard FXLMS algorithm, used with an adaptive FIR filter. The algorithm effectively calculates the "slope" of the error surface and hence calculates weights that will cause the error to move down the slope to a smaller value. When the slope is reduced to zero, the algorithm will stop converging.

3.3 FLANN Filter

LMS and FxLMS algorithm perform better when there is no non-linearity in the noise present in the environment. Various methods were derived to counter the non-linear noise in the system. These include Volterra Series, memory polynomial filters, FLANN filter. FLANN is Functional Link Artificial Neural Network. Here, we have designed a FLANN filter using trigonometric expansions. We have designed the filter excluding the cross terms.

$$y(n) = \sum_{i=0}^{N_a-1} a_i x(n-i) + \sum_{j=1}^{N_b-1} b_j y(n-j) + \sum_{j=1}^{N_e-1} e_j \cos\left[\pi y(n-j)\right] + \sum_{j=1}^{N_e-1} g_j \sin\left[\pi y(n-j)\right]$$

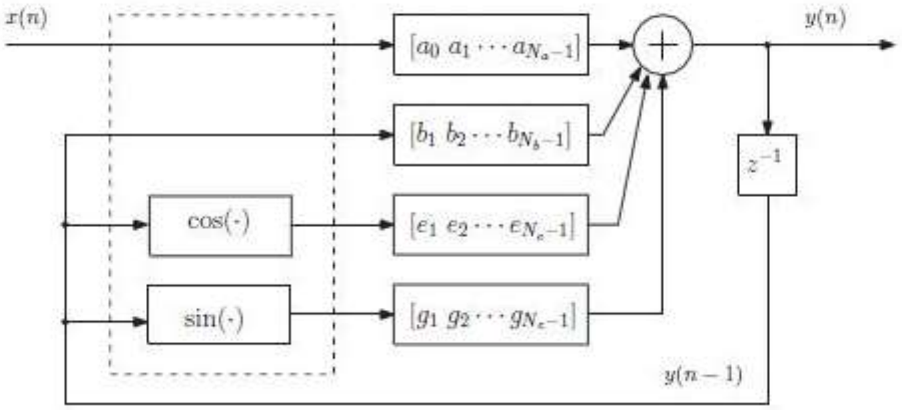

Fig. 3.4 Implementation of recursive FLANN filter of order P = 1

the expansion block at its output give the following signals :

$$x(n),\ \ y(n-1),\ \ \cos[\pi y(n-1)],\ \sin[\pi y(n-1)]$$

the FLANN filter is a member of the class of non-recursive, shift-invariant nonlinear filters with a characteristic property that their output depends linearly on the filter coefficients.

3.4 Particle Swarm Optimization (PSO)

The proposed PSO-based Active Noise Control algorithm does not require the estimation of secondary path transfer function unlike LMS, FXLMS algorithm and, hence, is immune to time varying nature of the secondary path. It is an evolutionary computational technique. It is based on the movement and intelligence of swarms looking for the most fertile feeding location. Developed in 1995 by James Kennedy and Russell Eberhart this is a very simple algorithm, easy to implement and has very few parameters to adjust, mainly the velocity and the position of each particle.

A “swarm” is basically a disorganized collection of moving particles or flies that slowly come closer while each individual seems to be moving in a random direction. Each particle or fly is treated as a point in a D-dimensional space which adjusts its “flying” i.e. the speed and the direction according to its own flying experience as well as according to the flying experience of other particles. Each particle keeps track of its coordinates in the problem space which are associated with the best possible fitness that it has achieved so far. This best individual value is called pbest. Another best value is tracked by the PSO that is the best value obtained so far by any particle in the neighbors of the particle. This value is referred to as gbest. The PSO concept consists of changing the velocity of every particle toward its pbest and the gbest position at each time step, finally resulting in all the particles reaching the gbest, ie. the point of global minima.

3.4.1 PSO Algorithm

1. Step 1

   For each particle

   initialize particle with feasible random number

   End

2. Step 2

   Calculate the fitness value

   If the fitness value is better than the pbest in history

   current value = pbest

   End

3. Step 3

The particle with best fitness value is chosen as the gbest.

4. Step 4

   For each particle,

   (i) Calculate particle velocity according to velocity update equation

   (ii)Update particle position according to position update equation

   End

5. Step 5

   Continue

   While minimum error criteria is not attained.

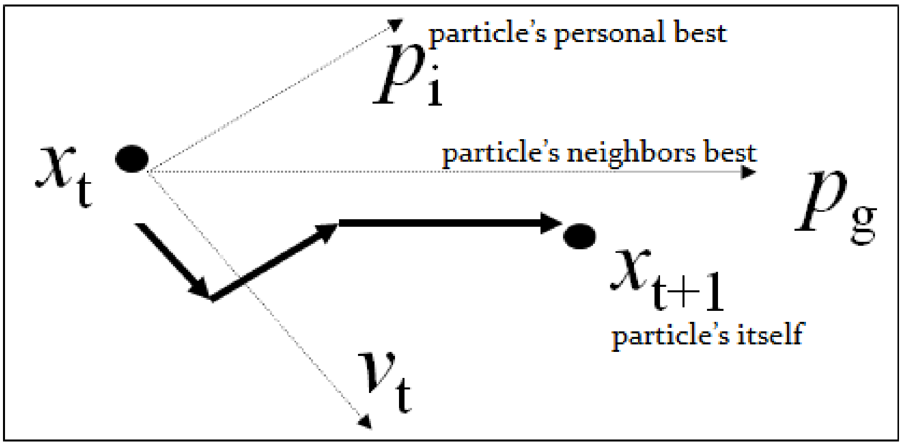

Fig. 3.5 Basic mathematical équations in PSO:

$$\vec{v}_i(t) = \varphi\, v_i(t-1) + r_1 c_1 (\vec{x}_{pbest_i} - \vec{x}_i(t)) + r_2 c_2 (\vec{x}_{gbest} - \vec{x}_i(t))$$

$$\vec{x}_i(t) = \vec{x}_i(t-1) + \vec{v}_i(t)$$

where

$\vec{x}_{i}(t)$ is the Location of ith particle

$\vec{v}_{i}(t)$ is the Velocity of ith particle

$\vec{x}_{pbest\ i}$ is the pbest position of particle

$\vec{x}_{gbest}$ is the gbest position of swarm

r1, r2 are random numbers between 0 and 1

c1 is the acceleration factor related to gbest

c2 is the acceleration factor related to pbest

Chapter

FOUR

SIMULATION RESULTS & COMPARISON

4.1 Simulation 1

In this experiment we have used Least Mean Square (LMS) as adaptive algorithm. As we discussed previously the weights of the adaptive algorithm are not fixed, rather they are adjustable according to the external environment. First the weight value is randomly initialized. Then the input is applied to both the unknown system and the adaptive filter.

Then both the outputs are compared and the error is used to update the weights of the adaptive filter using LMS algorithm. The behaviour of the system is taken as

$$S (z) = 0.45+0.32z^{-1}+0.67z^{-2}$$

Then the process is repeated for 10000 times and the experiment is conducted for 50 times to get an average value of the learning error.

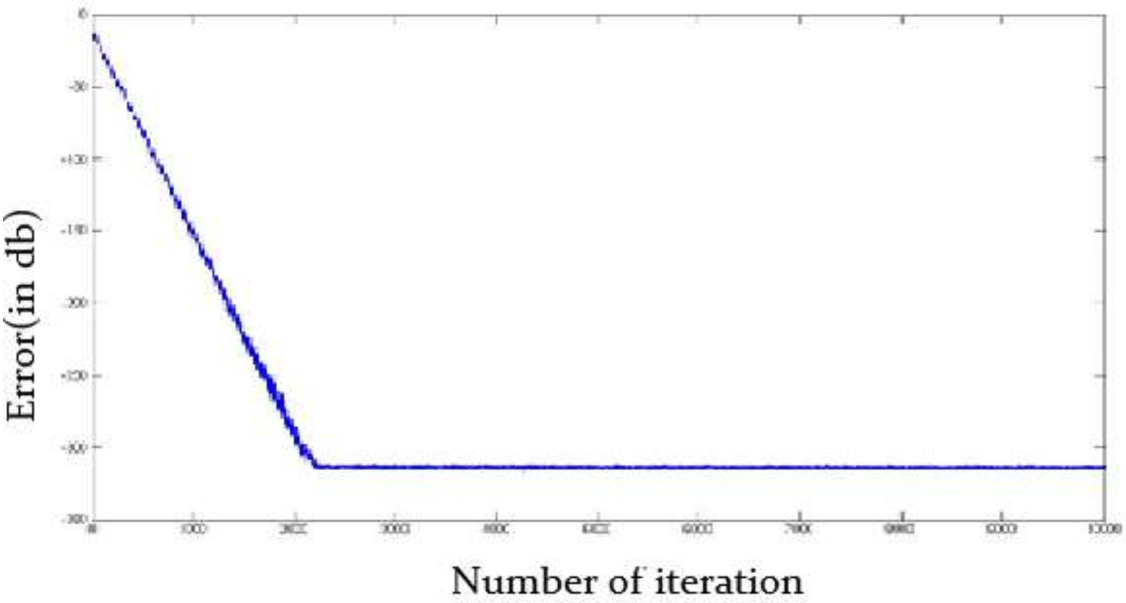

Fig 4.1. Learning error of the adaptive filter using LMS algorithm

4.2 Simulation 2

In this experiment we have used FxLMS algorithm for noise cancellation. Here due to presence of a small acoustic path from the loudspeaker to the error microphone, also known as the secondary path the weight adaptation using simple LMS algorithm does not give any result. But noise cancellation is achieved if the secondary path is identified and the input signal is filtered to update the weights. Here the primary path is taken to be $P(z) = 0.45+0.32z-1+0.67z-2$

and the secondary path is identified as

$S(z) = [0.03\ 0.05\ 0.07]$

Then the weight updating equation is used as usual.

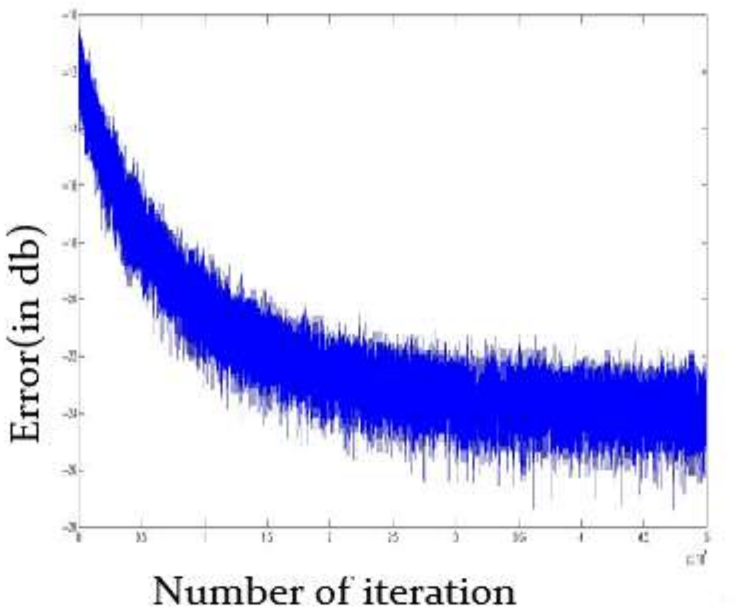

Fig. 4.2 Learning error of FxLMS algorithm

4.3 Simulation 3

In this experiment I have tried to compare the behavior of system with FxLMS in presence of linear noise input- environment with non-linear noise environment. Three different graph plotted shows the behavior of the system when the input noise is completely linear, some amount of non-linearity and when high non-linearity in the noise is present.

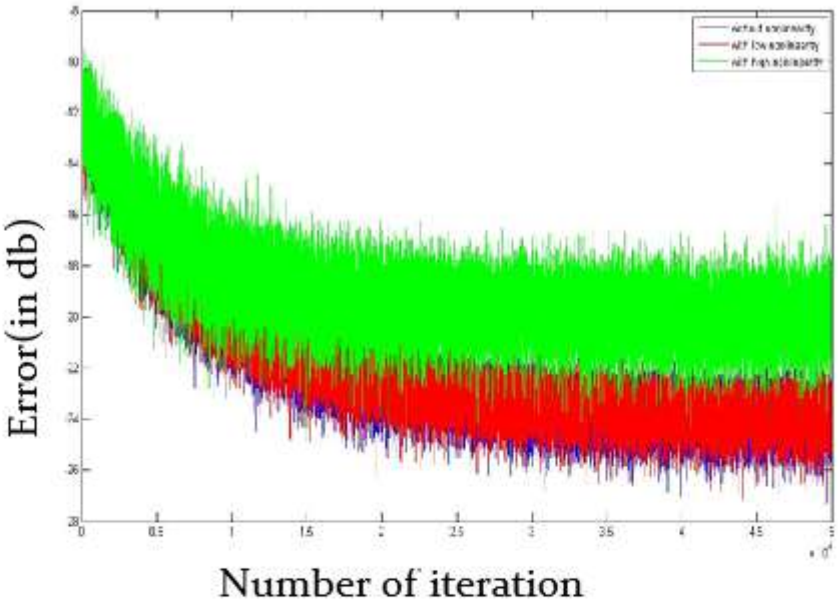

Fig. 4.3 FxLMS output in presence of non-linearity

The graph shows that when there is linear input noise the FxLMS reduces the error to maximum but as the non-linearity increases the system performance degrades to no correction in the noise in presence of highly non-linear environment.

4.4 Simulation 4

In this experiment we have added trigonometric nonlinearities in the primary path and compare the performance of FxLMS and the FLANN. The same primary paths are taken with trigonometric nonlinearity. For our simulation we take sinusoidal nonlinearity. Then the results using both cross terms and without cross terms are compared and it was found that using cross terms has better performance in terms of noise cancellation.

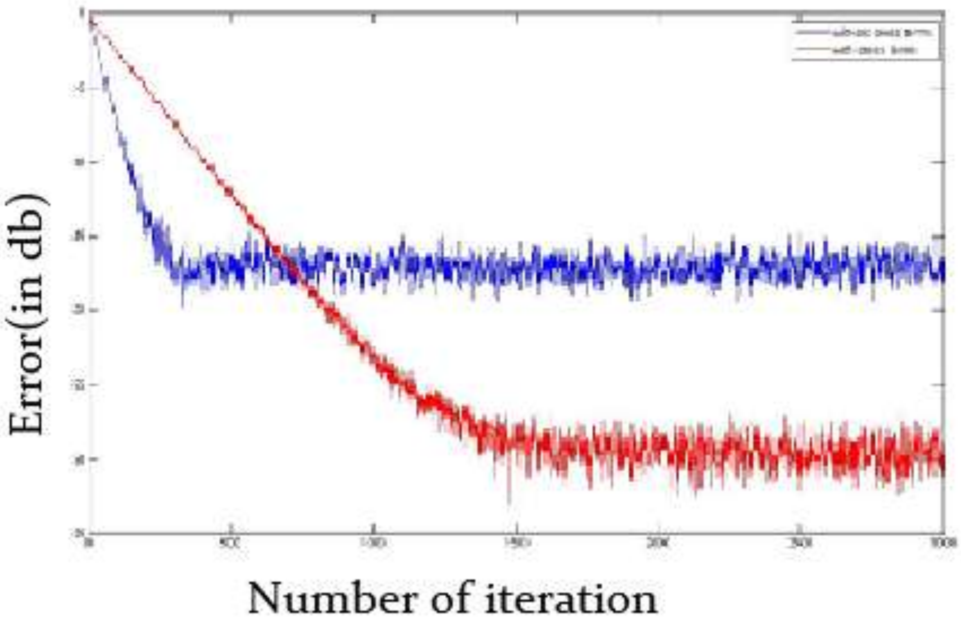

Fig. 4.4 Performance of FLANN filter using and without using cross-terms

4.5 Simulation 5

Keeping the noise environment same and input signal as said above a comparison is shown here between the output of the FxLMS system and the FLANN Filter. The result clearly indicates that FLANN is faster as compared to FxLMS but with time the error reduction improves when FxLMS is applied. The simulation here shown was only in Linear noise environment, and hence we can conclude here ,Where FLANN is faster than FxLMS the latter gives a more accurate result when given extra time.

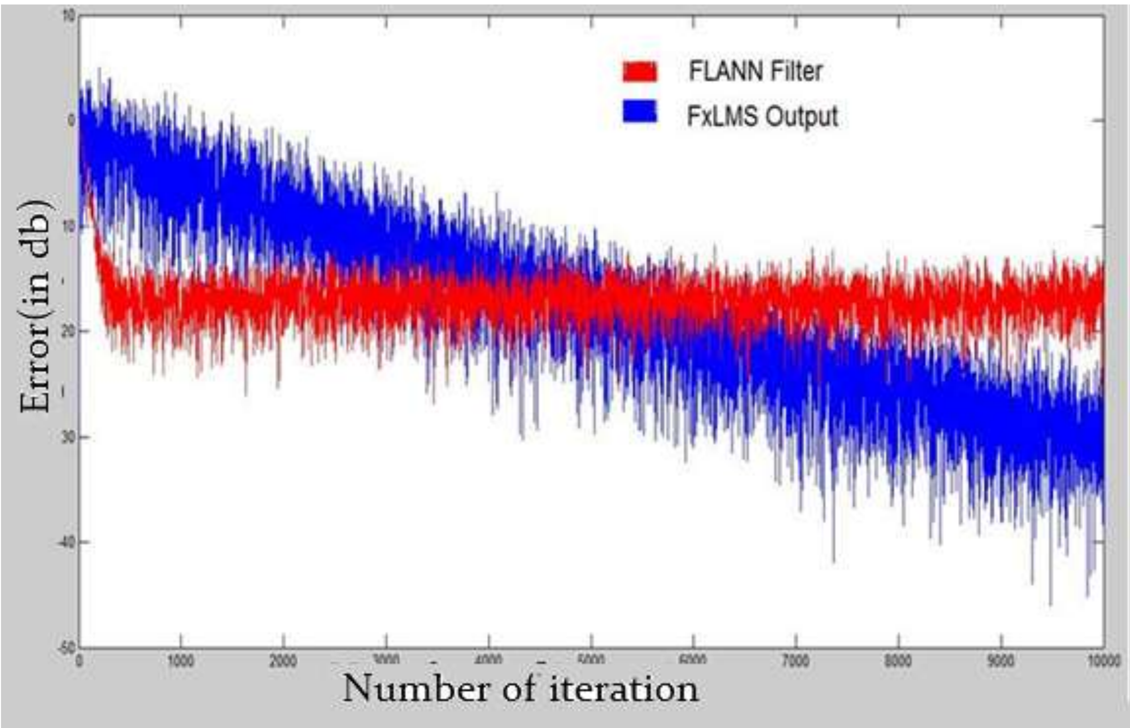

Fig. 4.5 Performance of FxLMS compared to FLANN Filter

4.6 Simulation 6

In this we introduce the PSO algorithm for improved performance in noise cancellation. The convergence speed of the algorithm is good as well as convergence of system to a global minima makes it a very good choice for implementation. This algorithm can also be applied to nonlinear systems with better performance.

In our work, we have plotted the global best result of all the particles initialized, which represents the best fitness value.

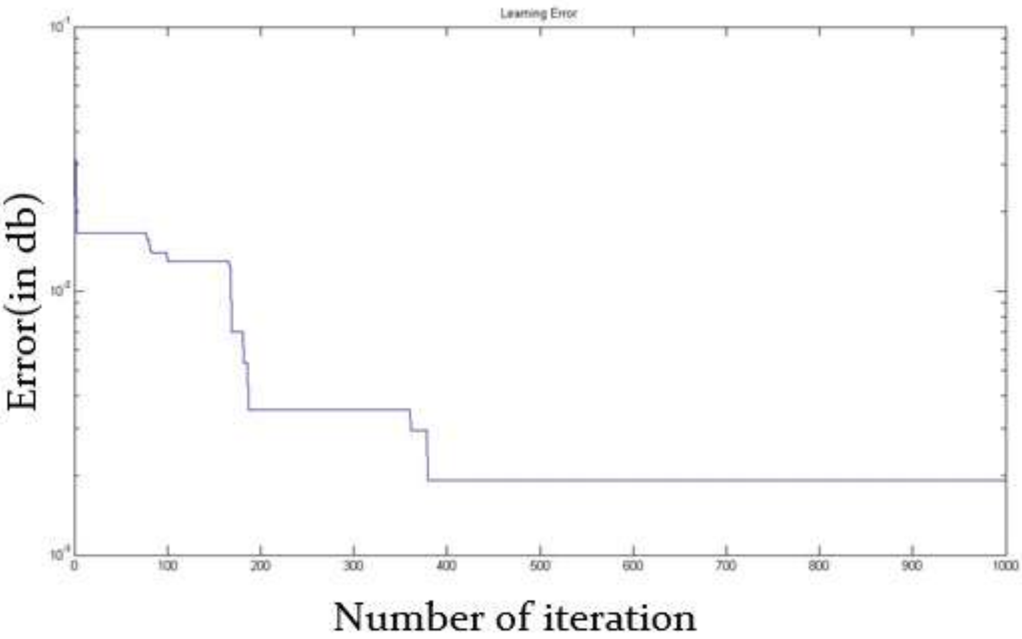

Fig. 4.6 Performance of PSO algorithm

Chapter

FIVE

CONCLUSION

Various algorithms for Active Noise Cancellation have been studied and compared. Four models for the cancellation of Noise have been discussed, LMS Algorithm, Filtered-x LMS algorithm, FLANN Filter, Particle Swarm Optimization Algorithm. Where, the first two algorithms are used mainly in the presence of linear noise varying environment, the latter two have successful implementation in the presence of linear as well as non-linear noise. The results show that Filtered-x LMS provides better attenuation to noise as compared to counterpart LMS Algorithm which is simple and easy to implement, comparatively. FLANN Filter gives a better output compared to the other two in the presence of non-linearity, though the error increases as the non-linearity in the environment increases. FLANN discussed here is without considering the cross-terms. If cross-terms are included the error will further reduce but the complexity and the cost of the controller increases. PSO technique is by far one of the latest developed Genetical Algorithm which gives minimum error considering. The particle rushes to the global minima position by comparing their present positions to their pbest and gbest.

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