



Echo Cancellation using PMSAF and Compare the performance with NLMS and improved PNLMS under different Impulse responses

Mohsin Ali
Muhammad Jamal Nasir

This thesis is presented as part of Degree of
Master of Science in Electrical Engineering

Blekinge Institute of Technology
December 2012

Blekinge Institute of Technology
School of Engineering
Department of Applied Signal Processing
Supervisor: Christian Schüldt

ABSTRACT

In the field of signal processing adaptive filtering is a major subject which has vast applications in speech processing e.g. speech coding, speech enhancement, echo cancellation and interference.

Echo is the major problem in the communication systems. There are two major types of echoes hybrid and acoustic echoes. In order to remove these echoes the most important method for removing these echoes is through cancellation. Adaptive filters are used to estimate the replication of echoes and then subtracted from the infected signal.

We introduced subband filters to improve the performance of adaptive filter (time domain). Due to small adaptive filters in the subband filter banks, we can improve the reduction of complexity, computational and convergence level as compared with others.

The major goal of this thesis is to present the echo cancellation using the multiband subband adaptive filtering and also compare the performance with NLMS and Improved PNLMS using different impulse responses. PMSAF algorithm behaves continuously better convergence rate with excitation signal (colored noise and speech signal) for both impulse responses (sparse and dispersive) as compared with IPNLMS and NLMS algorithms.

Keywords: Echo cancellation, IPNLMS, MSAF, NLMS, PNLMS, SAF.

Acknowledgement

We would like to thank all the following people for their support in completing this thesis work.

Christian Schüldt, our thesis supervisor, for their moral support and guidance throughout the thesis that helped us a lot.

Most importantly special thanks to our family for their support and love all the time.

To our class fellow, for their truly generous help through out the time span of engineering studies. They acted like real brothers and sisters who are really rare.

Finally, we say thanks to almighty Allah who always bless us and without His blessing this journey would not have been possible for us.

Mohsin Ali
Muhammad Jamal Nasir

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LIST OF ACRONYMS

AR	Autoregressive
IPNLMS	Improved proportionate NLMS
LMS	Least Mean square
MSAF	Mutilband SAF
MSE	Mean square error
NLMS	Normalized LMS
PNLMS	Proportionate NLMS
PQMF	Pseudo QMF
QMF	Quadrature mirror filter
SAF	Sub-band Adaptive filtering
SI	Sparse Index
SNR	Signal to noise ratio

Introduction

1.1 Usefulness of Echo Cancellation

Mobile communication or wireless phones have become need of everyone in this technological era of global communication. Wireless phones not only provide voice communication, they can also easily be used for other services. But voice quality is always preferable over other services of cellular networks. There is always tug of war among different wireless network providers in providing outstanding voice quality over services to the subscribers. This demand of superior voice quality, just nearly as like as wired line, over a wireless network has developed a technical term known as echo cancellation.

The quality of speech reflects the overall quality of network which shows the effectual deduction of echoes. There are two sources of echo inherited in telecommunication network infrastructure namely as acoustic echoes and hybrid echoes [1]. Adequate amount of research in the field of echo cancellation has been done in order to achieve good voice quality. Thus by applying echo cancellation techniques, quality of speech is significantly improved. More detail of echo and its problems are thoroughly discussed in this chapter.

1.2 Types of Echoes

There are two types of echo in telecommunication networks and one source for echo is acoustic and the other is electrical [1]. The reason behind the echo is impedance mismatch.

In Public Switched Telephony Network (PSTN) exchange subscriber's two –wire lines are connected with four-wire lines. During the communication between two fixed telephones only electrical echo can occur or can be observed. But with the development of teleconferencing systems which can be even hand-free gave rise to other kind of echo known as acoustic echo. This acoustic echo is due to the coupling between microphone and the loudspeaker [2]. These acoustic and electrical echoes are further discussed in chapter 2.

1.3 Echo Cancellation Process

The echo canceller is a device which detects and removes echo of signal from far away from end and it is further echoed on local end's equipment. While in case of long distance circuit switched networks, these echo cancellers devices reside in Metropolitan central office which connects long distance networks. The echo canceller devices can remove electrical echoes from long distance networks.

The Echo canceller contains three functional components. The block diagram of echo canceller shown in figure 1.

1. Doubletalk detector
2. Adaptive filter
3. Non-Linear processor

This chapter describes short overview of these components and chapter 3 provides detailed sketch and mathematical illustration of these components.

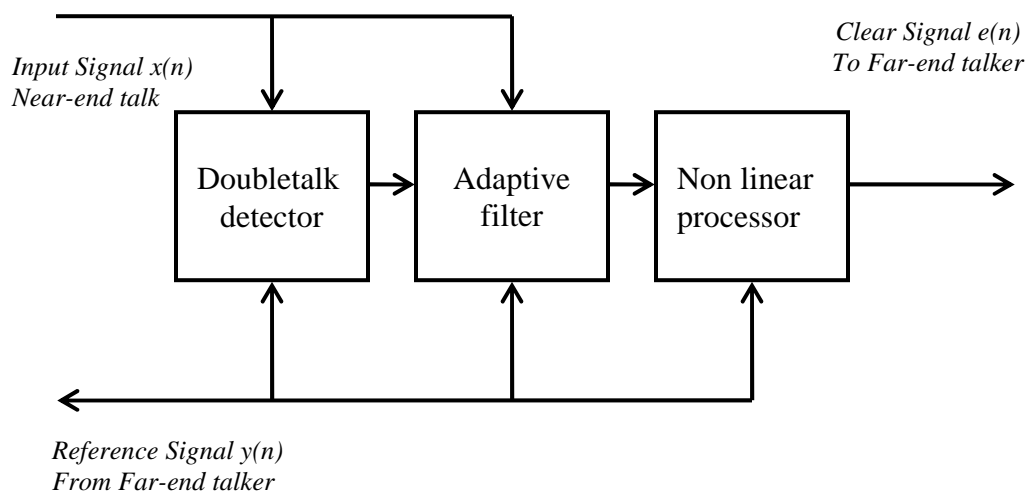


Figure 1.1: Block diagram of Echo Canceller

1.3.1 Doubletalk detector

The doubletalk detector is used with echo canceller to sense when near-end speech corrupts far-end speech. The main role of this function freezes the adaptation of model filter when near-end speech is there. This function of doubletalk detector prevents divergence of adaptive algorithm.

1.3.2 Adaptive filter

The adaptive filter consists of echo estimator and subtractor, echo estimator functionality is to monitor received path and to build a dynamic mathematical model for the line which creates returning echo.

The Mathematical model of line can be convolved with voice stream on received path, this can produce estimate of echo which is applied on subtractor. The function of subtractor

is to eliminate the linear part from the echo in sending path. The echo canceller converge the echo on the basis of estimate of line made by adaptive filter.

1.3.3 Non-Linear processor

The non-linear processor evaluates the residual echo, which is the amount of echo left after the signal is passed through adaptive filter. The non-linear processor function is to remove signals below a certain threshold; these removed signals are replaced with simulated background noise which is just like original background noise but without any echo.

1.4 Challenges of Echo Cancellation

In order to perform robust echo cancellation an echo canceller should be able to deal with a number of challenges. Some of them are illustrated as below.

1.4.1 Divergence Avoidance

Divergence is a problem due to adaptive filter and it arises when an appropriate solution for line model is not available through the mathematical model algorithm. Due to certain conditions, some certain algorithms can diverge and corrupt signals or some time can add echo to line. To solve this echo cancellers are tuned in such a way that they can avoid divergence and can handle different situation in all conditions.

1.4.2 Handling Doubletalk

During an active conversation, normally both persons speak at same time or may interrupt each other. These kinds of situations are known as “doubletalk”. This doubletalk presents special challenge to the echo cancellers. Doubletalk works as follows

1. X speaks: Echo canceller compares received speech of speaker X to what would be transmitted to speaker X, in order to reach an approximate echo point.
2. Y speaks on the echo signal and it constitutes doubletalk. Echo canceller should detect doubletalk and cancel echo without any effect on local voice, which are Speaker Y words.
3. Echo canceller should send Y’s speech and echo-cancelled version of X’s speech as well back to X.

It is challenging to handle doubletalk in such a way that it sounds natural and in this regard a good echo canceller should be able to handle following.

1.5 Research Motivation and Thesis outline

Today personal computers have tremendous features and powerful software has been evolved which make real-time signal processing possible in personal computers environment. The advancement in the technology capability was the motivation behind this research. The objective of this research was to implement simulation based echo canceller which can run on simple personal computer using MATLAB simulations.

This research provides overview of improved echo cancellation and the convergence rate. In this research chapter 1 describes echo definition, necessity of echo cancellers with in communication networks, basics and challenges of echo cancellations. Chapter 2 provides overview of sources and types of echo. It describes echo phenomena in communication systems. Chapter 3 discusses Multirate systems and filter banks and chapter 4 describes Multiband subband adaptive filtering algorithm. Chapter 5 describes different adaptive algorithms and chapter 6 provides details regarding the simulation environment and results. At the end in chapter 7 Summary of research and future work are discussed.

Echoes in Communication networks

Chapter 1 describes the basics and types of an echo while in this chapter communication networks echo problems will be covered.

2.1 Hybrid/Electric Echo

Since the age of telephony, electrical echo also called hybrid echoes are the main cause of distortion which is due to impedance mismatch in an analog local loop [2]. Hybrids are used in PSTN (Public Switched Telephone Network) which is main foundation of electrical echo. This hybrid consists of four wired trunk through which it connects local exchange to another distant exchange and also two-wire local loop circuit for subscriber's connection as shown in figure 2.1.

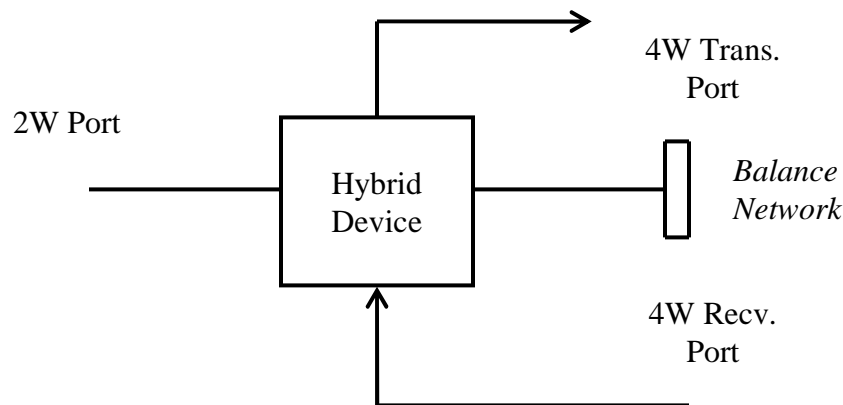


Figure 2.1: Hybrid Echo

Electrical mainly affect the long distance calls as compared to short distant calls since delay is proportional to distance. The function of the hybrid is to send/receive signal from two-wire subscriber circuit using four-wired trunk. The local loop of two-wire circuit is two separate pair of wires; one is used for transmission and other for receiving. Transmission path between two-wire local loop and four-wire trunk causes impedance mismatch due to which a portion of received signal is bounced back to speaker.

2.2 Acoustic Echo

Acoustic echoes arise from reflection of voice with different objects, like wall, room, earpiece in the same headset etc., to the microphone of the headset [3]. That is why acoustic echoes are also known as multipath echoes. Acoustic echoes have become more important to adaptive cancellation as new technological hands free communications are introduced like videoconferencing or teleconferencing. Echo cancellation of such echoes is very challenging because the input echo can arrive at any time instant and their behavior is highly unpredictable. However the case can be different in network echo cancellation.

2.3 Problems with Hybrid and Acoustic Echoes

Both acoustic and network echo paths have different problems. Some of them are:

Stationary Signal

The echo in network path is more stationary as compared to echo in acoustic path. Because head set can pick any kind of signal like reflected wave, car movement or people talking in a room etc.

Linearity and Impulse Response

The network path has a shorter impulse response as compared to acoustic echo path. Network echo path has a linear characteristic because loudspeaker of headset does not allow nonlinearity signals whereas acoustic signals are mixture of linear and nonlinear in case of acoustic echo path. That is why for producing fast converging algorithm AEC needs to have high computational power [4].

Multirate Systems

3.1 Basics Fundamentals of Multirate Systems

Multirate digital signal processing has so much attention over the last some decades for the applications in subband speech coding, multiple carrier data transmission, audio video coding, etc [5-6]. An important feature of Multirate system can increase or decrease the sampling rate after or before processing of individual signal and then different sampling rate signal simultaneously processed in different part of Multirate system. Secondly Multirate systems are high computational efficiency [5,7].

Most important applications of Multirate digital signal processing are Digital filter banks. Last few years there are great numbers of filter bank have been developed. Among all filter banks, Discrete Fourier Transform (DFT) polyphase filter bank [4] is very popular that gives high computational efficiency but the main disadvantage is that it has low capability to cancel alias components which occurred by sub sampling. Cosine Modulated filter bank are very easy to implement and gives perfect reconstruction of the desired signal [8-9]. Modified DFT filterbanks also gives Perfect reconstruction [10].

3.2 Sampling Rate Conversion

To identify the basics of multirate systems, it is important to know how the sampling rate increases or decreases [5]. There are two simple sampling rate conversion operations: Upsampling (increase the sampling rate) and Down sampling (decrease the sampling rate).

3.3 Downsampling

Downsampling simply decreases the sampling rate. Downsampling requires where the sampling rate was significantly greater than the bandwidth. The downsampling output can be written as

$$y[m] = x[n] \mid_{n=mM} \text{ for } n= 0,1,2,\dots N; m= 0,1,2,\dots N/M$$

Where M is the downsampling factor shown in figure 3.1, $x[n]$ is the input signal with high sampling rate converts it into low sampling rate output signal $y[m]$ keeping every M th sampling and rejected all other.

The simple relationship of downsampling can be described as below

$$F_{s_Low} = F_{s_high} / M$$

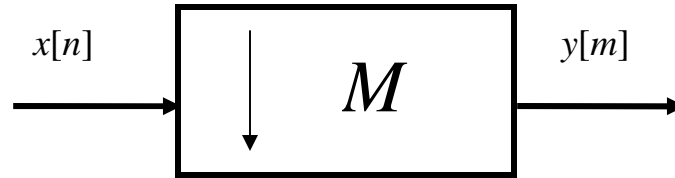


Figure 3.1: Downsampler

3.4 Upsampling

Upsampling simply increases the sampling rate by adding zero valued in between the original samples. Upsampling requires where the output of one system operates at lower sampling rate can processed with the higher sampling rate system. The upsampling output can be written as

$$y[n] = x[m] \mid \begin{matrix} m=n/L & \text{for } m \in \text{integer, } y[n]=0 & \text{otherwise} \\ n=0,1,2,\dots N; & m=0,1,2,\dots N/L \end{matrix}$$

Where L is the upsampling factor shown in figure 3.2, $x[n]$ is the input signal with low sampling rate converts it into high sampling rate output signal $y[m]$ every samples by adding $L-1$ zeros between the input signals.

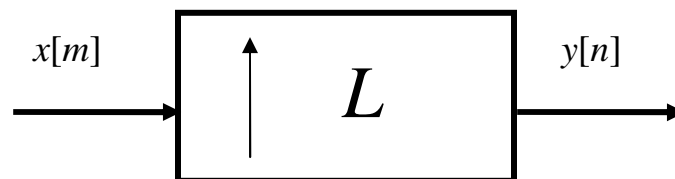


Figure 3.2: Upsampler

3.5 Decimation

Decimation is the method of filtering and downsampling. When we downsample a signal by rejected away the intermediate samples, this will cause of aliasing. To prevent or remove this aliasing we uses anti aliasing low pass filter $H(z)$ before the downsampler as shown in figure 3.3.

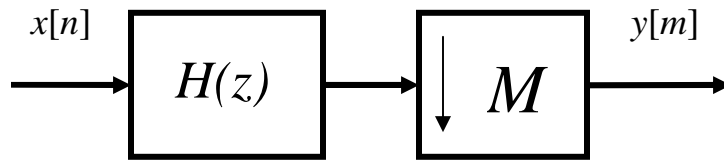


Figure 3.3: Decimator

3.6 Interpolation

Interpolation is the method of upsampling and filtering. When we upsample a signal by adding zeros samples, this will cause of extra spectral copies. To prevent or remove this we uses anti image low pass filter $G(z)$ after the upsampler as shown in figure 3.4.

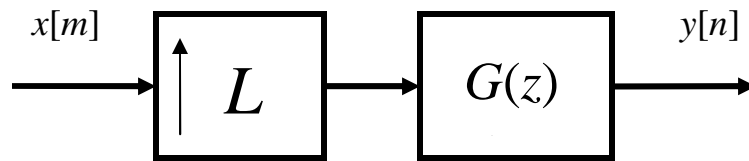


Figure 3.4: Interpolator

3.7 Noble Identities

The noble identities explain the reverse ordering property of downsampling/upsampling and filtering [11]. Noble identities for interpolation and decimation are shown in figure 3.5.

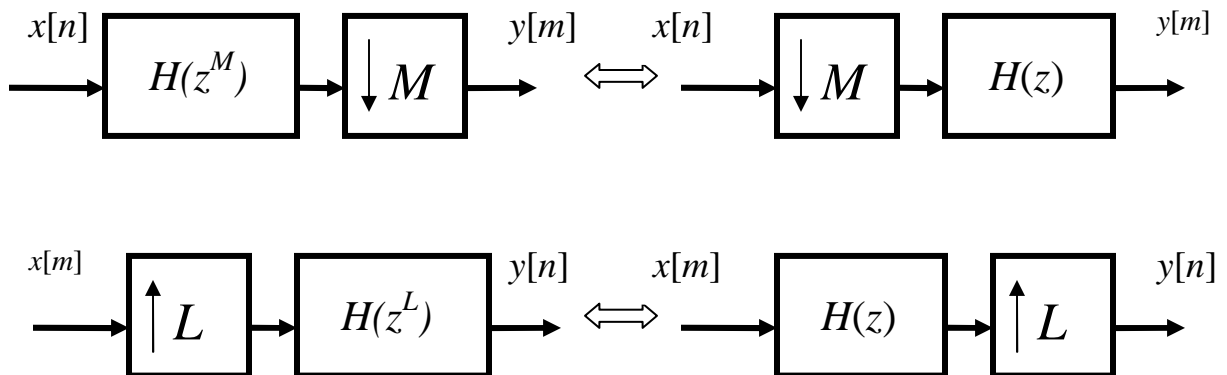


Figure 3.5: Noble Identities for (a) decimator and (b) Interpolator

3.8 Filter Bank

In the field of signal processing there are many useful applications, like to separate a full band signal into different ranges of frequency called sub-bands [5,11,13,14]. The full band spectrum portioned in the identical manner as shown in figure 3.6 (Ref: Connexions, by Phil Schniter), each sub-band has identical sub-band width $\Delta k = 2\pi / M$ and band centers are also identical intervals of $2\pi / M$.

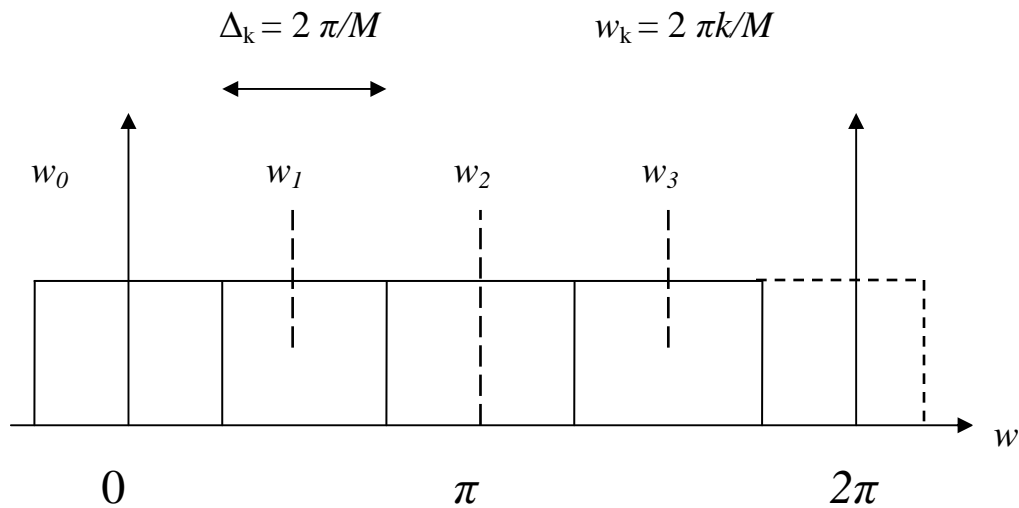


Figure 3.6: Uniform Spectrum

In our case, we will only discuss on identical spaced sub-bands. We can also have non identical spacing. The basic goal of sub-band signal separation is to make other processing more helpful or convenient.

When all filters are having equal bandwidth and centre frequencies are uniformly spaced of bandpass filters then that filter bank is called uniform filter bank. If N is the number of subbands and $X_i(n)$ is subband signal then by decomposition of fully band signal using N -channel uniform filter bank we get each subband signal which contains $1/N$ of original spectral band only. The decimation of the subband signals can be $1/N$ of original sampling rate because the BW is $1/N$ of the original signal $X(n)$. Thus subbands signals are $1/N$ of the original signal bandwidth wise while maintain the original data. When decimation factor is equal to no. of subbands, i.e. $D=N$, the filter bank is known as maximally decimated filter bank. This kind of decimation keeps the sampling rate effective, with N decimated subband signals $X_{i,D}(n)$ hence providing no. of subband samples similar to fullband signal $X(n)$. While synthesizing the interpolation of decimated subband signals are done by the same factor putting it by the synthesis filter bank. Therefore the reconstructed fullband signal $Y(n)$ contains the original sampling rate.

Standard structure of an N -channel or N -band filter bank as shown in figure 3.7 where $H_i(z)$ are the analysis filters $\{ H_0(z), H_1(z) \dots H_{N-1}(z) \}$ and $G_i(z)$ are the synthesis filters $\{ G_0(z), G_1(z) \dots G_{N-1}(z) \}$ and sub-band index $i = 0, 1 \dots, N-1$. The incoming signal $X(n)$ for the analysis filter bank partitions into N sub-band signals. The output signal $Y(n)$ reconstruct by the synthesis filter bank to approximate the input signal.

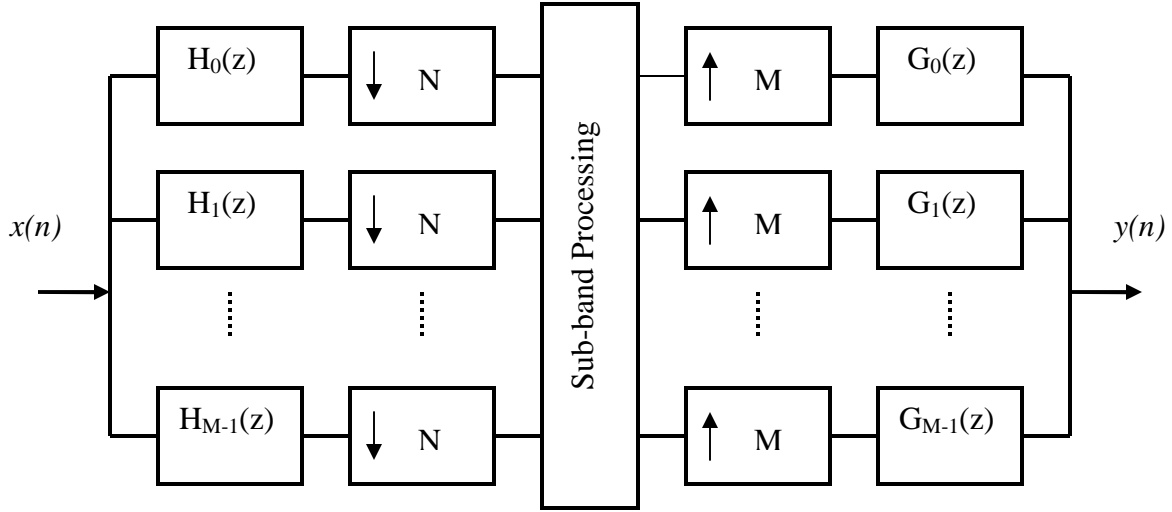


Figure 3.7: Standard structure of N-band filter bank

3.9 Cosine modulated filter Bank

Theory and design of cosine modulated filter banks are reported in the literature [11-12]. The figure 3.8 (a) depicts a low pass filter $P(z)$ with cutoff frequency $\pi/2N$ in frequency domain. Both analysis and synthesis filters are cosine modulated description of prototype low pass filter $P(z)$.

The cosine-modulated analysis filters can be derived as:

$$H_i(z) = \alpha_i P \left[z W_{2N}^{(i+0.5)} \right] + \alpha_i^* P \left[z W_{2N}^{-(i+0.5)} \right], \quad i = 0, 1, \dots, N-1 \quad (1)$$

Where $W_{2N} = e^{-j\pi/N}$ is the unity root of $2N$ th and α_i is unit magnitude constant.

$$\alpha_i = \exp \left\{ j \left[\theta_i - \frac{\pi}{N} (i + 0.5) \left(\frac{L-1}{2} \right) \right] \right\}, \quad \theta_i = (-1)^i \frac{\pi}{4} \quad (2)$$

here L is the length of prototype filter. Above is the cosine modulated analysis filter in order to obtain synthesis filters we can apply time reversing on analysis filters in the form

$$F_i(z) = z^{-L+1} H_i(z^{-1}) \quad (3)$$

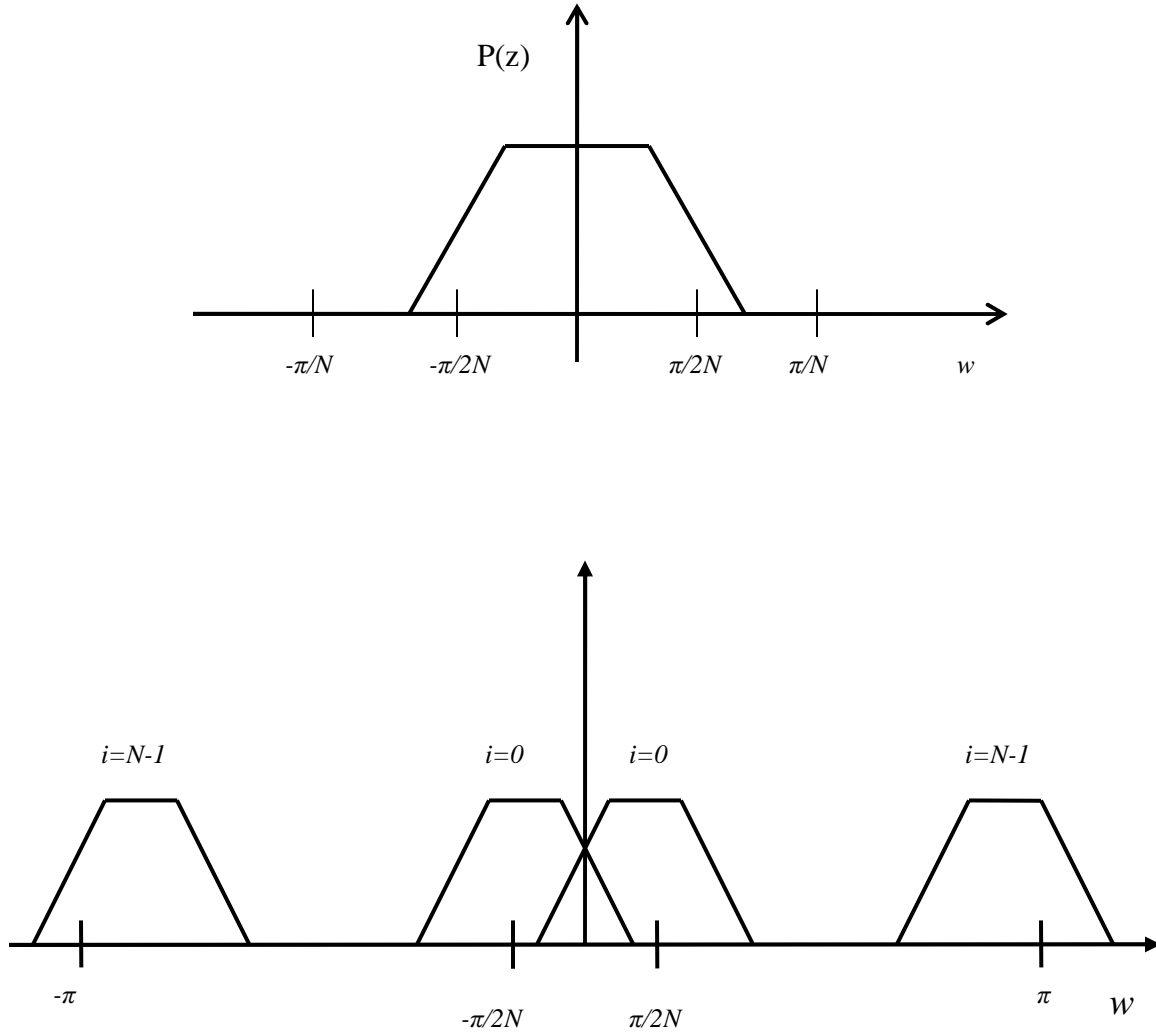


Figure 3.8: Cosine modulated for: (a) frequency response of prototype low pass filter and (b) frequency response of analysis filter

$$P \left[z W_{2N}^{-(i+0.5)} \right] = P \left[z e^{j \frac{\pi}{N} (i+0.5)} \right] \quad (4)$$

$$P \left[z W_{2N}^{(i+0.5)} \right] = P \left[z e^{-j \frac{\pi}{N}(i+0.5)} \right] \quad (5)$$

The output is a linear phase filter of the prototype with real valued symmetric $p(z)$ impulse response. But the cosine modulation in synthesis and analysis filters doesn't give linear phase. However the time reversing property results in linear phase. Also $T(z)$ the distortion transfer function gives a linear phase as shown below. Hence the design of prototype filter minimizes complexity in the design of complete filter bank and the prototype filter can be optimized in a way with the help of predefined constraints for the approximate perfect reconstruction of synthesis or analysis system [15].

$$T(e^{jw}) = \frac{1}{N} \sum_{i=0}^{N-1} F_i(e^{jw}) H_i(e^{jw}) \quad (6)$$

$$T(e^{jw}) = \frac{1}{N} \sum_{i=0}^{N-1} \left[e^{-jw(L-1)} \tilde{H}_i(e^{jw}) \right] H_i(e^{jw}) \quad (7)$$

$$T(e^{jw}) = \frac{1}{N} \sum_{i=0}^{N-1} e^{-jw(L-1)} H_i^*(e^{jw}) H_i(e^{jw}) \quad (8)$$

$$T(e^{jw}) = \frac{e^{-jw(L-1)}}{N} \sum_{i=0}^{N-1} \left| H_i(e^{jw}) \right|^2 \quad (9)$$

As from equation (1) and figure 3.8 (b), $P(z)$ generated two complex conjugate pair of complex valued filters due to complex modulation embedded in cosine modulated analysis filter $H_i(z)$. Combination of these impulse responses gives $H_i(z)$ and thus $F_i(z)$ synthesis filter's real valued impulse responses are as follows:

$$h_i(n) = 2p(n) \cos \left[\frac{\pi}{N} (i + 0.5) \left(n - \frac{L-1}{2} \right) + \theta_i \right] \quad (10)$$

$$f_i(n) = 2p(n) \cos \left[\frac{\pi}{N} (i + 0.5) \left(n - \frac{L-1}{2} \right) - \theta_i \right] \quad (11)$$

Multiband Subband Adaptive filters

4.1 Subband adaptive filters

The input signal is divided into multiple bands by filter banks which lie close to each other in frequency band. In subband adaptive filter (SAF), multiple parallel channels are obtained due to the decomposition of the input thus developing the subband properties to be more efficient in signal processing [17,18]. Also computational complexity is minimized by subband systems since the signals can be decimated at a lower rate when processed with lower order sub filters.

Let $B(z)$ be an unknown system. Then a set of adaptive subfilters will be used to identify the unknown system as shown in the figure 4.1. Analysis filter $H_i(z)$, $i = 0, 1, \dots, N-1$ is used in the decomposition of desired response $d(n)$ and fullband input $u(n)$ into N spectral bands. Here n is time index for the fullband input signals. Then all of these subbands are handled by adaptive subfilters $W_i(z)$ and decimated using factors D same for all to a low rate. The desired signal and output after adaptive filters $y_{i,D}(z)$ are summarized to obtain error signal $e_{i,D}(k)$ which is put in adaptation loop into each subfilter for minimizing the subband error signal. Here k is time index for desired signal. Finally fullband error signal $u(n)$ is obtained by applying time-reversing on each subband error signals and combining them [16,17].

4.1.1 Computation reduction

The main purpose of using SAF is to minimize the computing complexity, which can also be done by using shorter length adaptive subfilters that operate at low decimated rate, and enhance the convergence performance for the input signal. Let us assume that the analysis system is real valued and unknown system $B(z)$ is represented by fully band transversal filter $W(z)$ of M length. The length can be reduced to $M_s = M/D$ of subfilters because as shown in figure that subfilters are decimated by a factor D . Now multiplying both sides by N subbands and thus the amount of multiplications required for N subfilters will become MN/D^2 . Hence it can be expressed as:

$$\frac{\text{Complexity of fullband filter}}{\text{Complexity of subfilters}} = \frac{D^2}{N} \quad (12)$$

Above equation is derived on assumption that analysis filter is real valued however the subband signals are complex for DFT filter banks. In DFT filter banks, analysis filter is in complex conjugate pair so only $N/2 + 1$ subbands are processed while N is considered even. Hence the number of complex multiplications for N subfilters will be $2MN/D^2$.

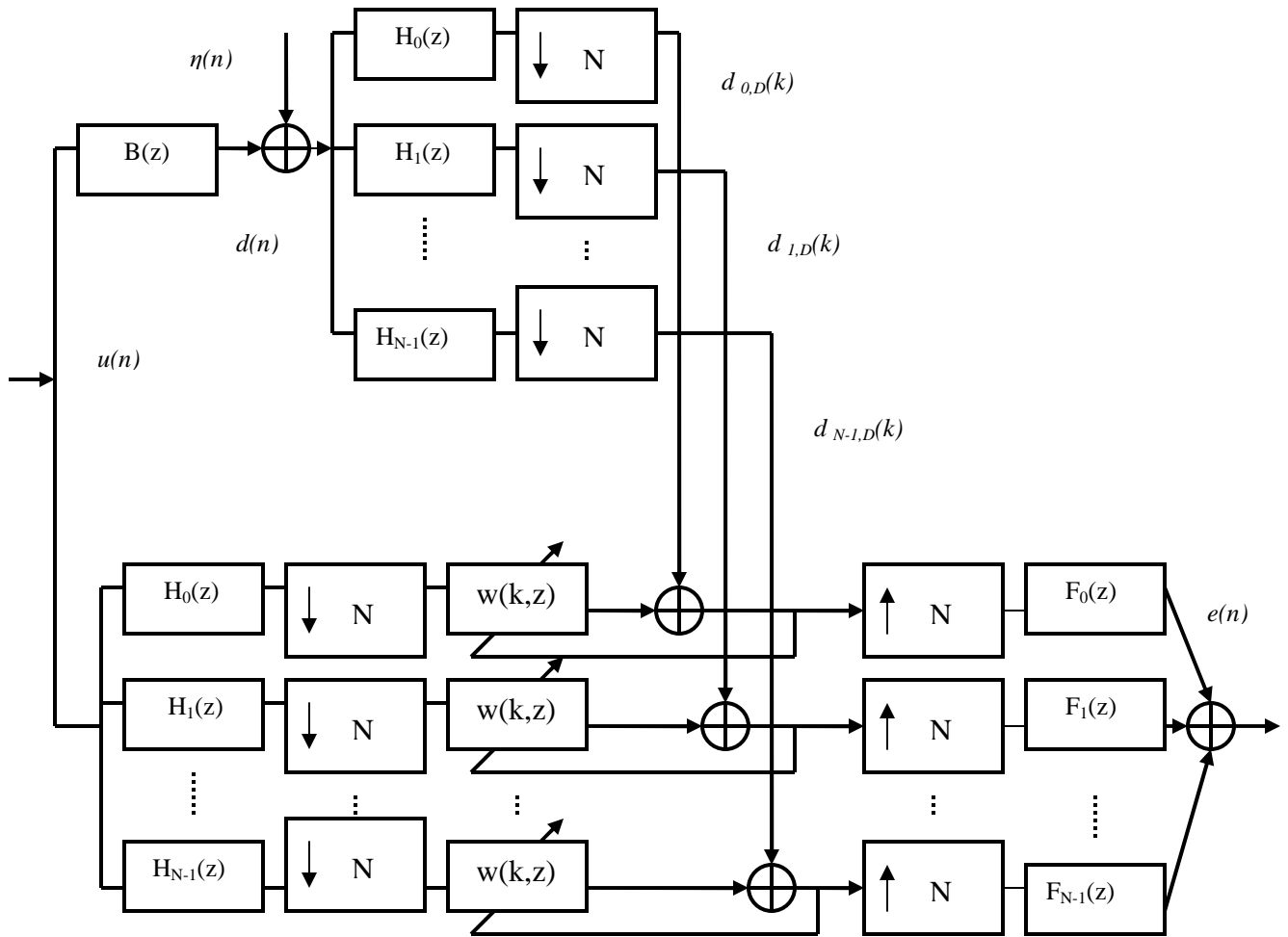


Figure 4.1: SAF using adaptive subfilters to identify unknown system

4.1.2 Spectral dynamic range

When there is high correlation in input signal LMS and NLMS (gradient based algorithms) bear very slow convergence just like as in large spectral dynamic range(SDR) of input causes huge eigenvalue spread in input autocorrelation matrix [19,20]. Critical decimation ($D=N$) minimizes the SDR after the subband decomposition. If N is the length of analysis filter which is 64 then the figure 4.2 and 4.3 shows the magnitude response of four-channel cosine modulated filter bank and power spectrum of an AR(2) (Autoregressive 2nd order) signal. The power spectrum of subband signal $\Gamma_{ii}(e^{j\omega})$ can be obtained by taking product of squared magnitude response $|H_i(e^{j\omega})|^2$ of analysis filter and signal power spectrum $\Gamma_{uu}(e^{j\omega})$. As shown in the equation below:

$$\Gamma_{i i}(e^{j\omega}) = \left| H_i(e^{j\omega}) \right|^2 \Gamma_{u u}(e^{j\omega}) \text{ for } i = 0, 1, \dots, N-1 \quad (13)$$

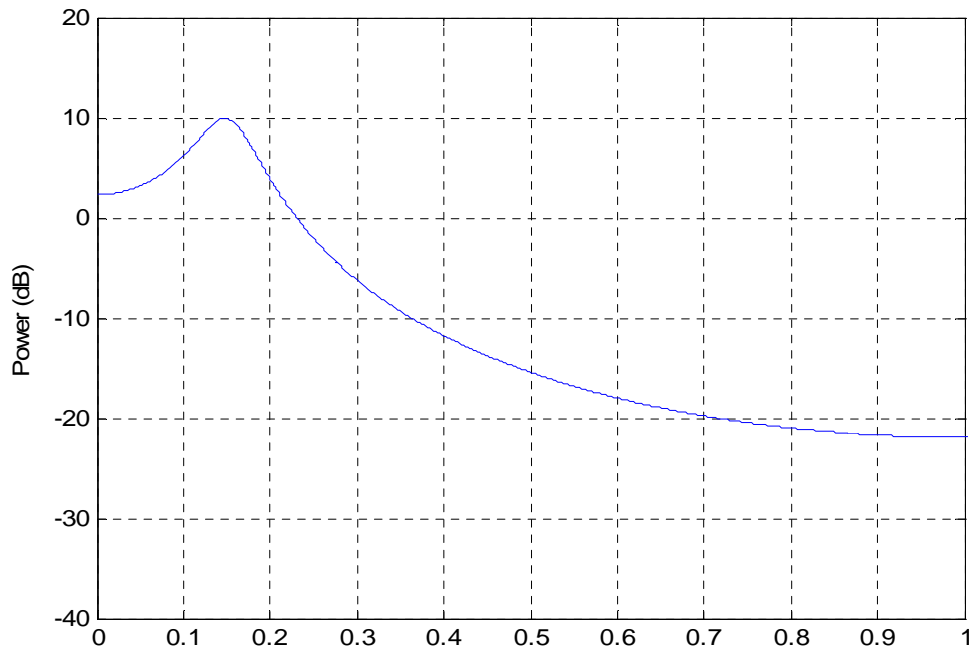


Figure 4.2: Power spectrum of AR(2) signal

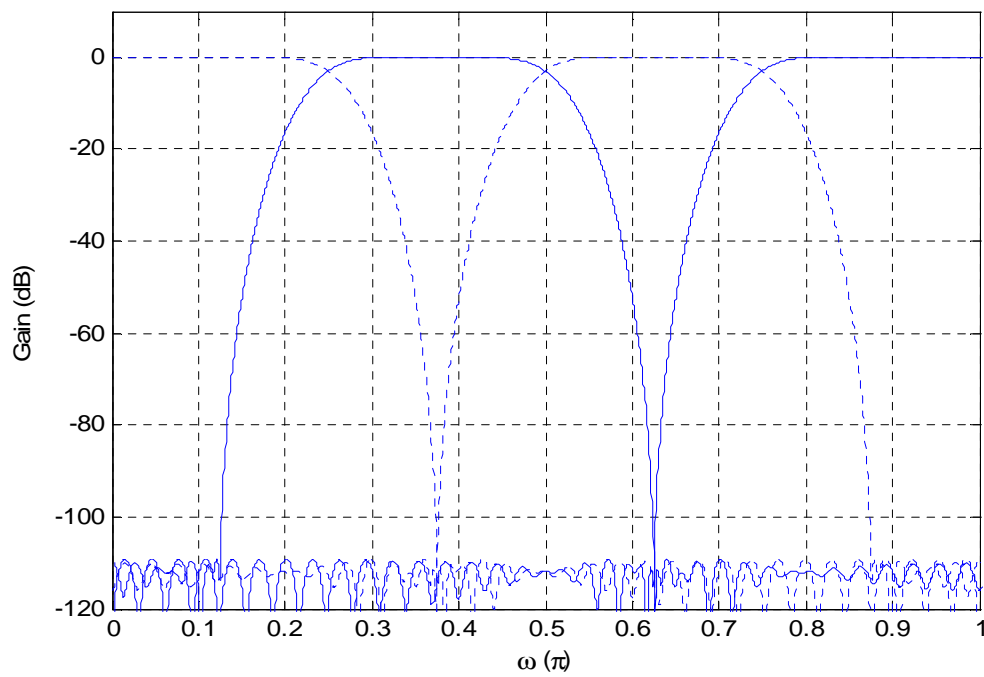


Figure 4.3: Magnitude responses of analysis filters (4-channel pseudo-QMF cosine modulated filter bank)

$$\Gamma_{i i, D}(e^{j \omega}) = \frac{1}{N} \sum_{l=0}^{N-1} \Gamma_{i i}(e^{j(\omega-2\pi l)/N}) \quad (14)$$

The power spectrum of subband signal is implemented on MATLAB and results can be seen in figure 4.4 which shows that as compared to original fullband signal $u(n)$ the subband signals have a narrower bandwidth. The frequency components of subband signals mostly lie in the pass band frequency range of analysis filter. The spectral dynamic range can be reduced by decimating the subbands signals to a lower rate. The PS for decimated version of autocorrelation function of the subband signal can be achieved as:

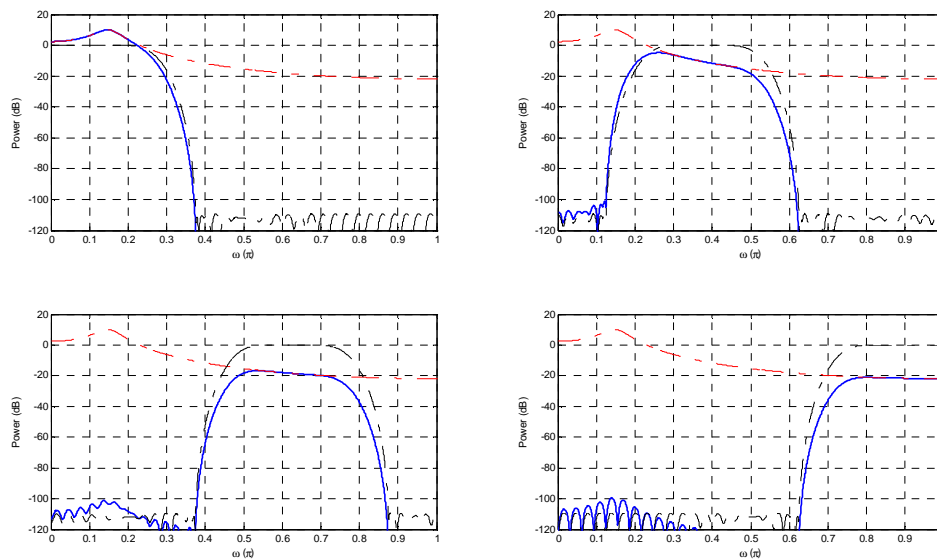


Figure 4.4: Power spectra of subband signal (blue curves), fullband spectrum (red curves) and magnitude responses (black curves)

The blue curves shows the power spectra of subband signals, red curves shows the full band spectrum and black curves shows the squared magnitude responses.

4.2 Multiband Structure

The band edge and aliasing effects cause decrease in convergence rate of subband adaptive filtering in which every subband uses independent subband adaptive filtering in its own adaptation loop. A multiband subband adaptive filtering has been introduced in order to cater the structural problems. The multiband subband adaptive filtering is based on recursive weight control mechanism in which fullband adaptive filter is restructured by input subband signals normalized by respective variances. This chapter shows the competence of multiband subband adaptive filtering algorithms while dealing with speech signals and multiband subband adaptive filtering equivalence to normalized least mean square algorithm [21, 22, 24].

As shown in the figure 4.5 [21], the filter output $y(n)$ and desired response $d(n)$ are divided into N subbands using analysis filter $H_i(z)$. Then output from analysis filter is decimated to lower rate using sampling rate of $1/N$.

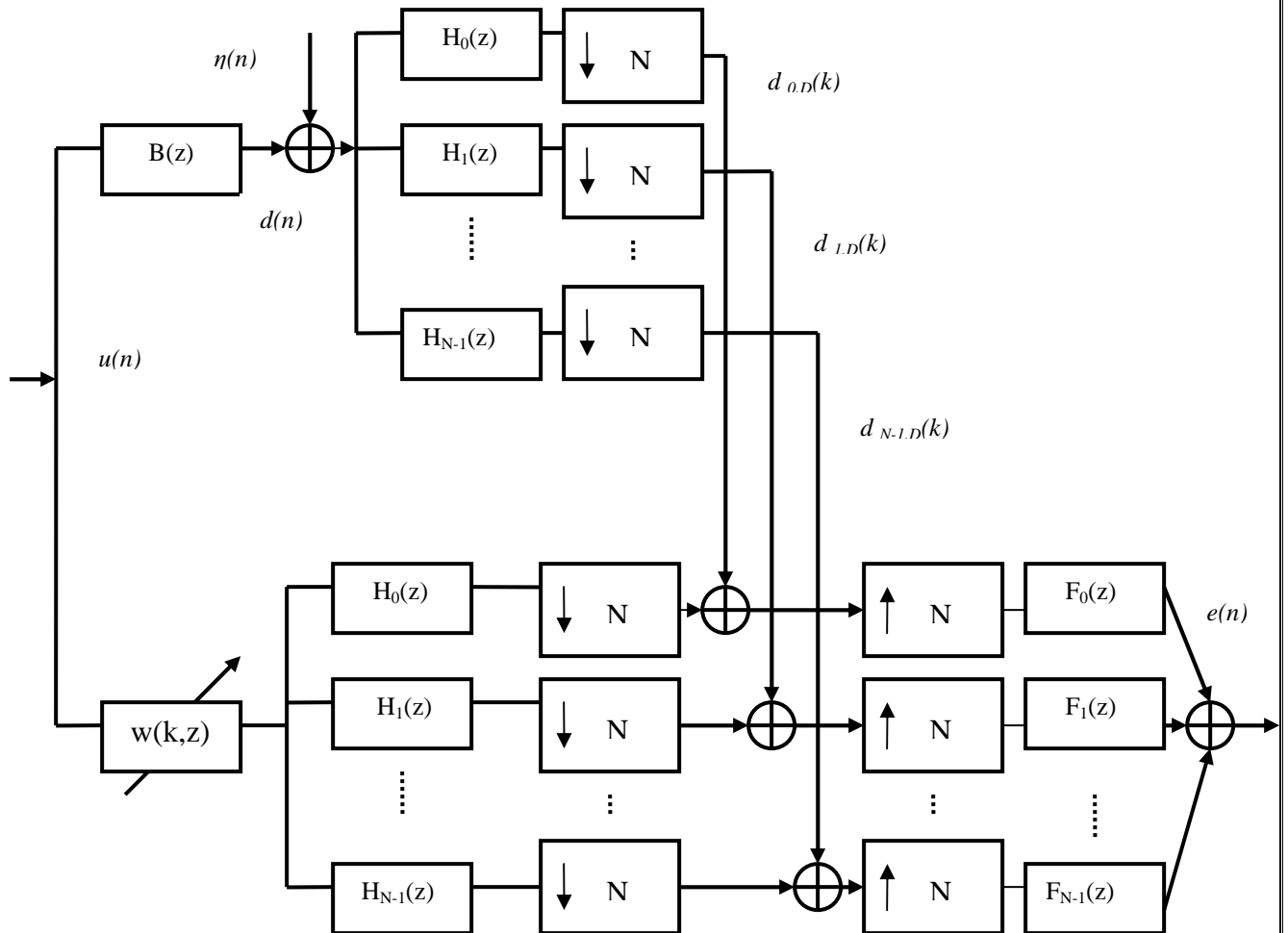


Figure 4.5: Multiband Structure

From the figure there is only single fullband adaptive subfilter. The dashed lines in figure indicate multiband system. If there is N input N output system as shown in figure 4.6.

N subband signals

$$y_i(n) = \sum_{m=0}^{M-1} w_m(k) u_i(n-m) \quad \text{for } i = 0, 1, \dots, N-1 \quad (15)$$

Decimated output subband signals

$$y_{i,D}(k) = y_i(kN) \quad (16)$$

$$y_i(n) = \sum_{m=0}^{M-1} w_m(k) u_i(kN-m) \quad (17)$$

$$y_i(n) = w^T(k) u_i(k) \quad (18)$$

Weight vector of fullband adaptive filter

$$w(k) = [w_0(k), w_1(k), \dots, w_{M-1}(k)]^T \quad (19)$$

$$u_i(k) = [u_i(kN), u_i(kN-1), \dots, u_i(kN-N+1), u_i(kN-N), \dots, u_i(kN-M+1)]^T \quad (20)$$

$$e_{i,D}(k) = d_{i,D}(k) - w^T(k) u_i(k) \text{ for } i = 0, 1, \dots, N-1 \quad (21)$$

N subband error signals

$$e_D(k) = [e_{0,D}(k), e_{1,D}(k), \dots, e_{N-1,D}(k)]^T \quad (22)$$

Subband signal matrix and desired response vector as follows:

$$U(k) = [u_0(k), u_1(k), \dots, u_{N-1}(k)] \quad (23)$$

$$d_D(k) = [d_{0,D}(k), d_{1,D}(k), \dots, d_{N-1,D}(k)]^T \quad (24)$$

Here the adaptive filters appear as parallel filters having the same $W(k,z)$ transfer function. $u_i(n)$ represents the band limited signal which is sampled at the original rate. The subband data sets $\{U(k), e_D(k)\}$ update the tap weights $\{w_m(k)\}_{m=0}$ on every iteration.

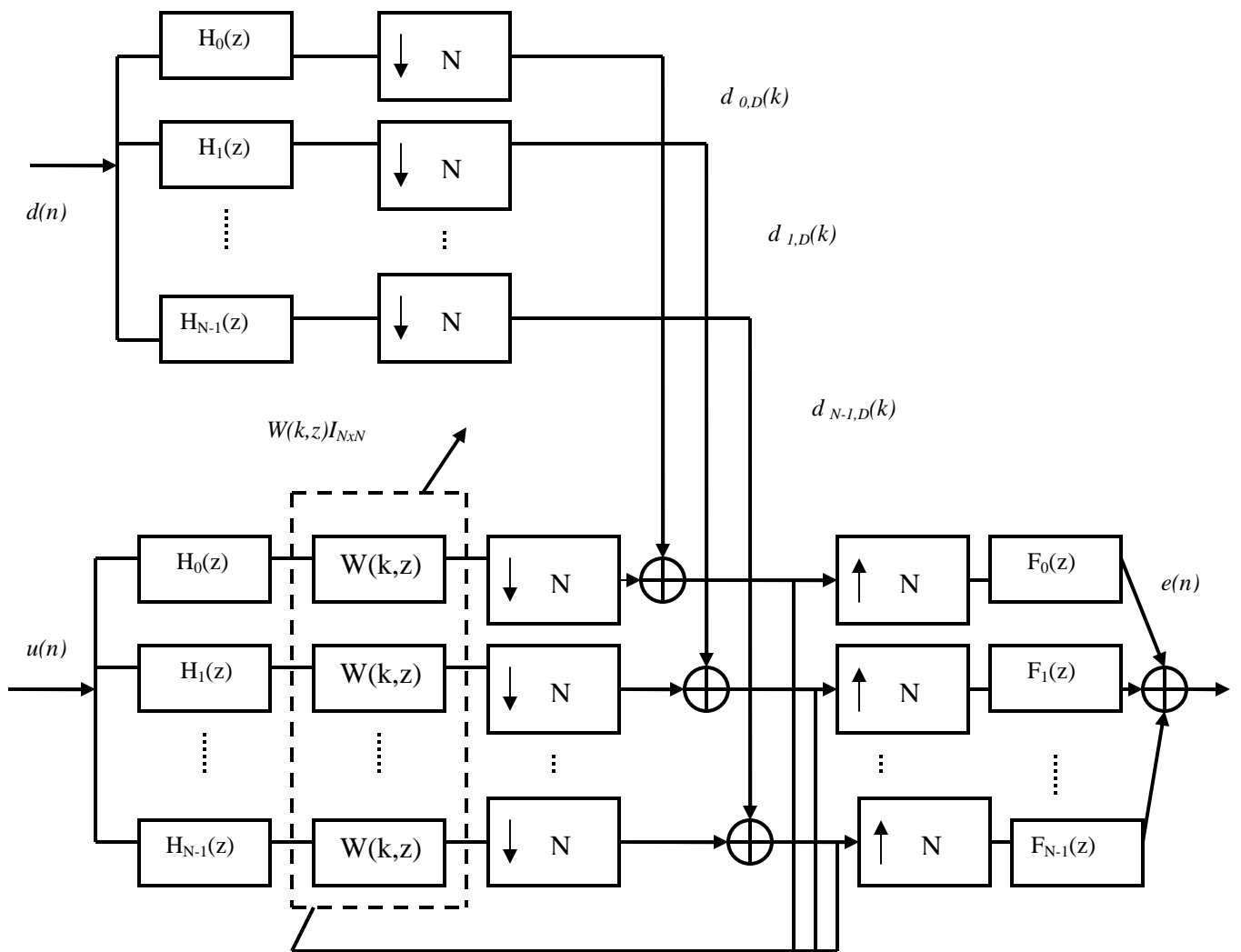


Figure 4.6: Mutiband SAF Structure

Adaptive Algorithms

5.1 Adaptive Filtering

A filter whose transfer function is automatically adjusted according to an optimization algorithm which is driven by an error signal is called Adaptive Filter [25]. But since the optimization algorithms are complex so most adaptive filters are digital filters. On the contrary a filter which has a static transfer function is a non-adaptive filter.

The optimum performance of the adaptive filter is due to the use of a cost function to nourish the algorithm. This criterion finds out how to adjust filter transfer function to minimize the cost on the next iteration.

In the modern age, adaptive filters play a vital role and can easily be found in devices which are routinely used in our life e.g. cellular phones, digital cameras some medical monitoring equipment etc [26].

5.2 NLMS and PNLMS algorithm

In this section we explain little bit the Normalized Least Mean Square and Proportionate Normalized Least Mean Square algorithms [26]. Following notation and derivations is used:

$$x(n) = \textit{Far end Signal}$$

$$y(n) = \textit{Echo Signal}$$

$$\mathbf{x}(n) = [x(n), \dots, x(n-L+1)]^T \quad \textit{Excitation Vector}$$

$$\mathbf{h} = [h_0, \dots, h_{L-1}]^T \quad \textit{Echo path}$$

$$\hat{\mathbf{h}}(n) = [\hat{h}_0(n), \dots, \hat{h}_{L-1}(n)]^T \quad \textit{Estimated echo path}$$

Length of adaptive filter is L and time index is n .

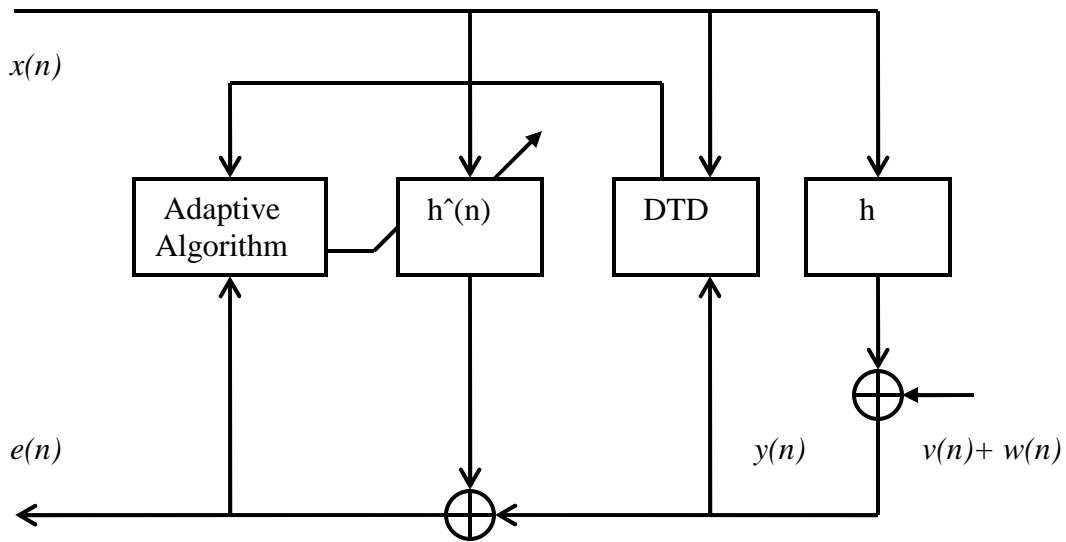


Figure 5.1: Echo canceller and double talk detector

According to the block diagram of echo canceller as shown in figure 5.1, adaptive filter adapt the echo path and it can subtract the duplicate of returned echoes $y(n)$. Normalized least mean square algorithms are given by: [26]

Error signal:

$$e(n) = y(n) - \hat{\mathbf{h}}^T(n-1) \mathbf{x}(n) \quad (25)$$

Coefficient updating equation:

$$\hat{\mathbf{h}}(n) = \hat{\mathbf{h}}(n-1) + \frac{\mu \mathbf{x}(n) e(n)}{\mathbf{x}^T(n) \mathbf{x}(n) + \delta_{NLMS}} \quad (26)$$

Where μ is the adaptation step and δ_{NLMS} is the regularization factor.

The proportionate normalized least mean square error algorithm each filter coefficient has individual step size. Step sizes are decided according to the last estimation of filter coefficients in that way larger increment for larger coefficient to improve the convergence rate of coefficient. According to this way active coefficients are adjusted faster as compare to the non active coefficient (small or zero coefficient). For the sparse impulse response proportionate normalized least mean square converges faster than normalized least mean square.

The proportionate normalized least mean square algorithm is explained by the following derivations: [27]

$$e(n) = y(n) - \hat{\mathbf{h}}^T(n-1) \mathbf{x}(n) \quad (27)$$

$$\hat{\mathbf{h}}(n) = \hat{\mathbf{h}}(n-1) + \frac{\mu \mathbf{G}(n-1) \mathbf{x}(n) e(n)}{\mathbf{x}^T(n) \mathbf{G}(n-1) \mathbf{x}(n) + \delta_{PNLMS}} \quad (28)$$

$$\mathbf{G}(n-1) = \text{diag} [g_0(n-1), g_1(n-1), \dots, g_{L-1}(n-1)] \quad (29)$$

Where μ is the step size parameter, $G(n-1)$ is a diagonal matrix (the off diagonal elements are zero) and δ_{PNLMS} is the regularization factor. The $G(n)$ diagonal elements are calculated by following equation: [27,28]

$$\gamma_l(n) = \max \left\{ \rho \max \left[\delta_p, \left| \hat{h}_0(n) \right|, \dots, \left| \hat{h}_{L-1}(n) \right| \right], \left| \hat{h}_l(n) \right| \right\} \quad (30)$$

$$g_l(n) = \frac{\gamma_l(n)}{\sum_{i=0}^{L-1} \gamma_i(n)} \quad 0 \leq l \leq L-1 \quad (31)$$

δ_p and ρ with typical values $\delta_p = 0.01$ $\rho = 5/L$ and are positive numbers. The first part of equation (30) ρ prevents $\hat{h}_l(n)$ from stalling when it has smaller value as compare to the largest coefficient and δ_p regularize the updating continuously when all coefficients are zero.

A comparison between normalized least mean square and proportionate normalized least mean square algorithm the main advantage is that convergence rate is better.

5.3 Improved PNLMS Algorithm

In this part we explain an improved proportionate normalized least mean square algorithm. Why we are introducing improved proportionate normalized least mean square algorithm. The main fact is that proportionate normalized least mean square is slower with dispersive impulse responses means that equation (30) has to be modified. [27]

Adaptive filter is defined by 1-norm:

$$\left\| \hat{\mathbf{h}}(n) \right\|_1 = \sum_{l=0}^{L-1} \left| \hat{h}_l(n) \right| \quad (32)$$

New form of equation (30) is:

$$\kappa_l(n) = (1-\alpha) \frac{\left\| \hat{\mathbf{h}}(n) \right\|_1}{L} + (1+\alpha) \left| \hat{h}_l(n) \right| \quad l = 0, 1, \dots, L-1 \quad (33)$$

where $-1 < \alpha < 1$. Taking 1-norm of vector κ :

$$\|\mathbf{\kappa}(n)\|_1 = \sum_{l=0}^{L-1} |\kappa_l(n)| = \sum_{l=0}^{L-1} |\kappa_l(n)| \quad (34)$$

$$= 2 \|\hat{\mathbf{h}}(n)\|_1 \quad (35)$$

The Improved proportionate normalized least mean square algorithm is given by the following equations:

$$e(n) = y(n) - \hat{\mathbf{h}}^T(n-1)\mathbf{x}(n) \quad (36)$$

$$\hat{\mathbf{h}}(n) = \hat{\mathbf{h}}(n-1) + \frac{\mu \mathbf{K}(n-1) \mathbf{x}(n) e(n)}{\mathbf{x}^T(n) \mathbf{K}(n-1) \mathbf{x}(n) + \delta_{IPNLMS}} \quad (37)$$

$$\mathbf{K}(n-1) = \text{diag}[k_0(n-1), k_1(n-1), \dots, k_{L-1}(n-1)] \quad (38)$$

where

$$\kappa_l(n) = \frac{\kappa_l(n)}{\|\mathbf{\kappa}(n)\|_1} \quad (39)$$

$$\kappa_l(n) = \frac{(1-\alpha)}{2L} + (1+\alpha) \frac{|\hat{h}_l(n)|}{2\|\hat{\mathbf{h}}(n)\|_1} \quad l = 0, 1, \dots, L-1 \quad (40)$$

In general to avoid a zero division in equation (40), in the beginning of adaptation where all filter taps are initialized to zero, now slightly modified form

$$\kappa_l(n) = \frac{(1-\alpha)}{2L} + (1+\alpha) \frac{|\hat{h}_l(n)|}{2\|\hat{\mathbf{h}}(n)\|_1 + \varepsilon} \quad (41)$$

In the Initial stage all filter taps start with zero and vector \mathbf{x} is multiplied by $(1-\alpha)/2L$. The regularization parameter δ_{IPNLMS} equation as follows:

$$\delta_{IPNLMS} = \frac{(1-\alpha)}{2L} \delta_{NLMS} \quad (42)$$

Both improved proportionate normalized least mean square and normalized least mean square algorithms are identical for $\alpha = -1$ and improved proportionate normalized least mean square behaves like proportionate normalized least mean square algorithms for α close to 1. Improved proportionate normalized least mean square always behave much better than normalized least mean square and proportionate normalized least mean square whatever the impulse response for this case the best choice for α are (0 or -0.5).

5.4 MSAF Algorithm

The Multiband subband adaptive filtering algorithm see in figure 5.2 is an efficient subband adaptive filtering algorithm that separate the input signal $u(n)$ and $d(n)$ is the desired signal into many subbands for weight adaptation[29]. Fullband adaptive filter are as follows:

$$W(k, z) = \sum_{m=0}^{M-1} w_m(k) z^{-m} \quad (43)$$

Fullband weight vectors:

$$\mathbf{w}(k) = [w_0(k), w_1(k), \dots, w_{M-1}(k)]^T \quad (44)$$

$$\mathbf{w}(k+1) = \mathbf{w}(k) + \mu \mathbf{U}(k) \mathbf{\Lambda}^{-1}(k) e_D(k) \quad (45)$$

$$e_D(k) = d_D(k) - \mathbf{U}^T(k) \mathbf{w}(k) \quad (46)$$

$$\mathbf{\Lambda}(k) = \text{diag}[\mathbf{U}^T(k) \mathbf{U}(k) + \alpha \mathbf{I}] \quad (47)$$

Here α is the regularization parameter and μ is the step size. $u_i(k)$ is the $M \times 1$ subband signal vector, data matrix $\mathbf{U}(k)$ is the $N \times 1$ and $d_D(k)$ is the desired vector as follows: [30]

$$\mathbf{u}_i(k) = [u_i(kN), u_i(kN-1), \dots, u_i(kN-M+1)]^T \quad (48)$$

$$\mathbf{U}(k) = [u_0(k), u_1(k), \dots, u_{N-1}(k)] \quad (49)$$

$$\mathbf{d}_D(k) = [d_{0,D}(k), d_{1,D}(k), \dots, d_{N-1,D}(k)]^T \quad (50)$$

Equation (48) defined subband regressors $u_i(k)$ are bandlimited, they contain subband signals $u_i(n)$.

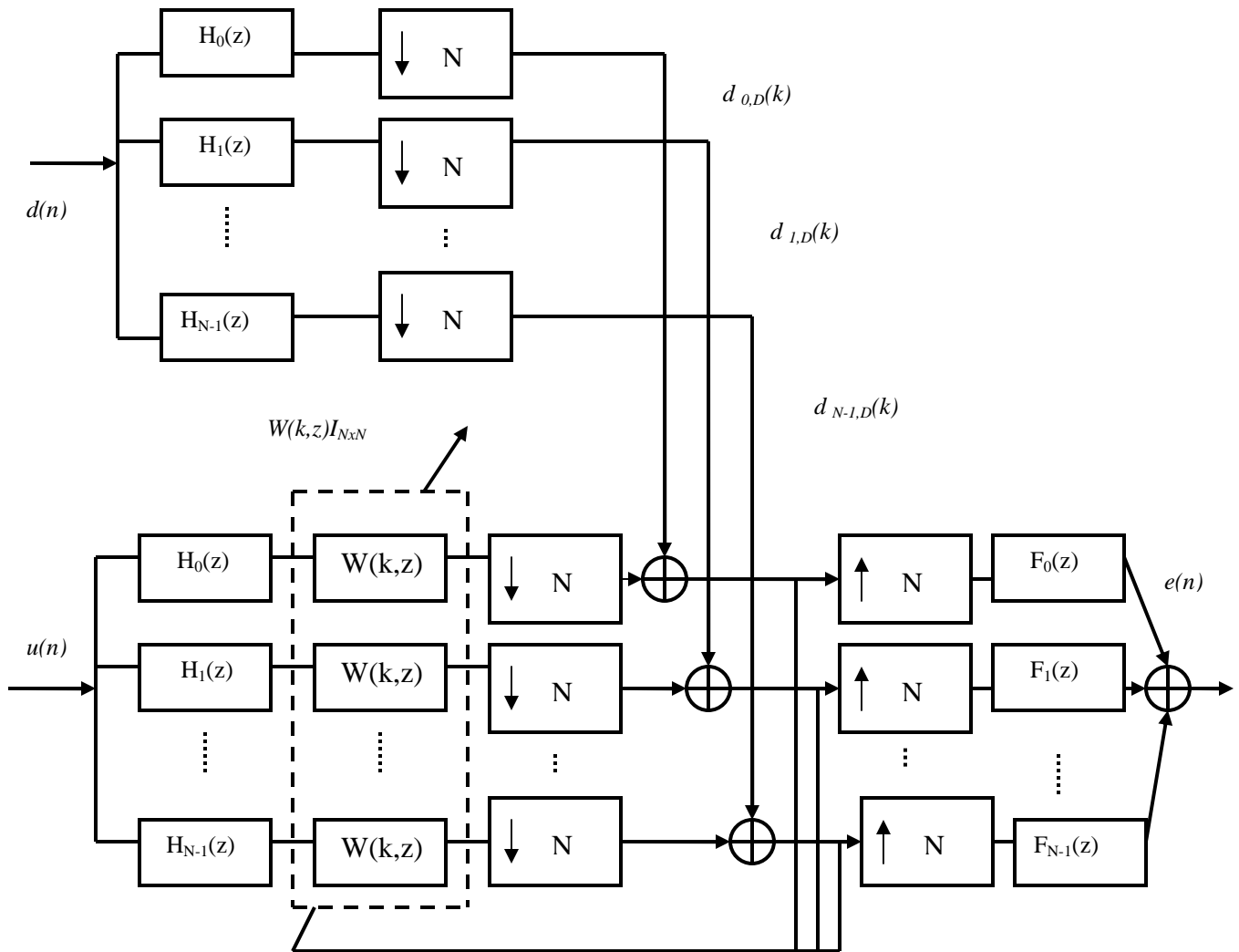


Figure 5.2: Multiband SAF. Input Subband and error signals are used to adapt the fullband filter $W(k,z)$ using decimated rate

5.5 Proportionate MSAF algorithm

The main idea of proportionate adaptive filter is to allocate individual step size for every tap weight according to the last estimation tap weight [31]. It uses larger step size for tap weights with large values and vice versa in near zero case, this factor results in a fast convergence to the unknown system to be identified for sparse impulse response [30].

We have already discussed the multiband adaptation in chapter 4. Multiband subband adaptive filtering algorithm is to adapt the fullband by using the group of subband signals in this process proportionate adaptation method is used for adaptation process. The PMSAF algorithm is as follows: [32]

Step size adaptation:
Diagonal control matrix

$$\mathbf{G}(k) = \text{diag} [g_0(k), g_1(k), \dots, g_{M-1}(k)] \quad (51)$$

Diagonal elements of control matrix are given by $g_m(k)$ is the gain applied to step size of every individual tap weights. α is an important used in control matrix to adjust the tap weights. For better result α should always be 0 or -0.5.

$$g_m(k) = \frac{1-\alpha}{2L} + (1+\alpha) \frac{|w_m(k)|}{2\|\mathbf{w}(k)\|_1 + \epsilon} \quad m = 0, 1, \dots, M-1 \quad (52)$$

$\|\cdot\|_1$ is l_1 norm operator and ϵ is a constant with a small value (normalized term used in equ. (52)).

Subband matrix with i th regressor is given by:

$$\mathbf{U}(k) = [u_0(k), u_1(k), \dots, u_{N-1}(k)] \quad (53)$$

where

$$\mathbf{u}_i(k) = [u_i(kN), u_i(kN-1), \dots, u_i(kN-M_s+1)]^T \quad \text{for } i = 0, 1, \dots, N-1 \quad (54)$$

Normalized matrix $\Lambda(k)$ and $e_D(k)$ is the error vector

$$\Lambda(k) = \text{diag} [\mathbf{U}^T(k) \mathbf{G}(k) \mathbf{U}(k) + \delta \mathbf{I}] \quad (55)$$

Subband weight vector:

$$\mathbf{w}(k+1) = \mathbf{w}(k) + \mu \mathbf{G}(k) \mathbf{U}(k) \Lambda^{-1}(k) \mathbf{e}_D(k) \quad (56)$$

Matlab Implementation and Results

There are various parameters that effects the performance of adaptive algorithms for echo cancellation like pitch variability, noise level, gender, age etc

In the first part of the thesis presents the MATLAB simulation for the performance of PMSAF, NLMS and Improved PNLMS and compare the results. In this simulation we are using different impulse responses like sparse and dispersive with length 512, for the acoustic path representation $B(z)$ using a sample frequency of 8kHz. Three different types of excitation signals are also used in the simulations; first one is white noise, second is colored input and finally third is speech signal. Add some white noise to the output of unknown system 40dB SNR. The PMSAF algorithm uses PQMF filter bank having filter length ($L=32$) and four channels and identical value 0.1 is used for the step size for all the algorithms. To obtain the MSE curves by using average over 100 independent trials.

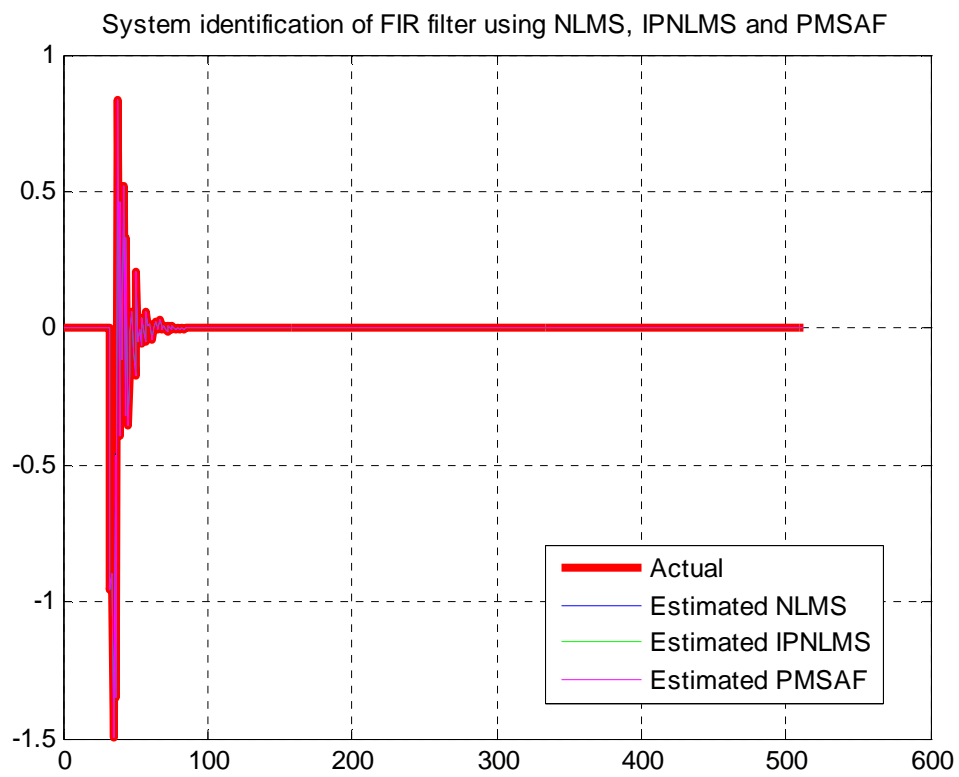
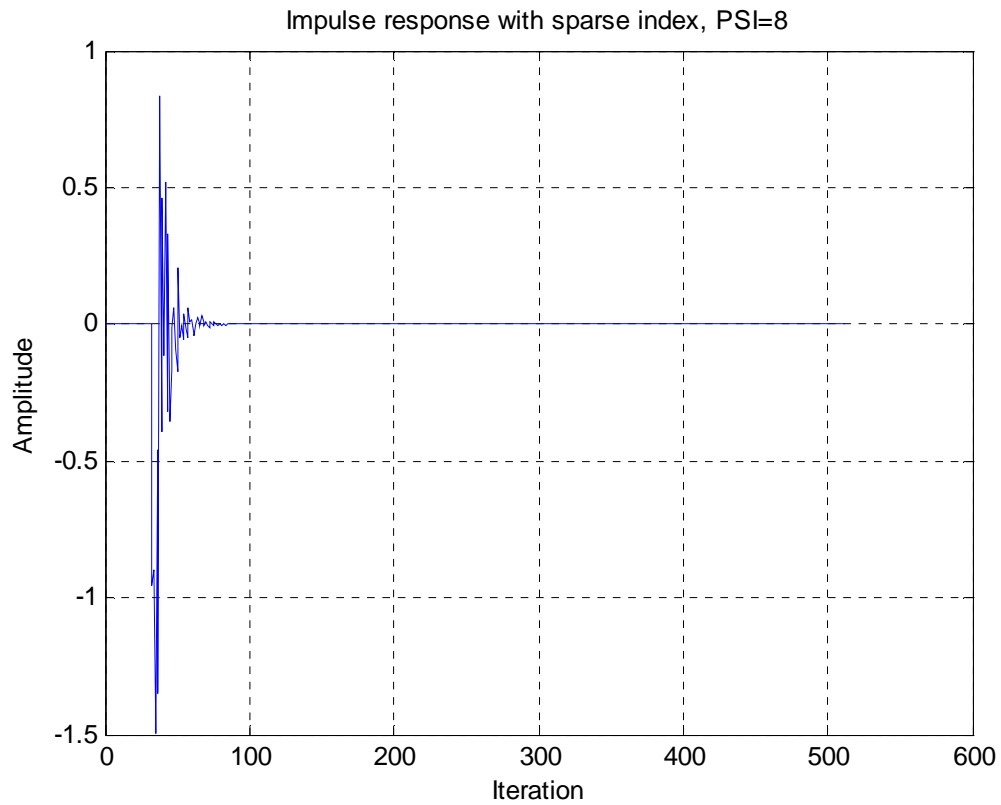
The following figures shows the Impulse response, System identification of FIR filter using PMSAF, NLMS and IPNLMS, Misalignments and Mean square Error. Compare the performance of each algorithm in echo cancellation system.

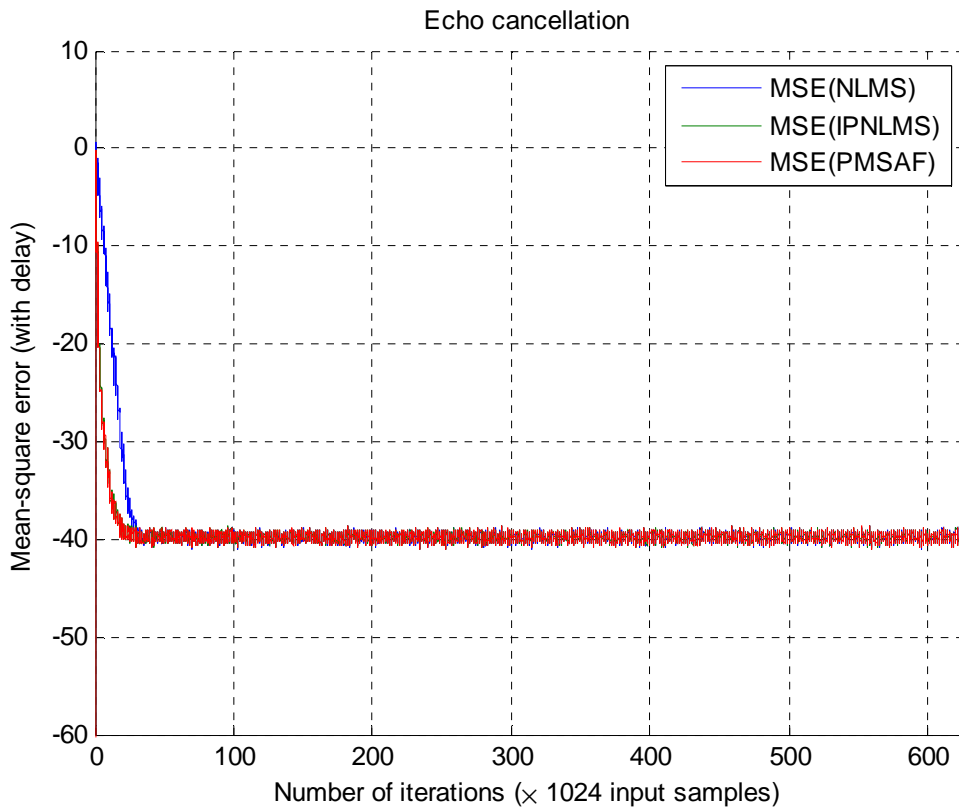
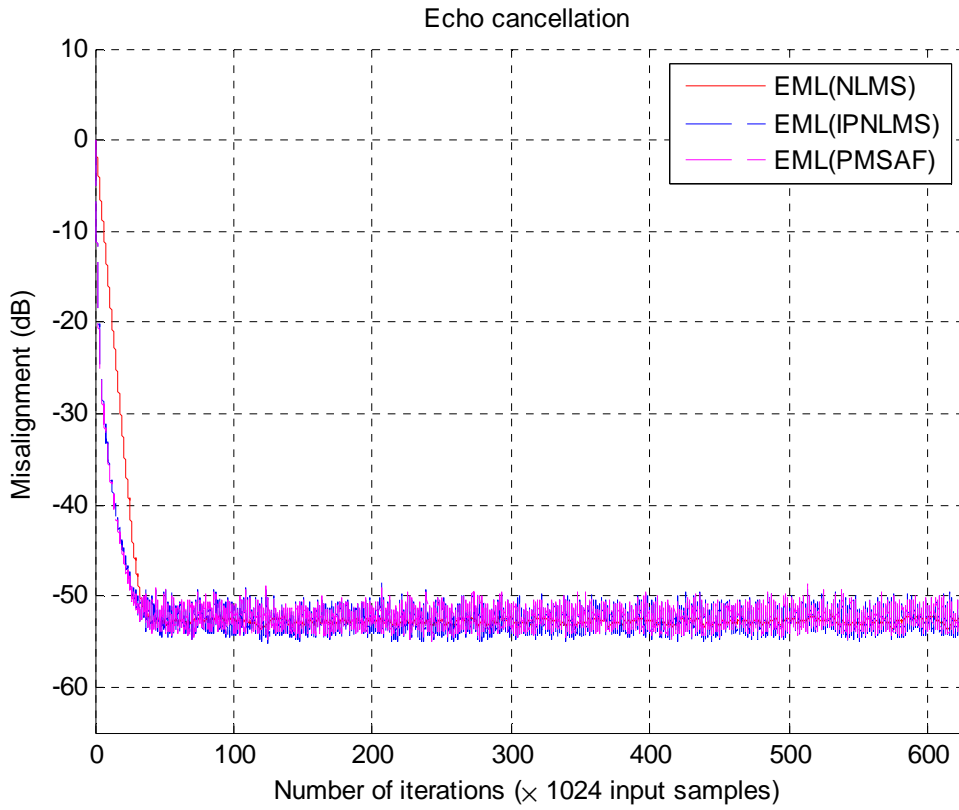
The following results shows the implementation for echo cancellation using PMSAF, NLMS and Improved PNLMS and than compare the performance level for different impulse responses (Sparse and Dispersive) and than compare all these results here we take the excitation signal and impulse response and add some external noise additive white Gaussian noise. We also give detailed comparison of MATLAB plots for impulse response, system identification, Misalignments, and Mean square error. All results plotted in MATLAB.

Results (Part 1)

6.1 Sparse Index using 8 decaying constant (Impulse response) and White noise (excitation signal)

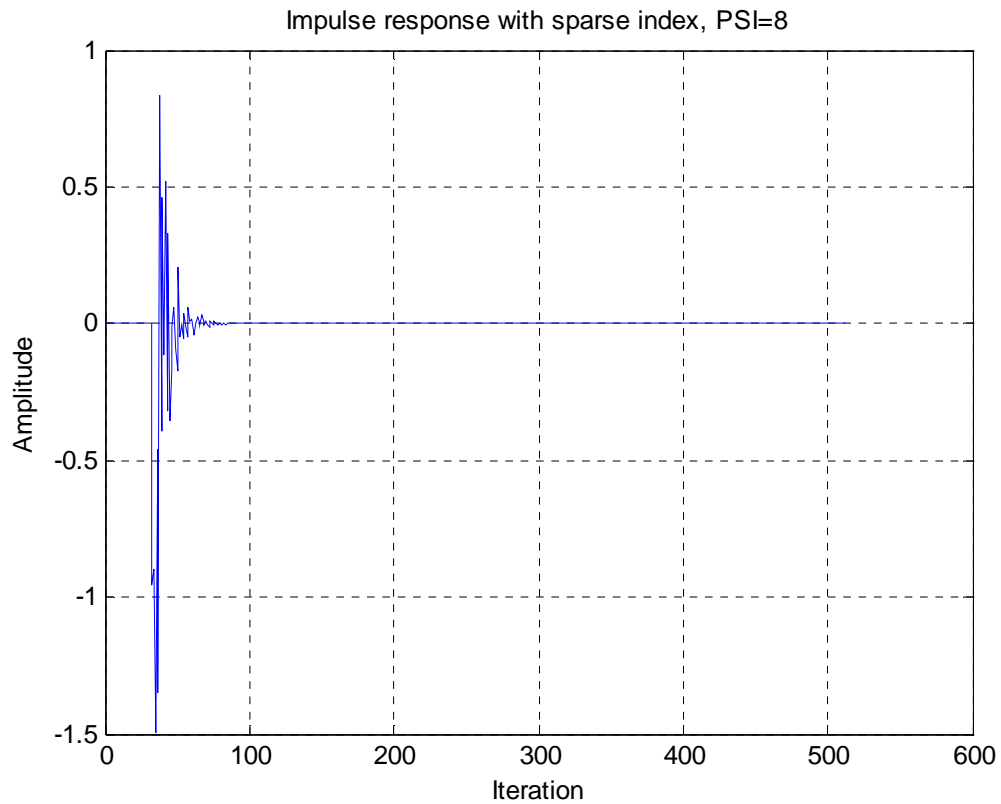
The below figures shows the output of the echo cancellation system. Fig a. is the sparse impulse response with 8 decay constant. Fig b. represent the system identification for FIR using PMSAF, Improved PNLMS and NLMS. Fig c. shows the misadjustments plot and Fig d. MSE learning curves.



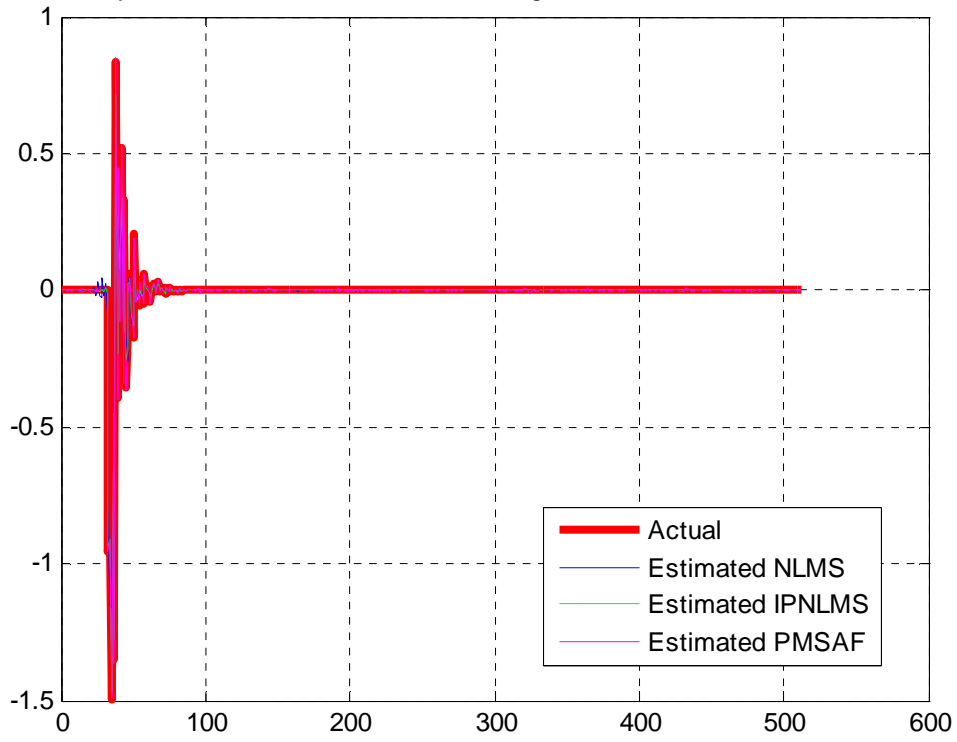


6.2 Sparse Index using 8 decaying constant (Impulse response) and Color input (excitation signal)

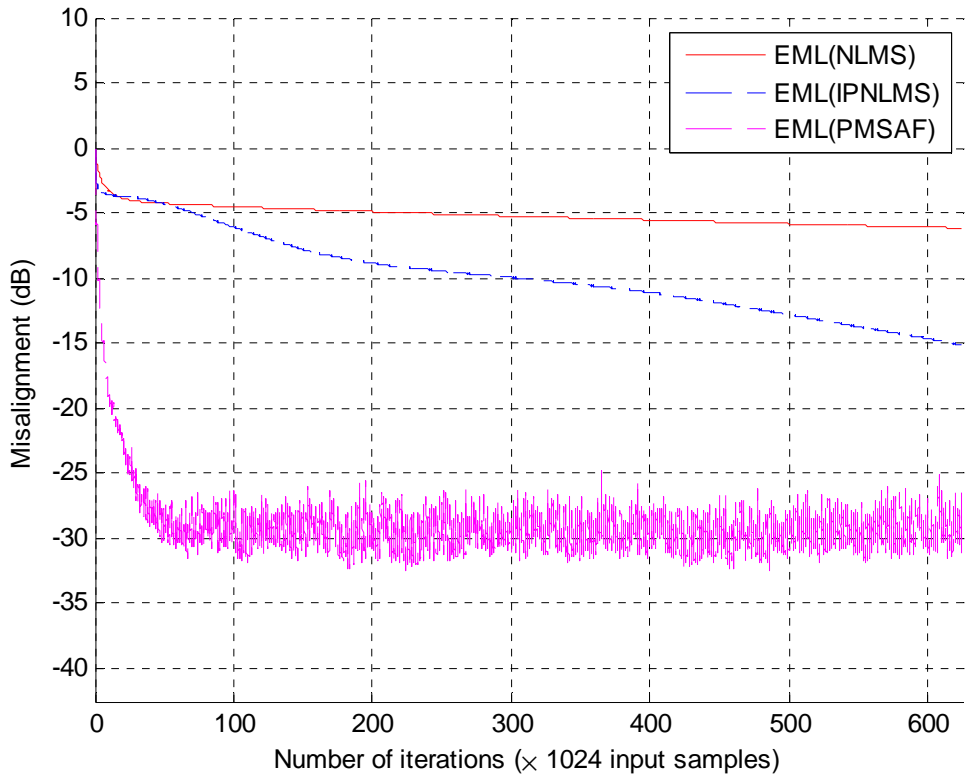
The below figures shows the output of the echo cancellation system. Fig a. is the sparse impulse response with 8 decay constant. Fig b. represent the system identification for FIR using PMSAF, Improved PNLMS and NLMS. Fig c. shows the misadjustments plot and Fig d. MSE learning curves.

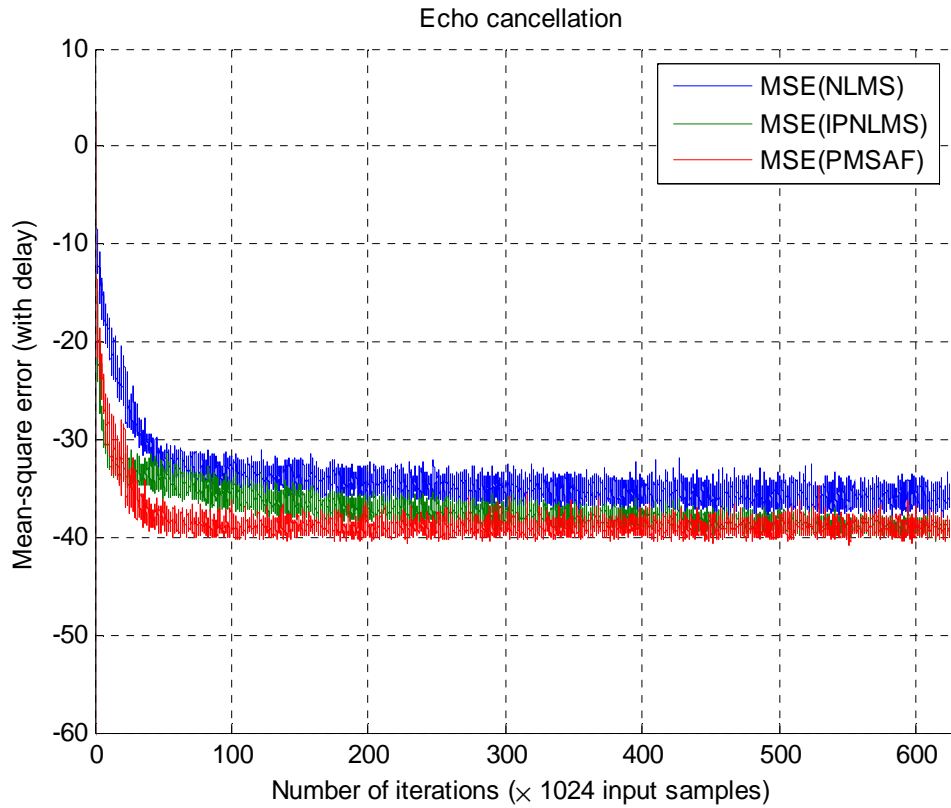


System identification of FIR filter using NLMS, IPNLMS and PMSAF



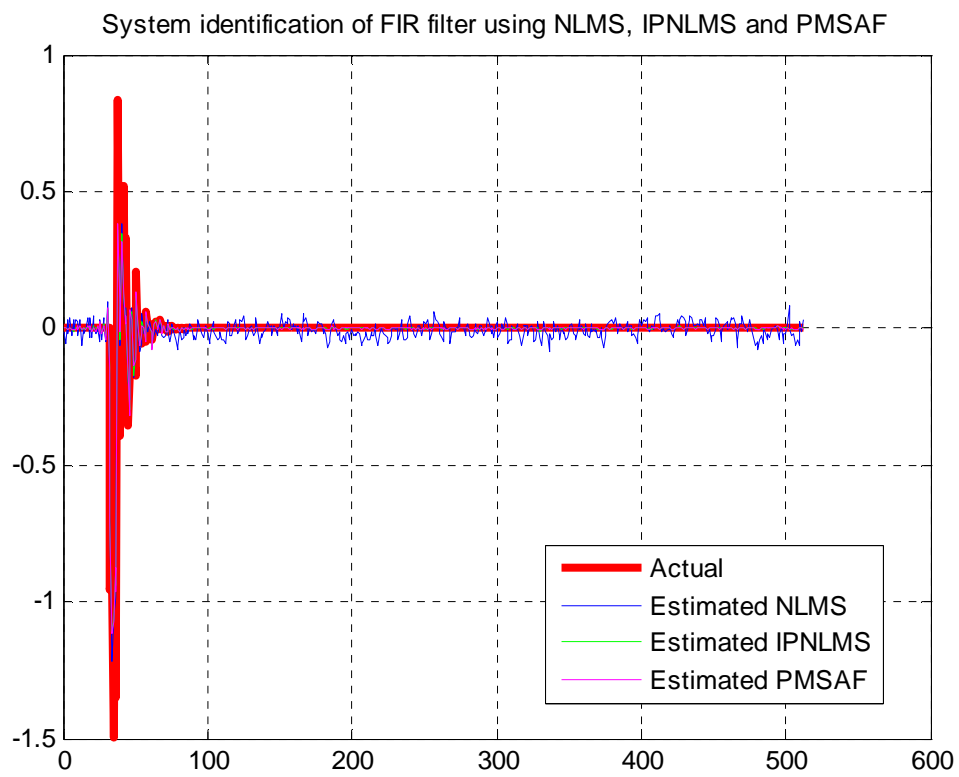
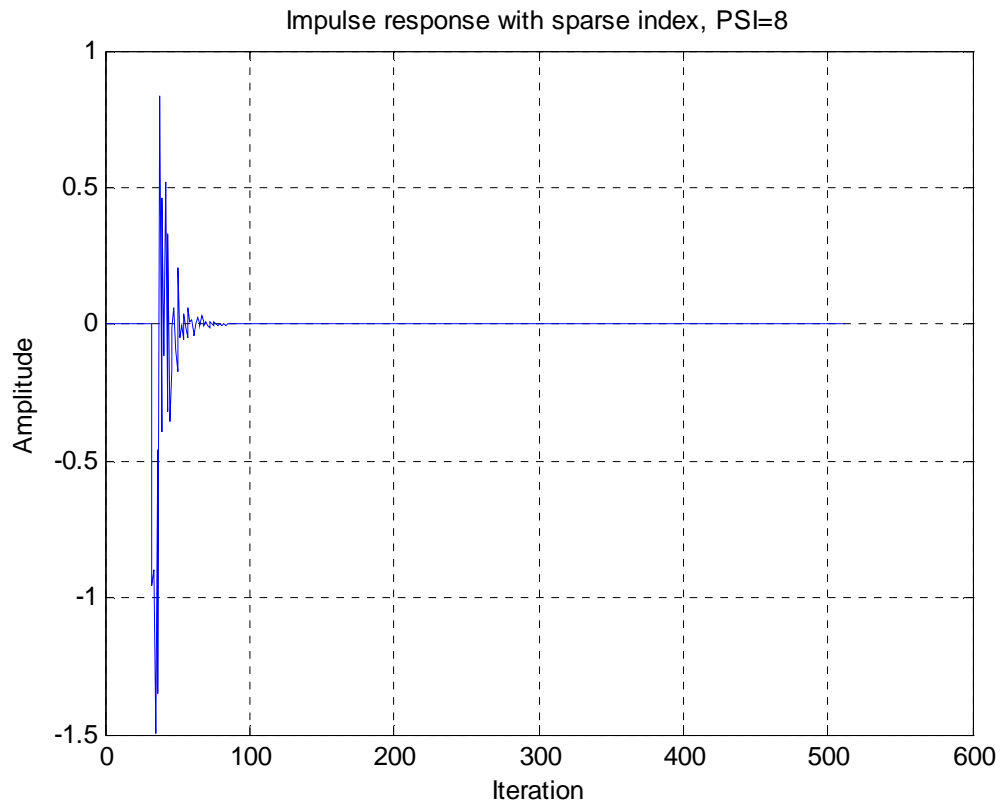
Echo cancellation

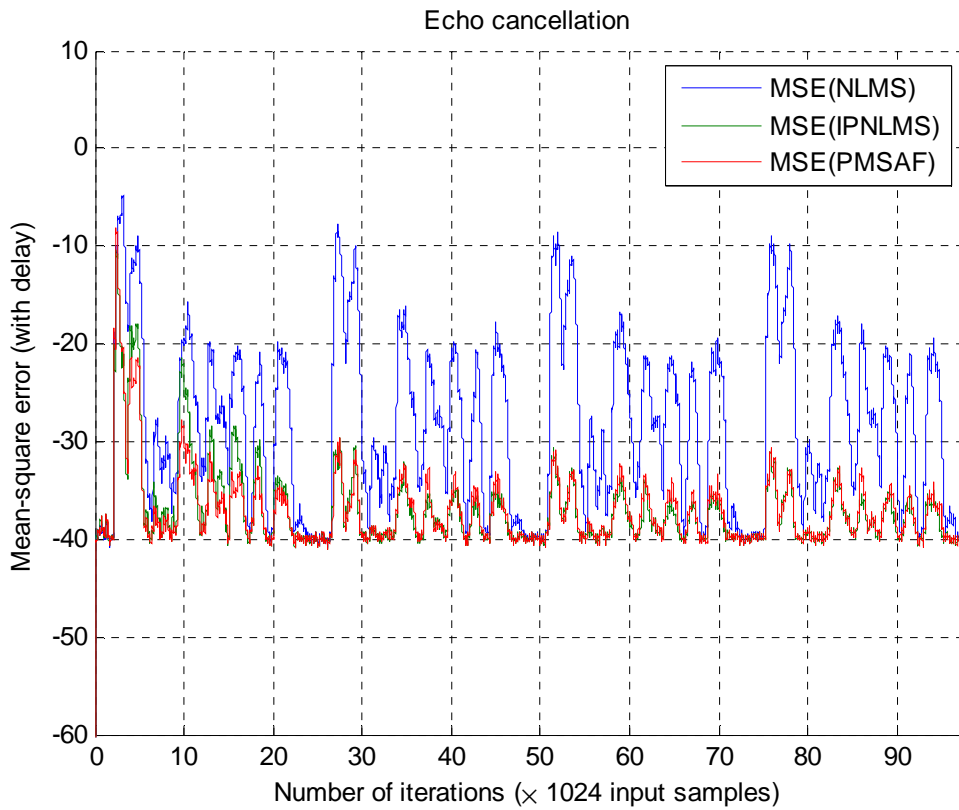
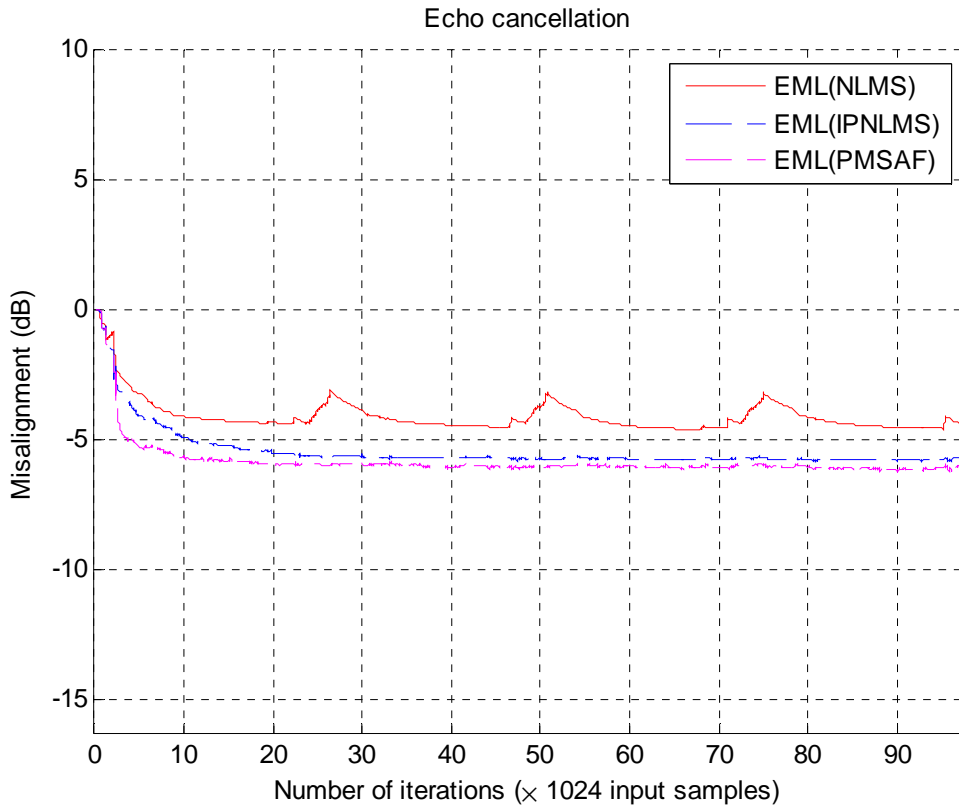




6.3 Sparse Index using 8 decaying constant (Impulse response) and Speech signal (excitation signal)

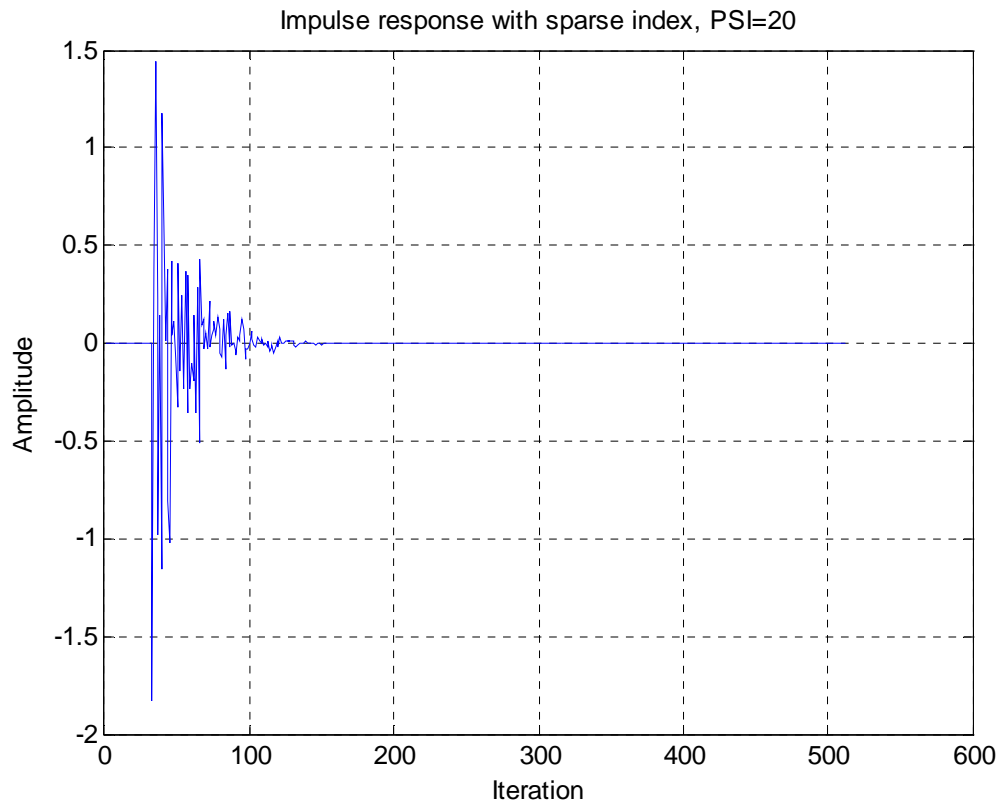
The below figures shows the output of the echo cancellation system. Fig a. is the sparse impulse response with 8 decay constant. Fig b. represent the system identification for FIR using PMSAF, Improved PNLMS and NLMS. Fig c. shows the misadjustments plot and Fig d. MSE learning curves.



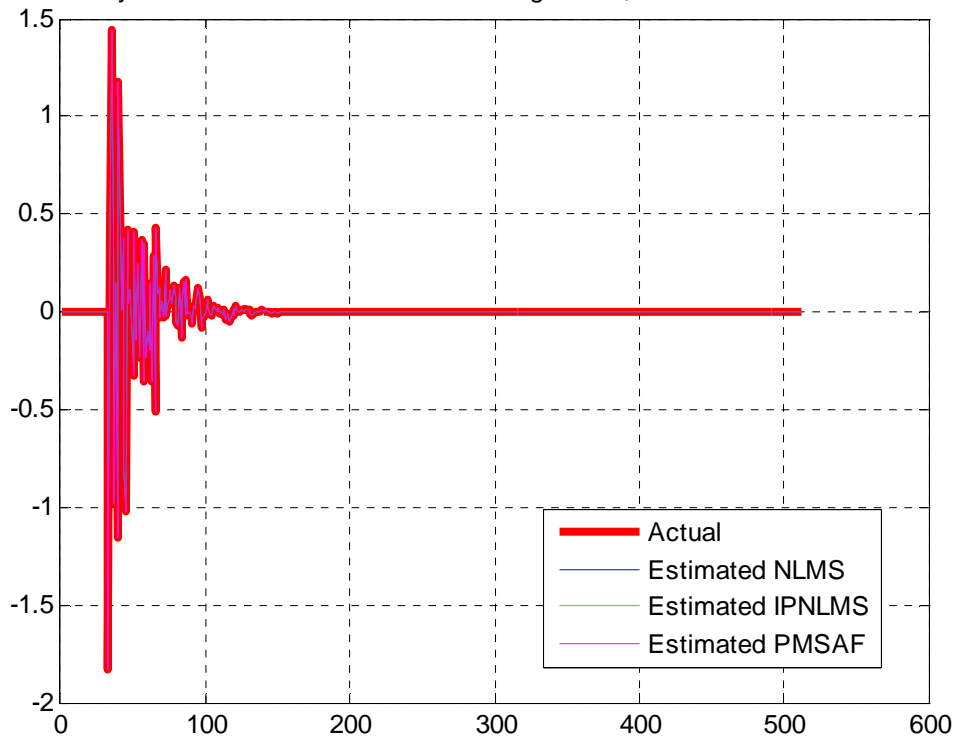


6.4 Sparse Index using 20 decaying constant (Impulse response) and White noise (excitation signal)

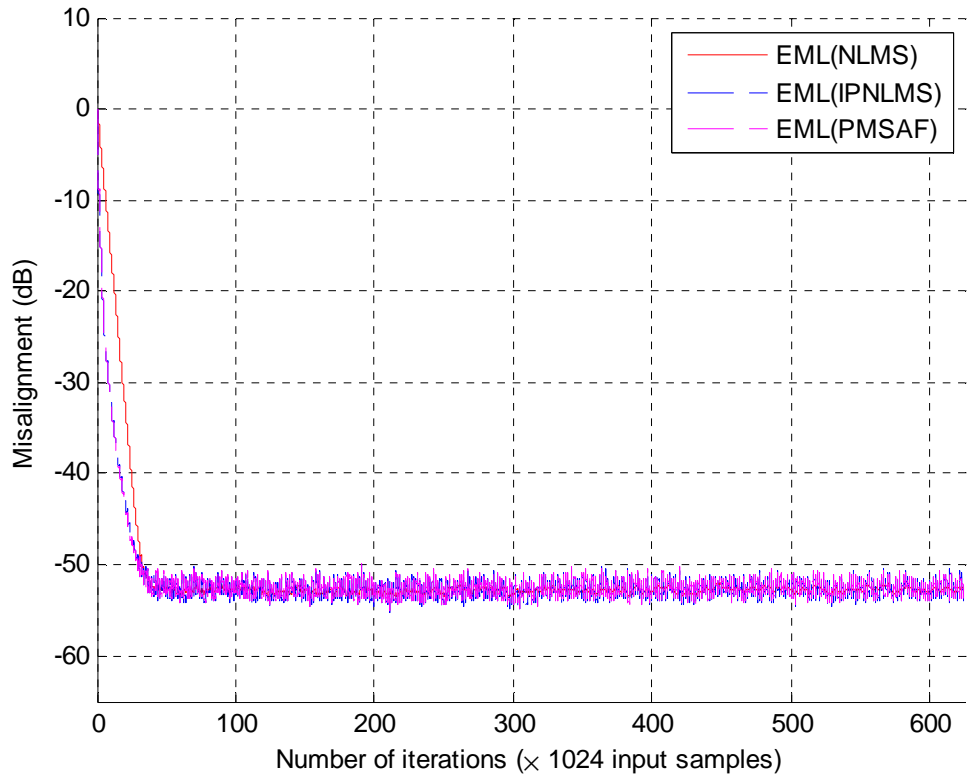
The below figures shows the output of the echo cancellation system. Fig a. is the sparse impulse response with 20 decay constant. Fig b. represent the system identification for FIR using PMSAF, Improved PNLMS and NLMS. Fig c. shows the misadjustments plot and Fig d. MSE learning curves.

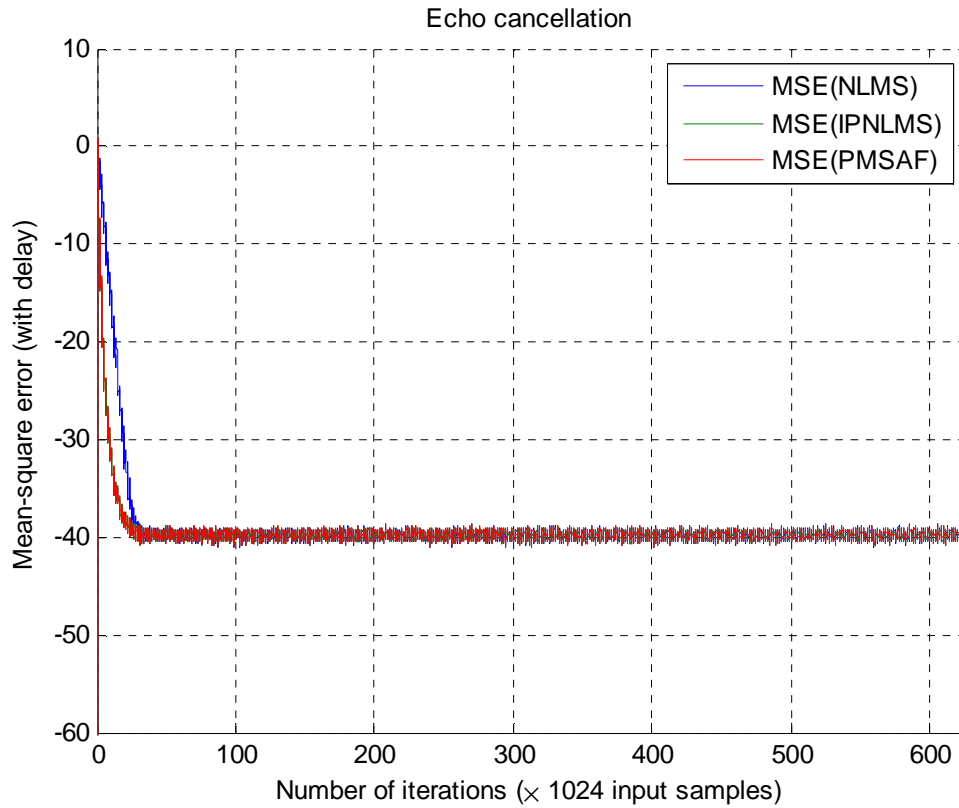


System identification of FIR filter using NLMS, IPNLMS and PMSAF



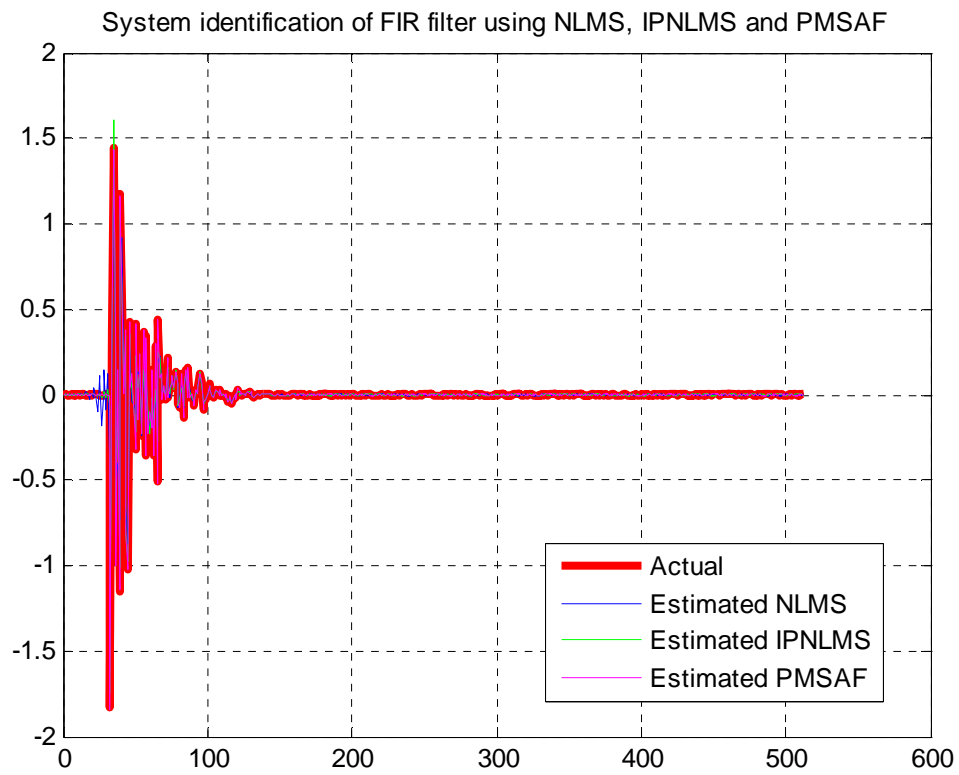
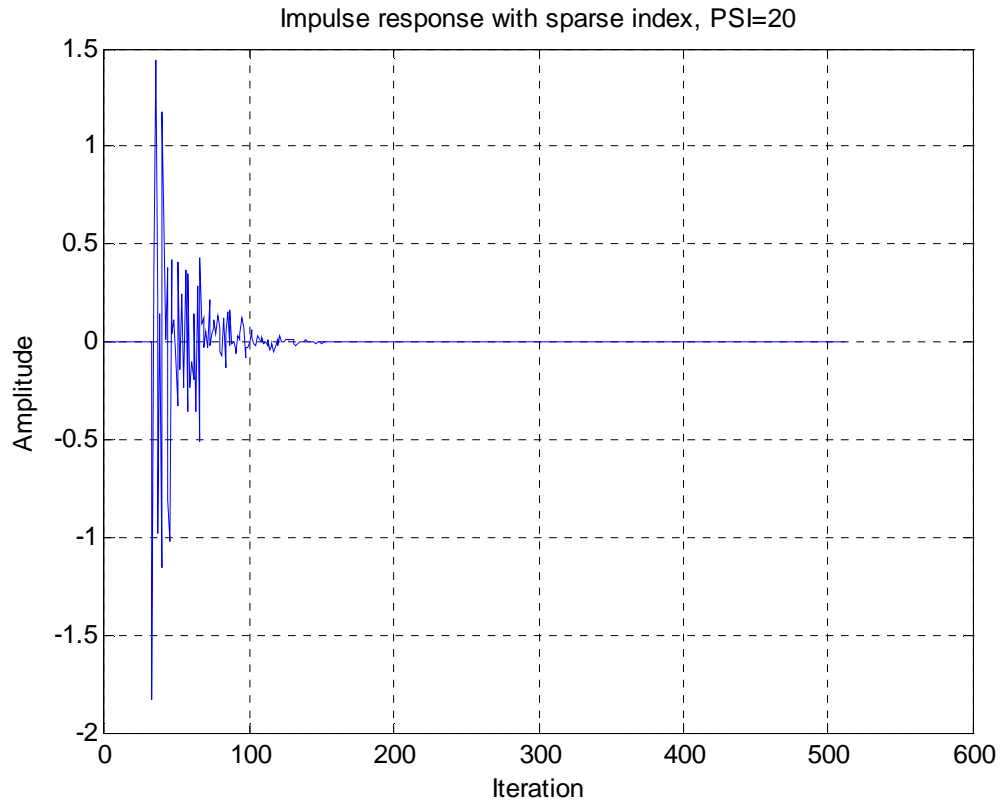
Echo cancellation

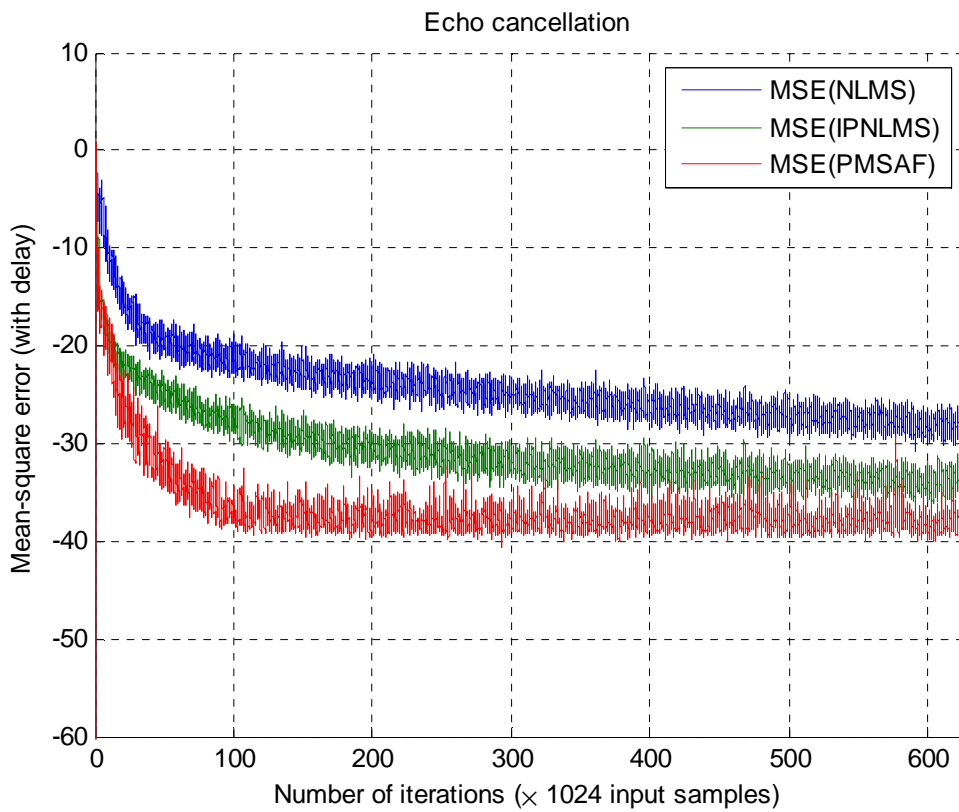
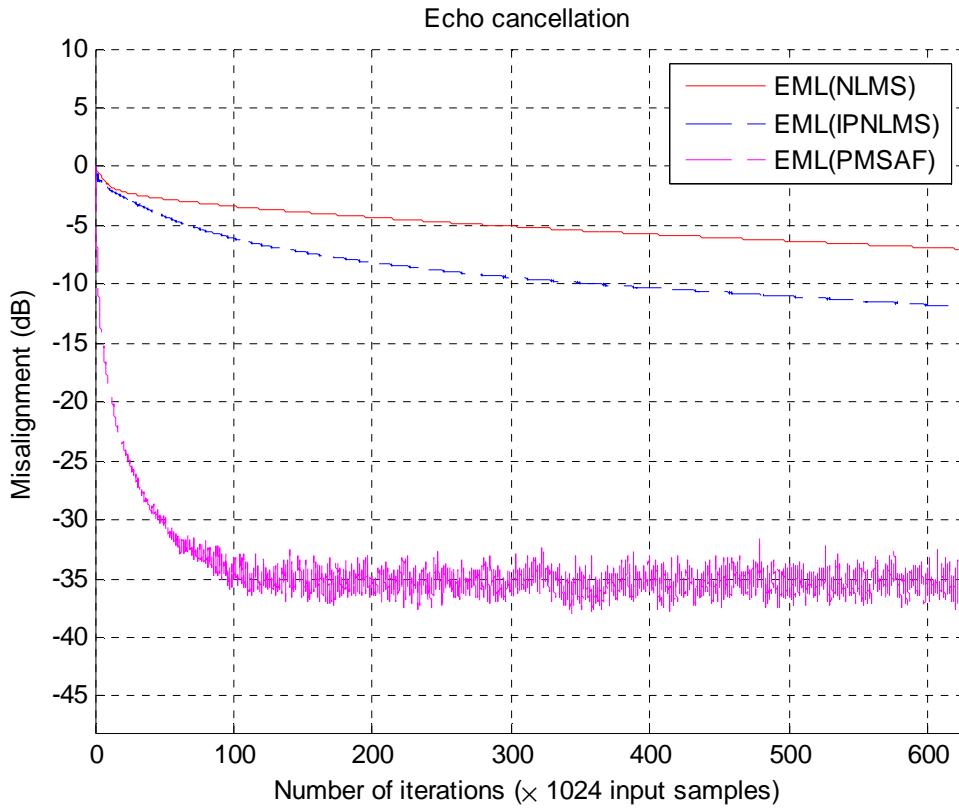




6.5 Sparse Index using 20 decaying constant (Impulse response) and Color input (excitation signal)

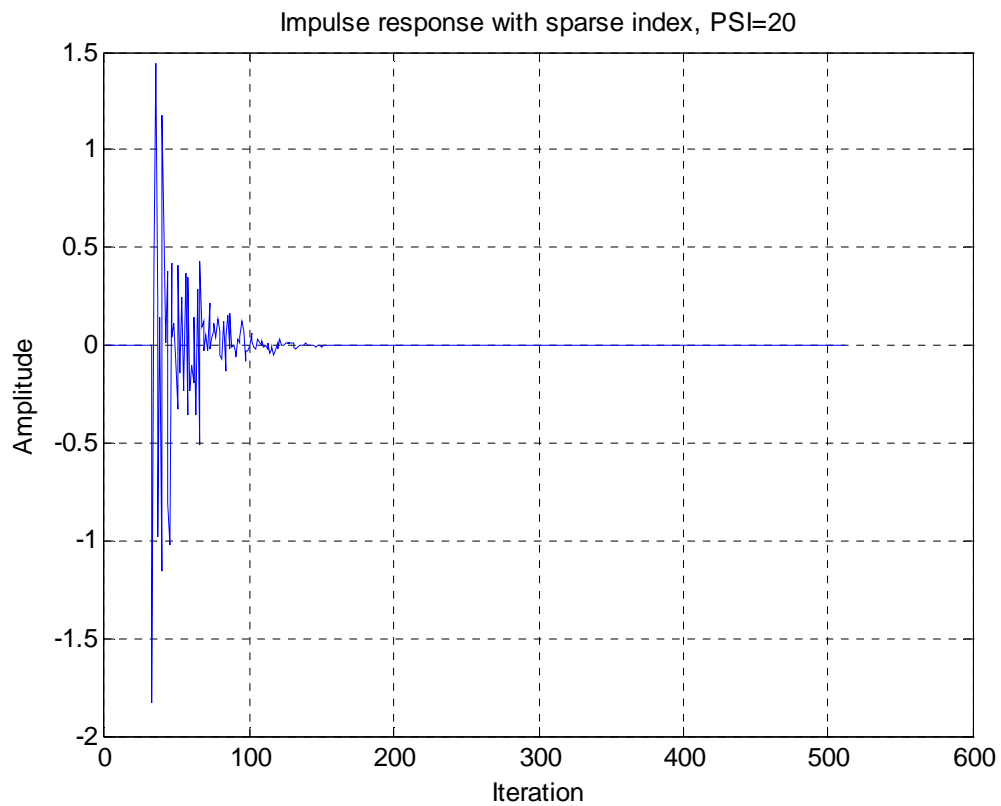
The below figures shows the output of the echo cancellation system. Fig a. is the sparse impulse response with 20 decay constant. Fig b. represent the system identification for FIR using PMSAF, Improved PNLMS and NLMS. Fig c. shows the misadjustments plot and Fig d. MSE learning curves.



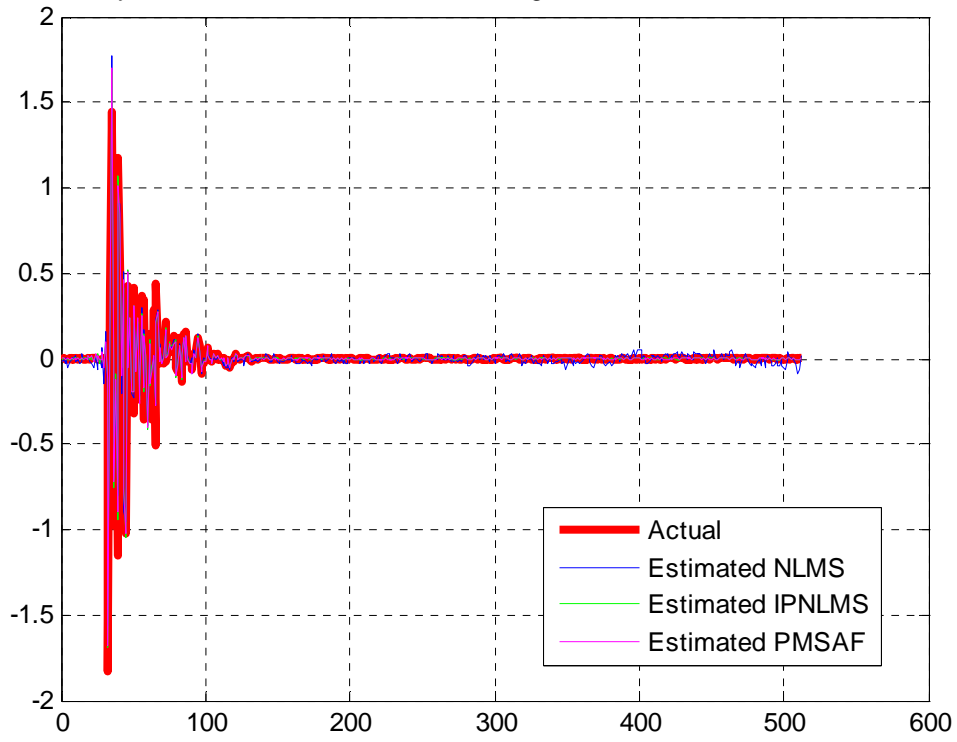


6.6 Sparse Index using 20 decaying constant (Impulse response) and Speech signal (excitation signal)

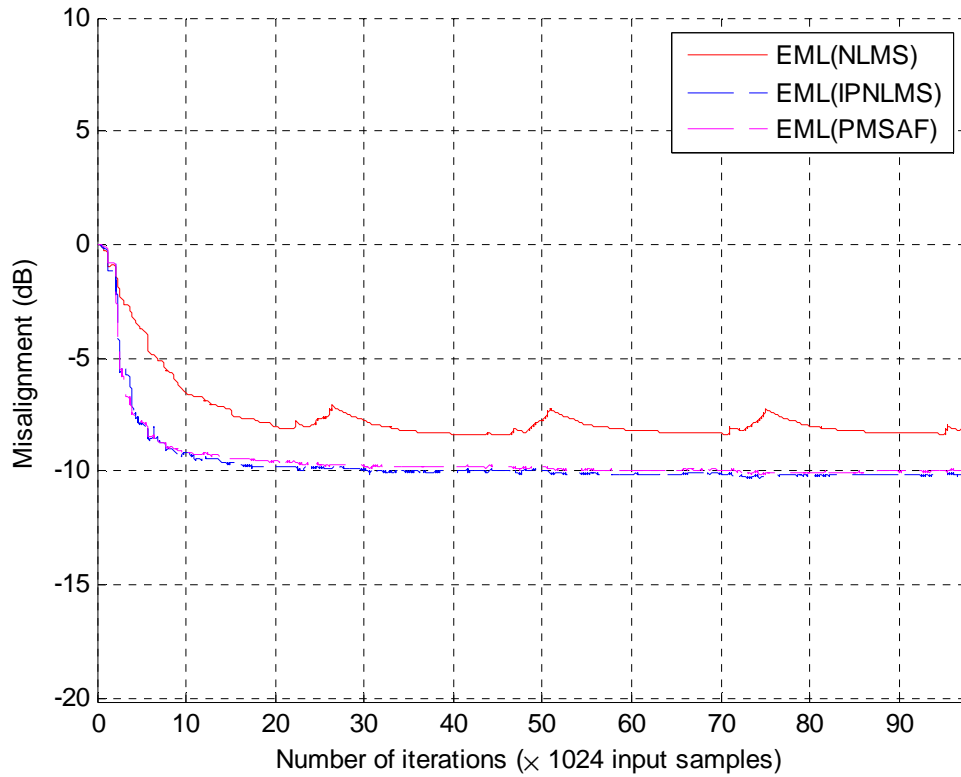
The below figures shows the output of the echo cancellation system. Fig a. is the sparse impulse response with 20 decay constant. Fig b. represent the system identification for FIR using PMSAF, Improved PNLMS and NLMS. Fig c. shows the misadjustments plot and Fig d. MSE learning curves.

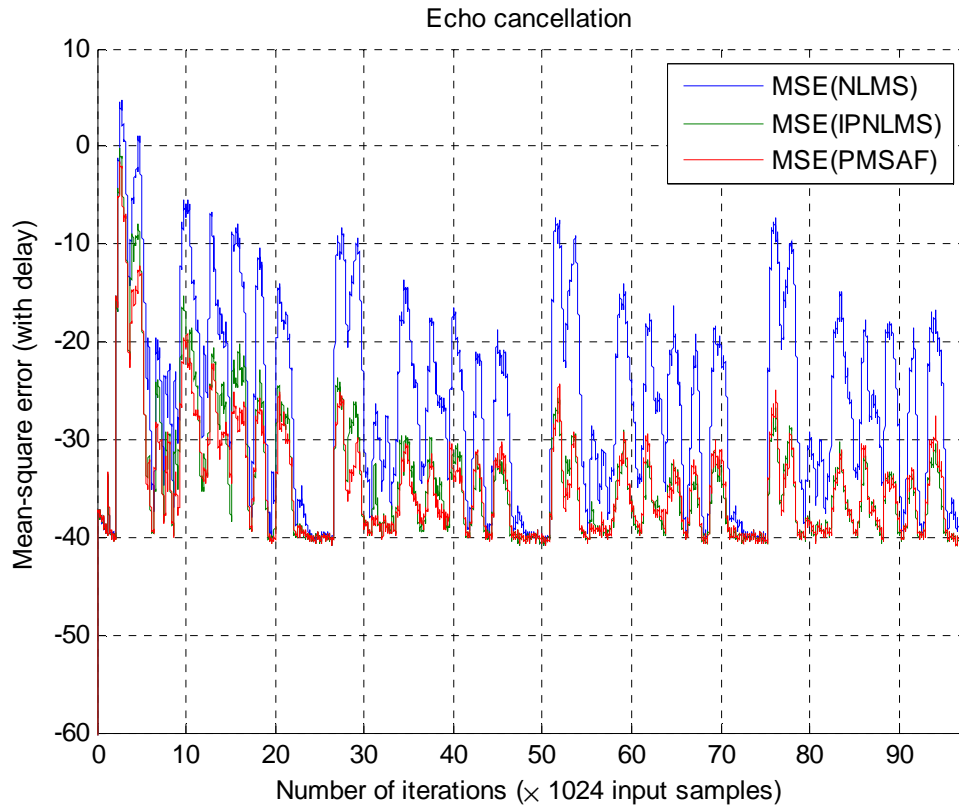


System identification of FIR filter using NLMS, IPNLMS and PMSAF



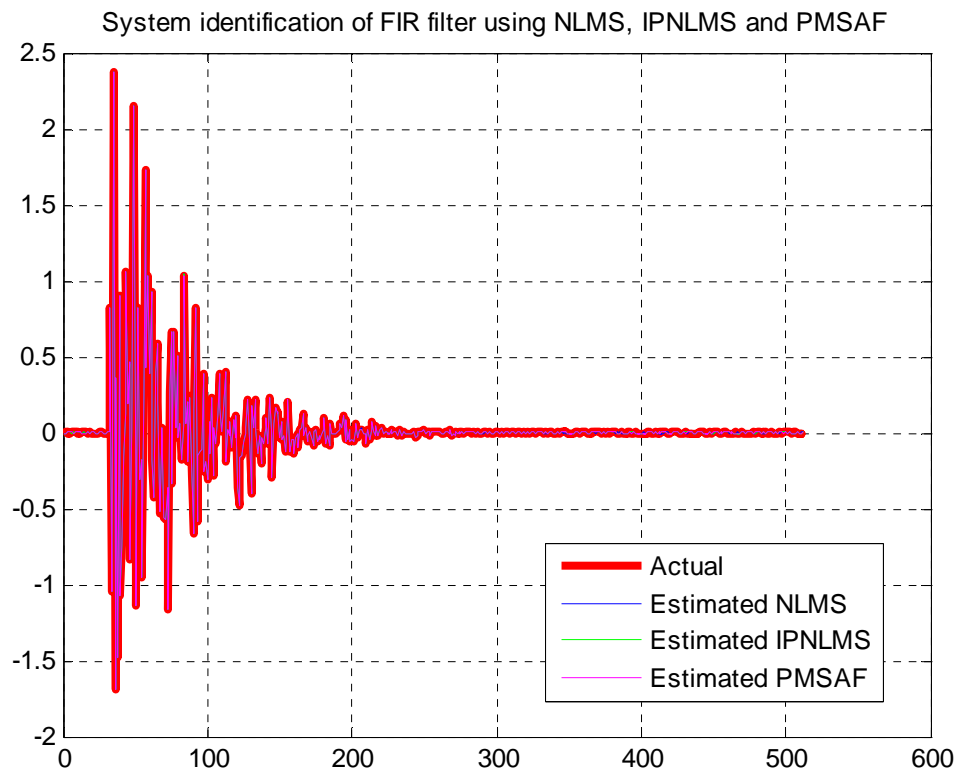
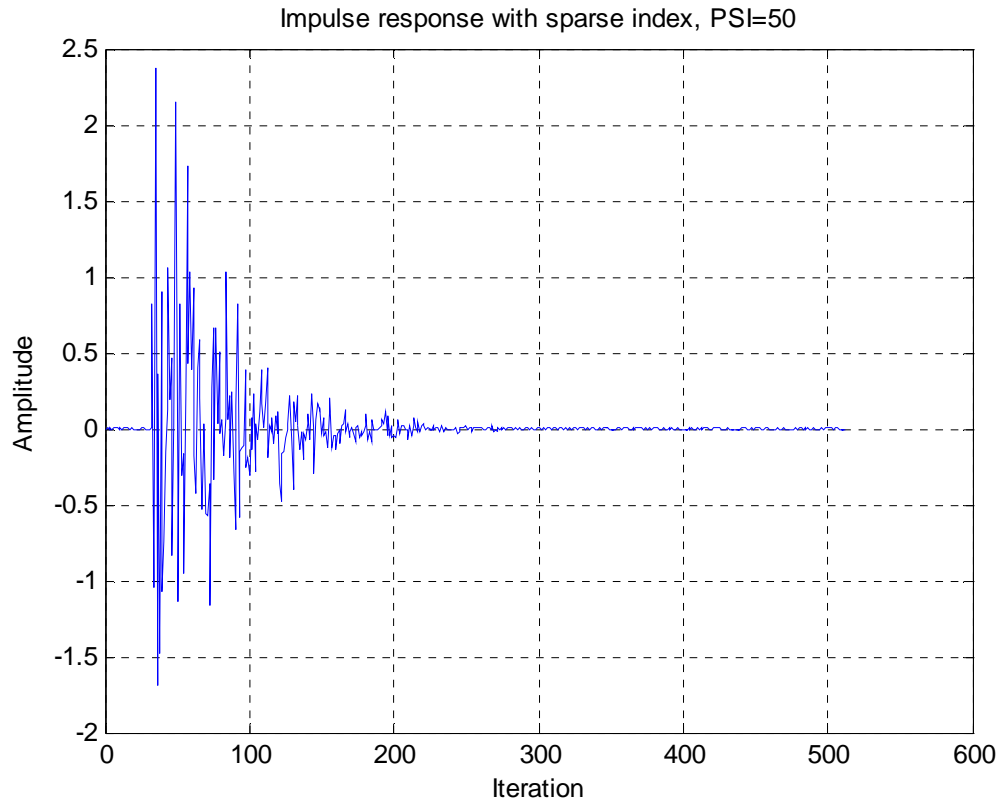
Echo cancellation

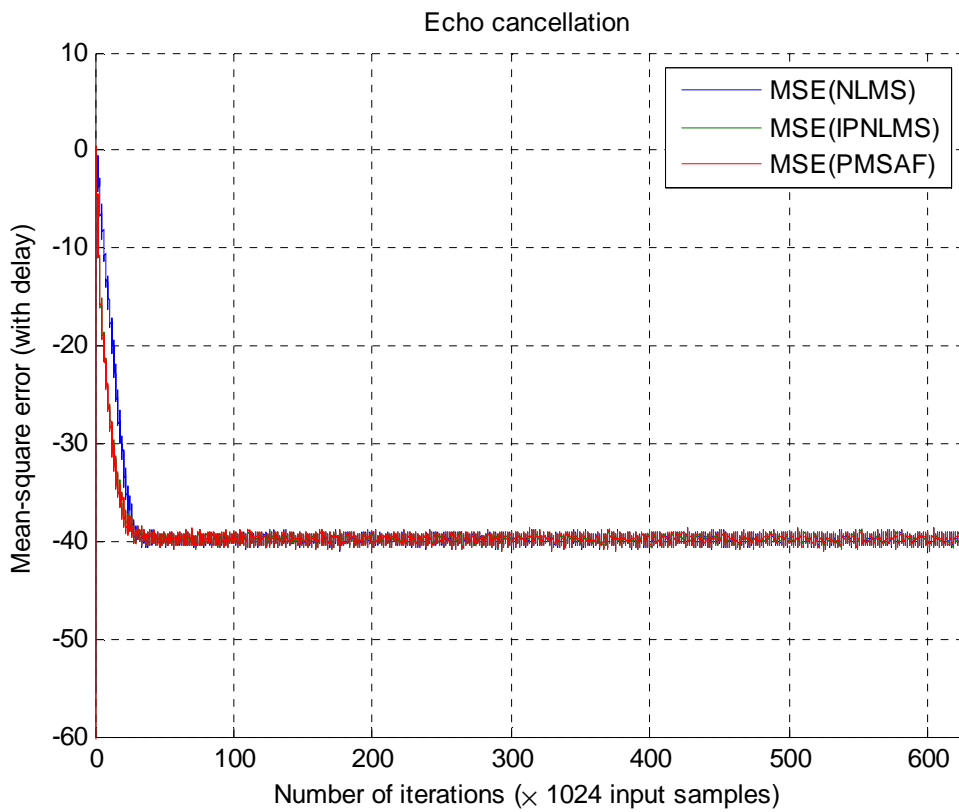
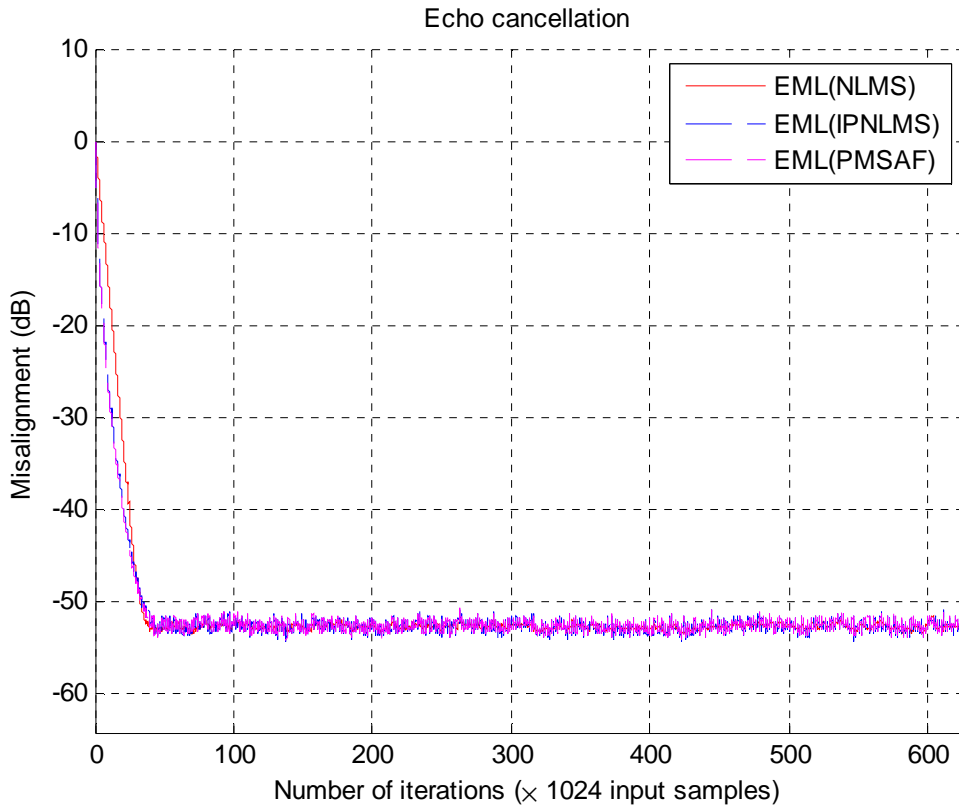




6.7 Sparse Index using 50 decaying constant (Impulse response) and White noise (excitation signal)

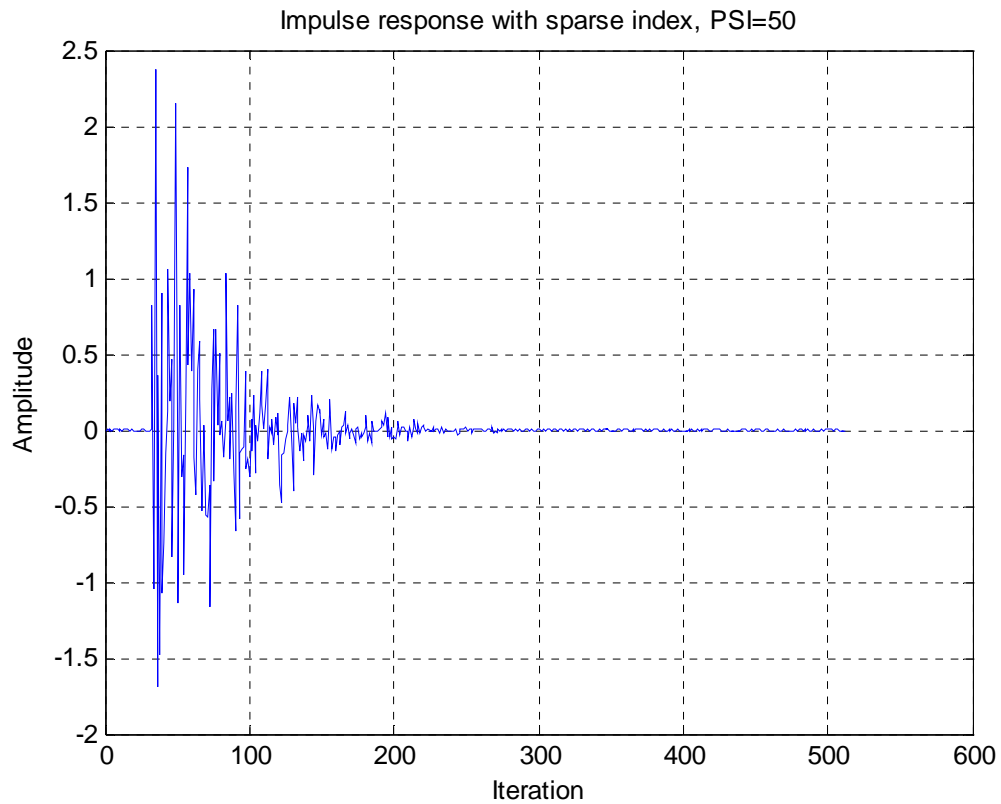
The below figures shows the output of the echo cancellation system. Fig a. is the sparse impulse response with 50 decay constant. Fig b. represent the system identification for FIR using PMSAF, Improved PNLMS and NLMS. Fig c. shows the misadjustments plot and Fig d. MSE learning curves.



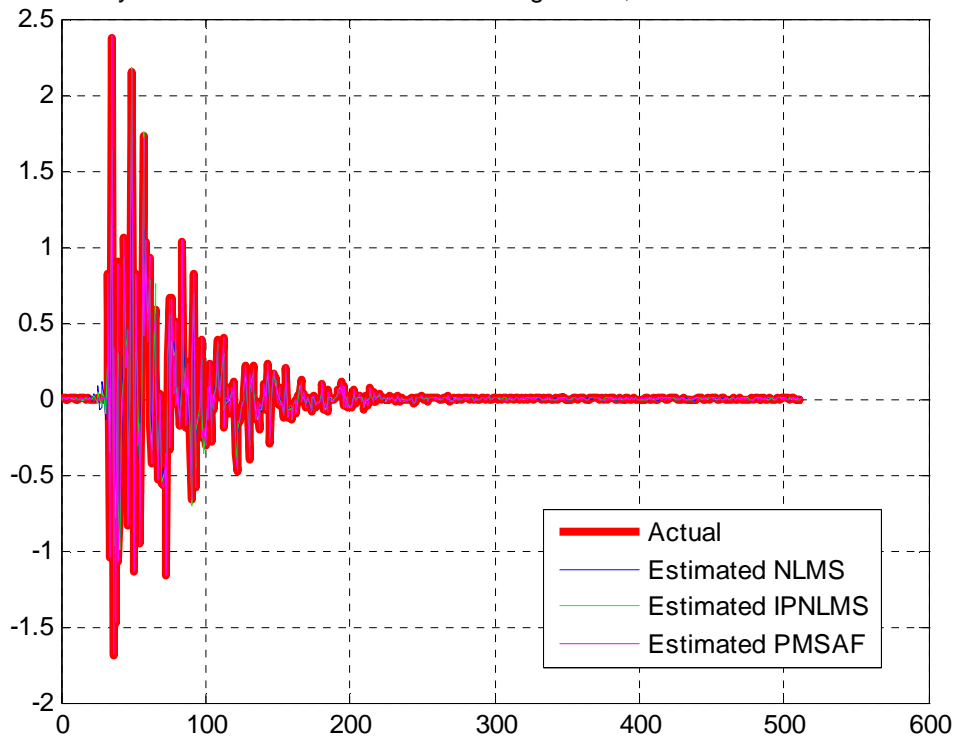


6.8 Sparse Index using 50 decaying constant (Impulse response) and Color input (excitation signal)

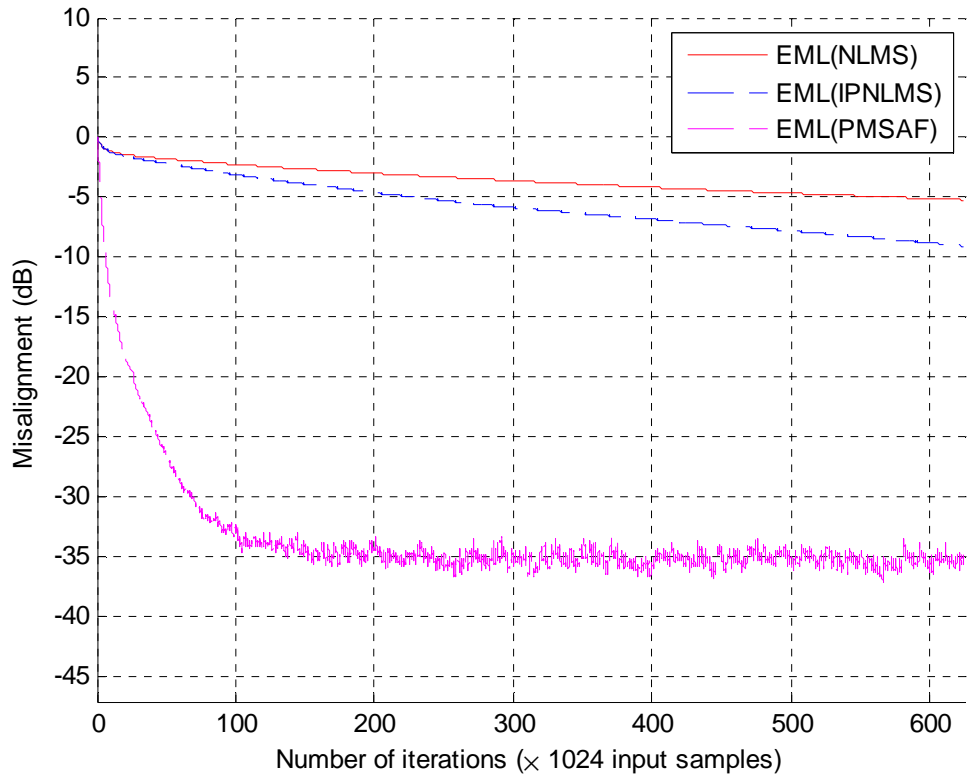
The below figures shows the output of the echo cancellation system. Fig a. is the sparse impulse response with 50 decay constant. Fig b. represent the system identification for FIR using PMSAF, Improved PNLMS and NLMS. Fig c. shows the misadjustments plot and Fig d. MSE learning curves.

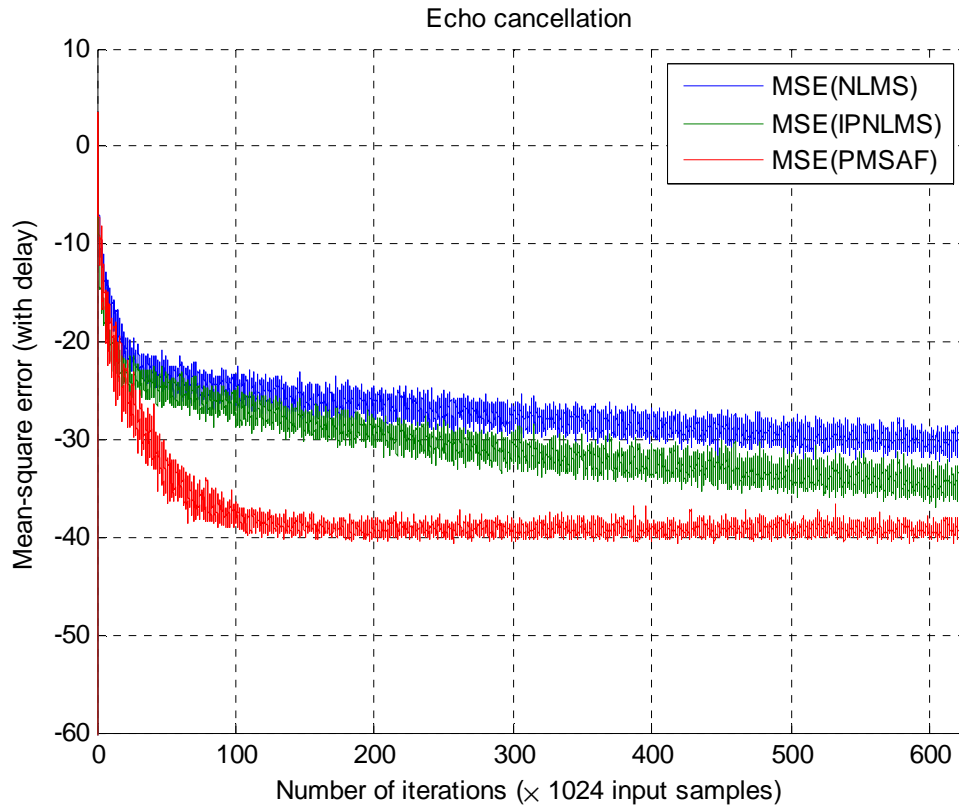


System identification of FIR filter using NLMS, IPNLMS and PMSAF



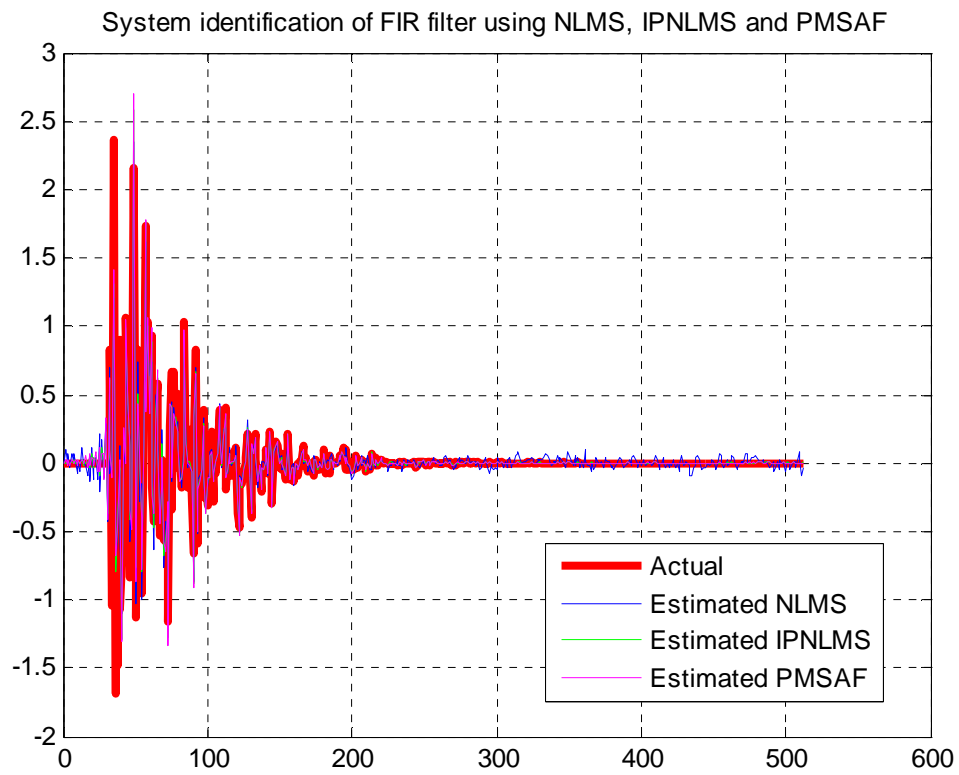
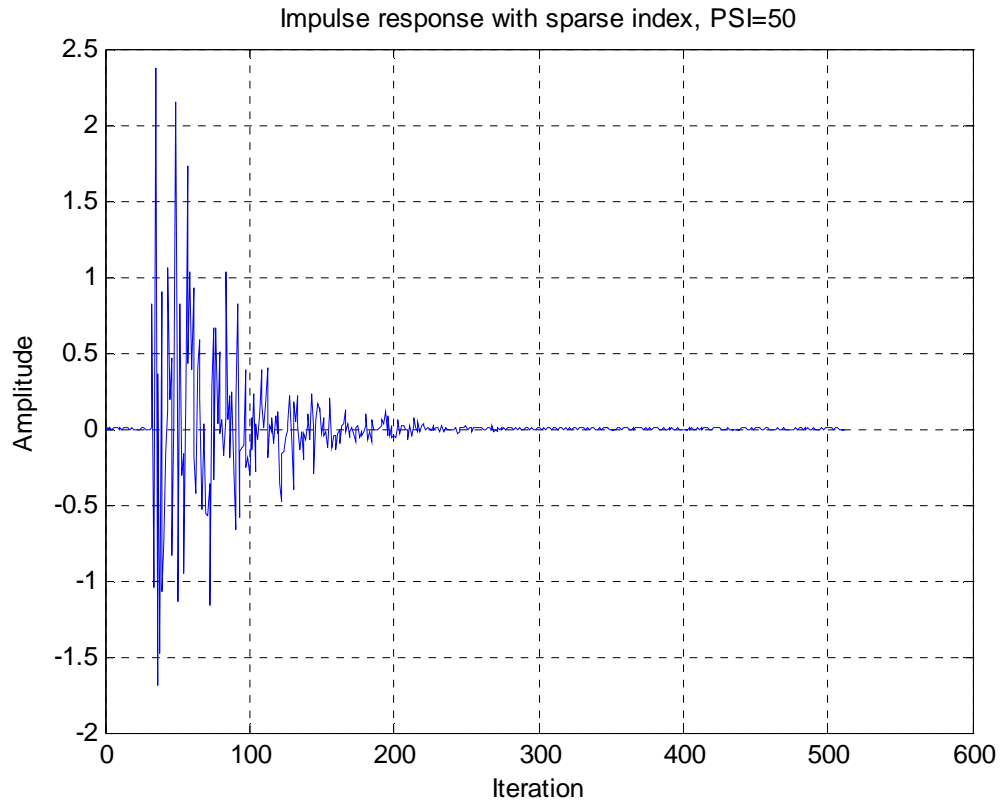
Echo cancellation

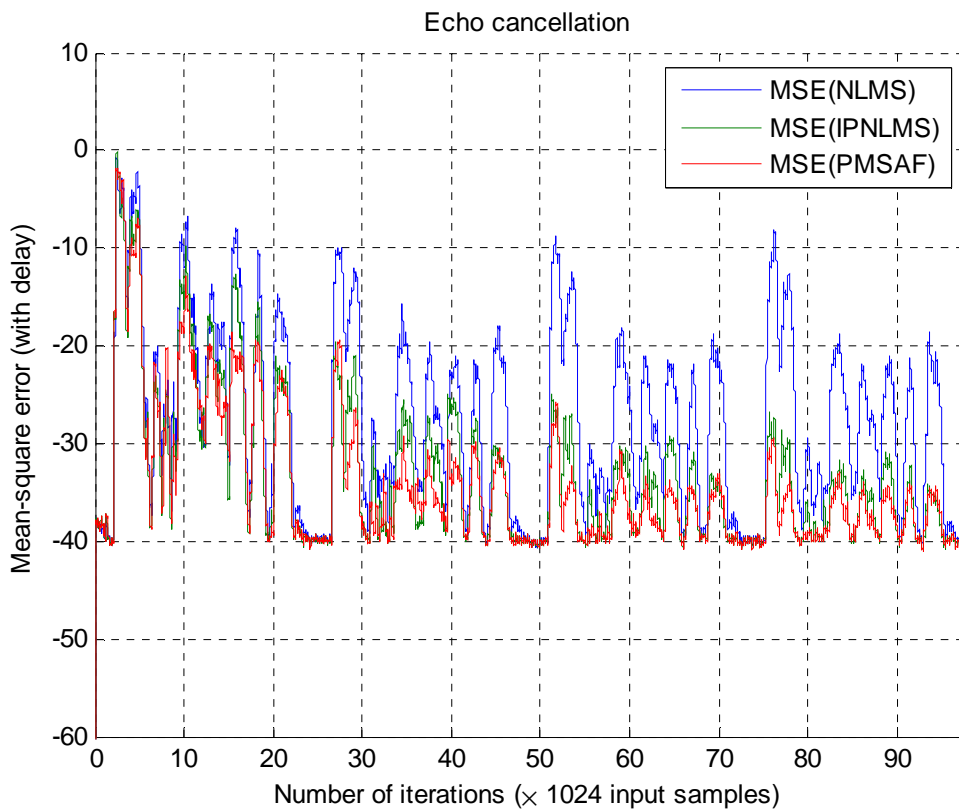
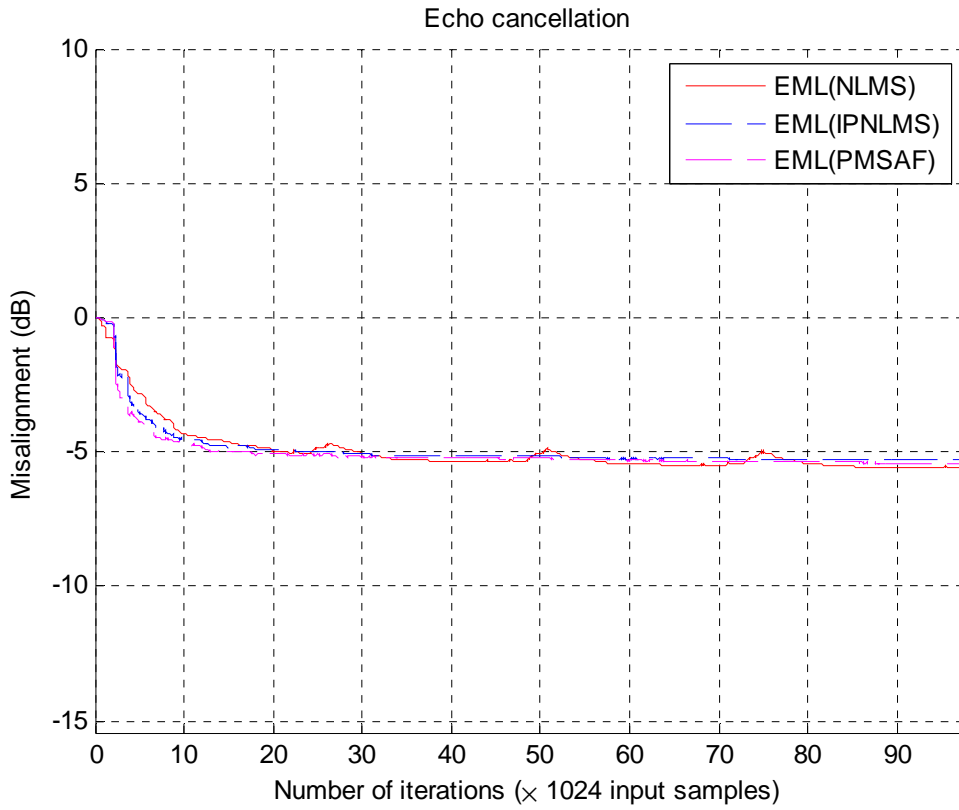




6.9 Sparse Index using 50 decaying constant (Impulse response) and Speech signal (excitation signal)

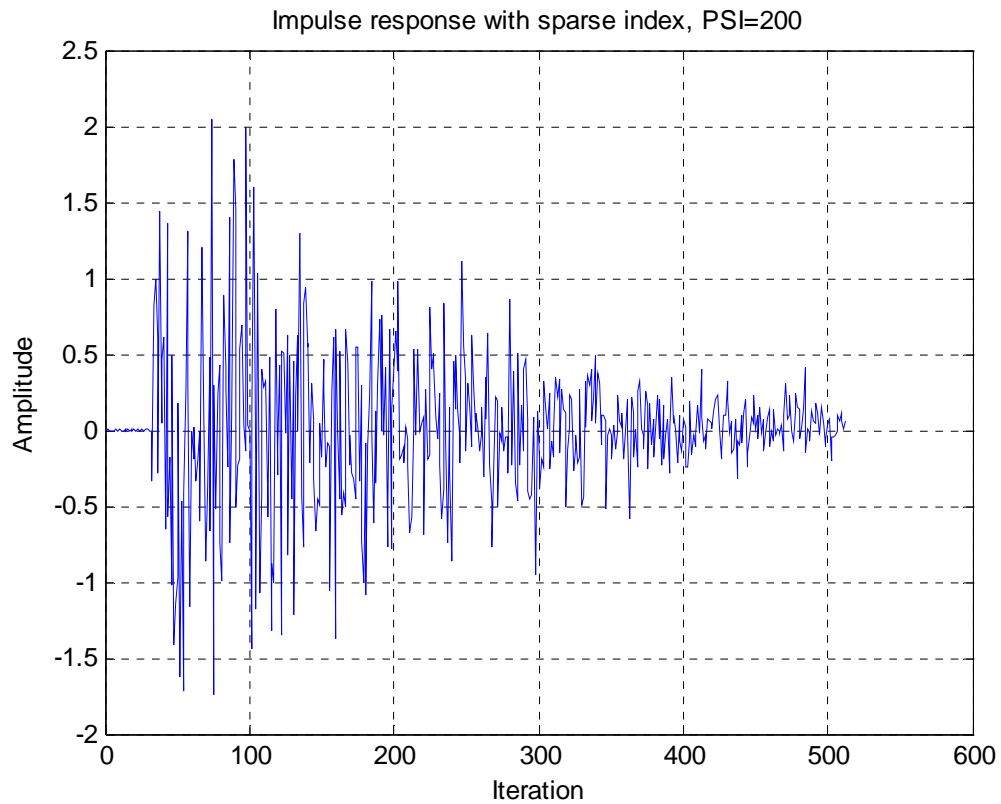
The below figures shows the output of the echo cancellation system. Fig a. is the sparse impulse response with 50 decay constant. Fig b. represent the system identification for FIR using PMSAF, Improved PNLMS and NLMS. Fig c. shows the misadjustments plot and Fig d. MSE learning curves.



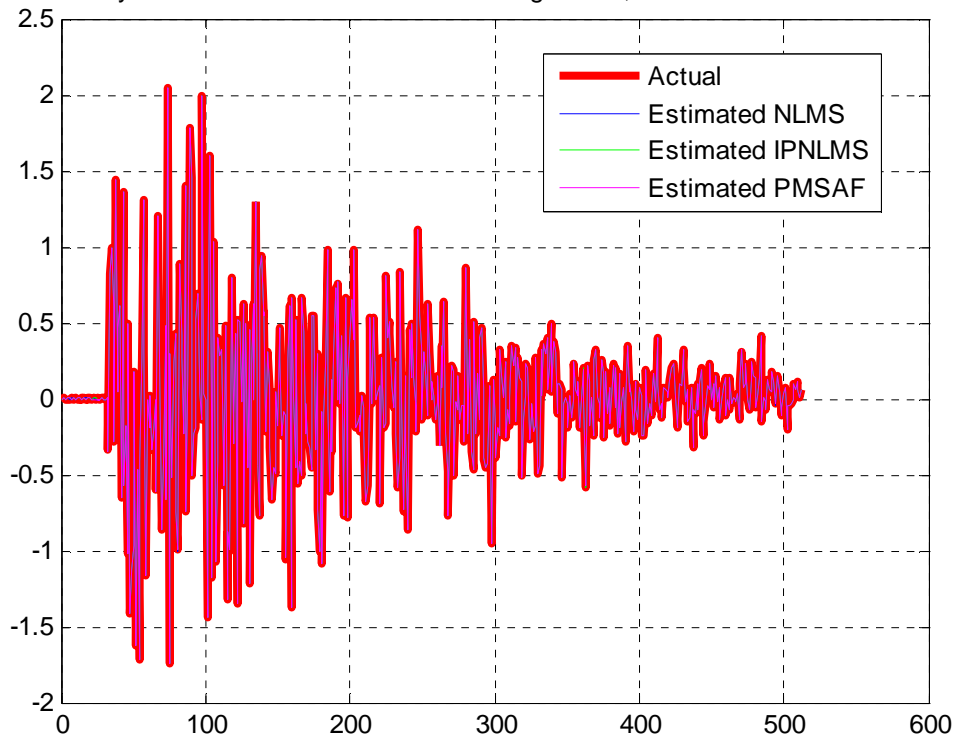


6.10 Sparse Index using 200 decaying constant (Dispersive Impulse response) and White noise (excitation signal)

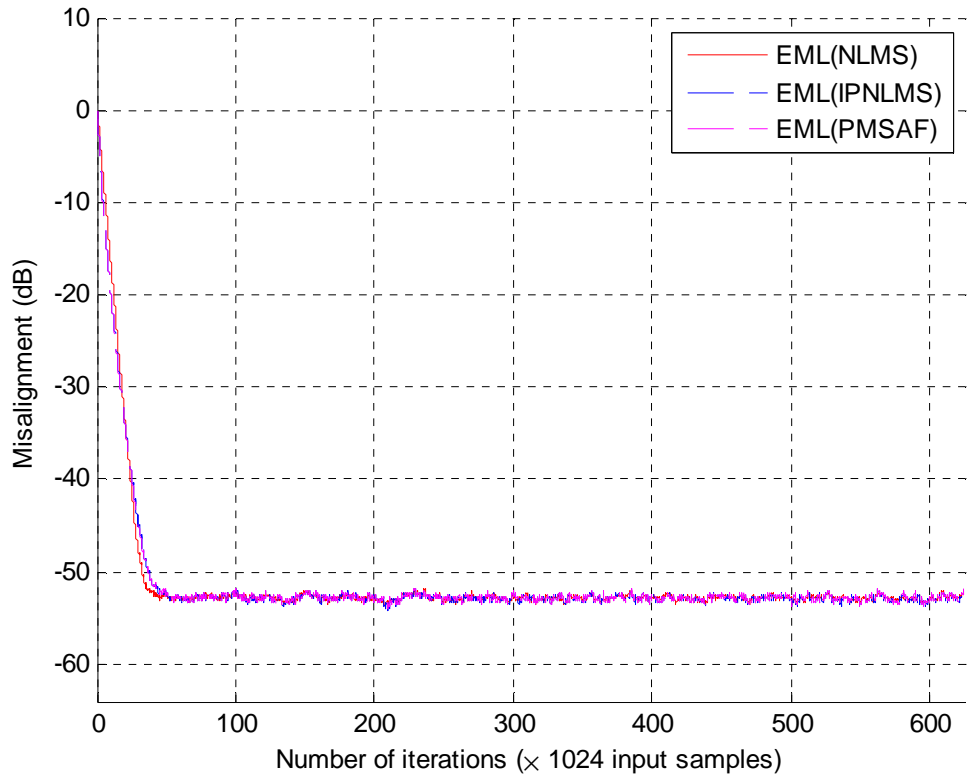
The below figures shows the output of the echo cancellation system. Fig a. is the dispersive impulse response with 200 decay constant. Fig b. represent the system identification for FIR using PMSAF, Improved PNLMS and NLMS. Fig c. shows the misadjustments plot and Fig d. MSE learning curves.

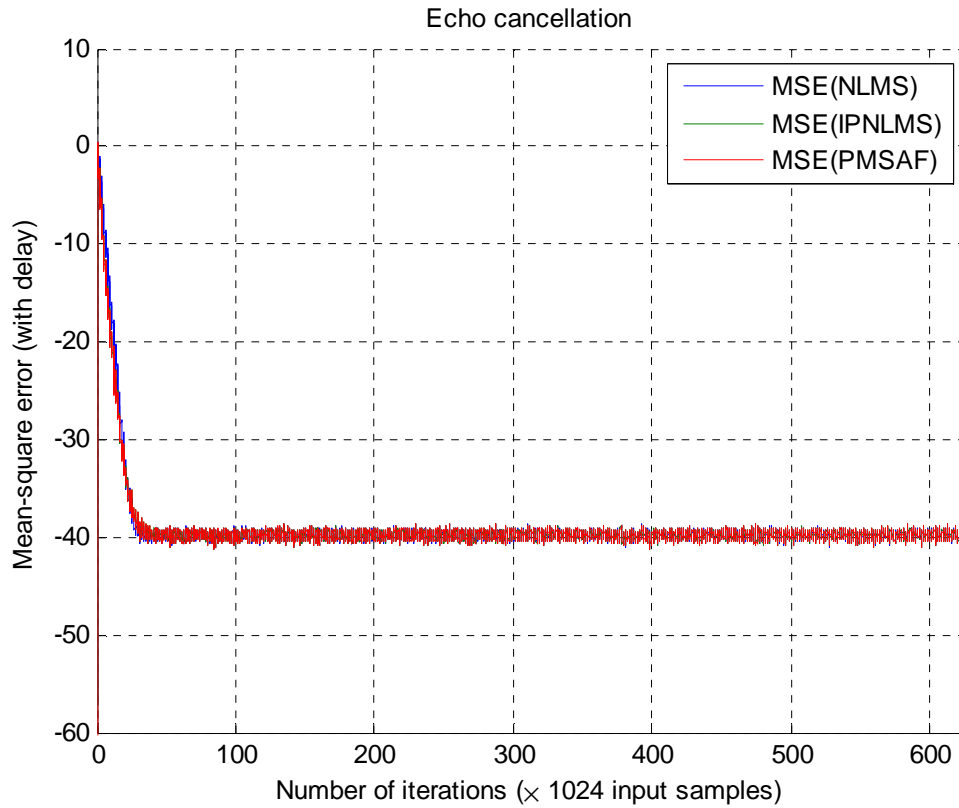


System identification of FIR filter using NLMS, IPNLMS and PMSAF



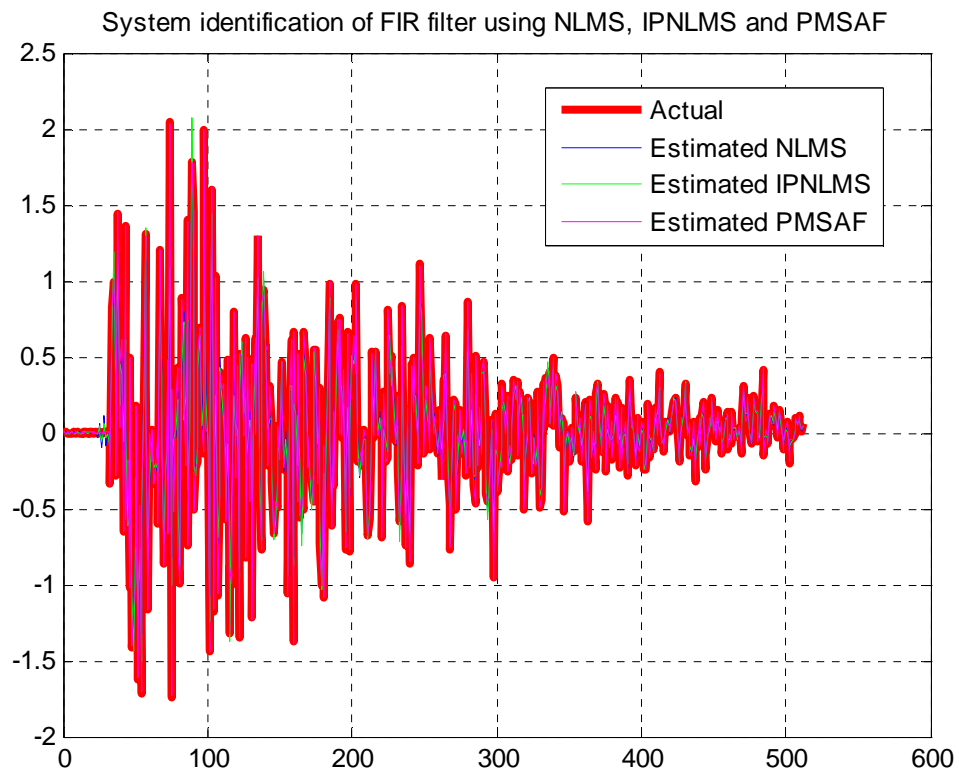
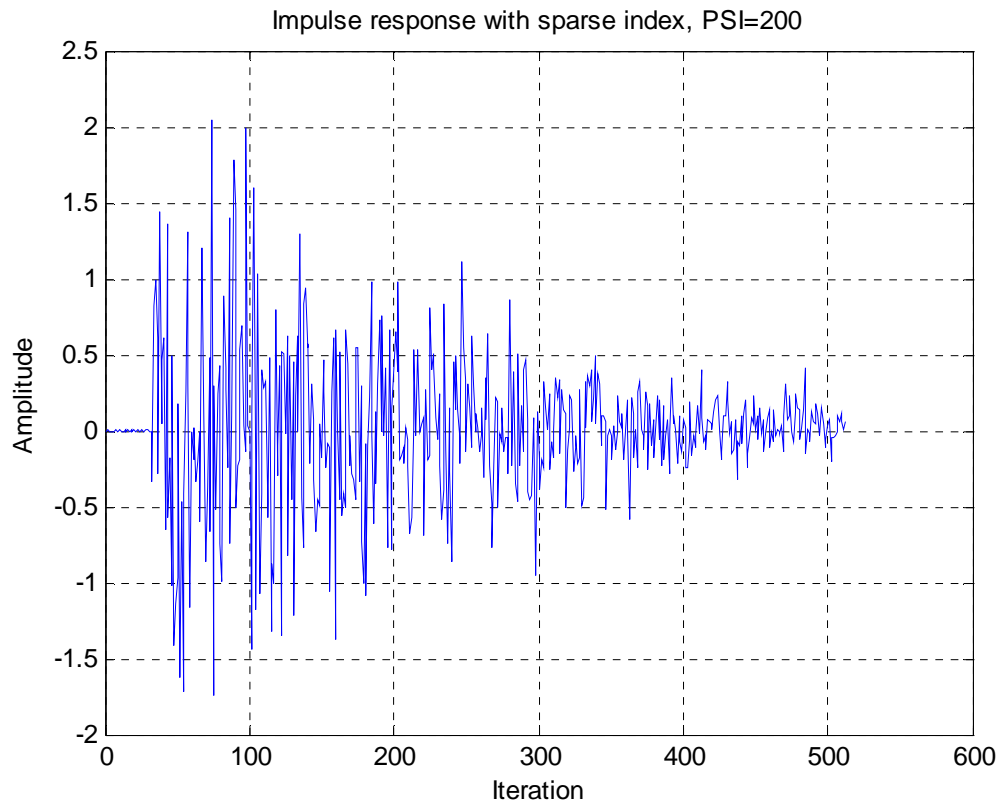
Echo cancellation

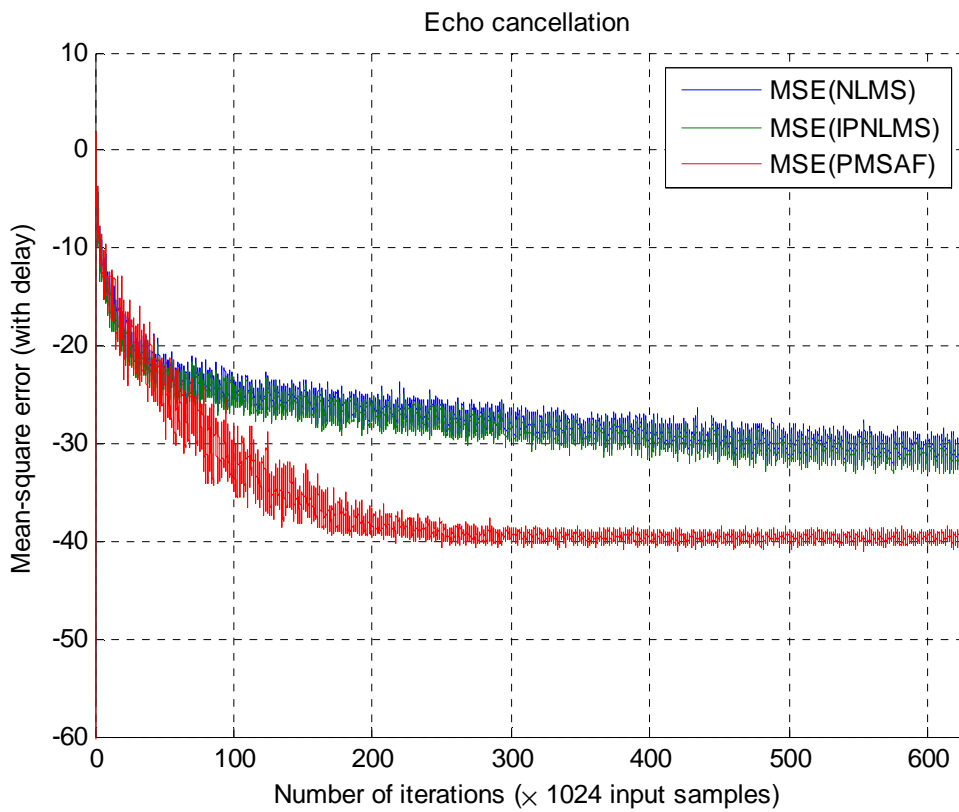
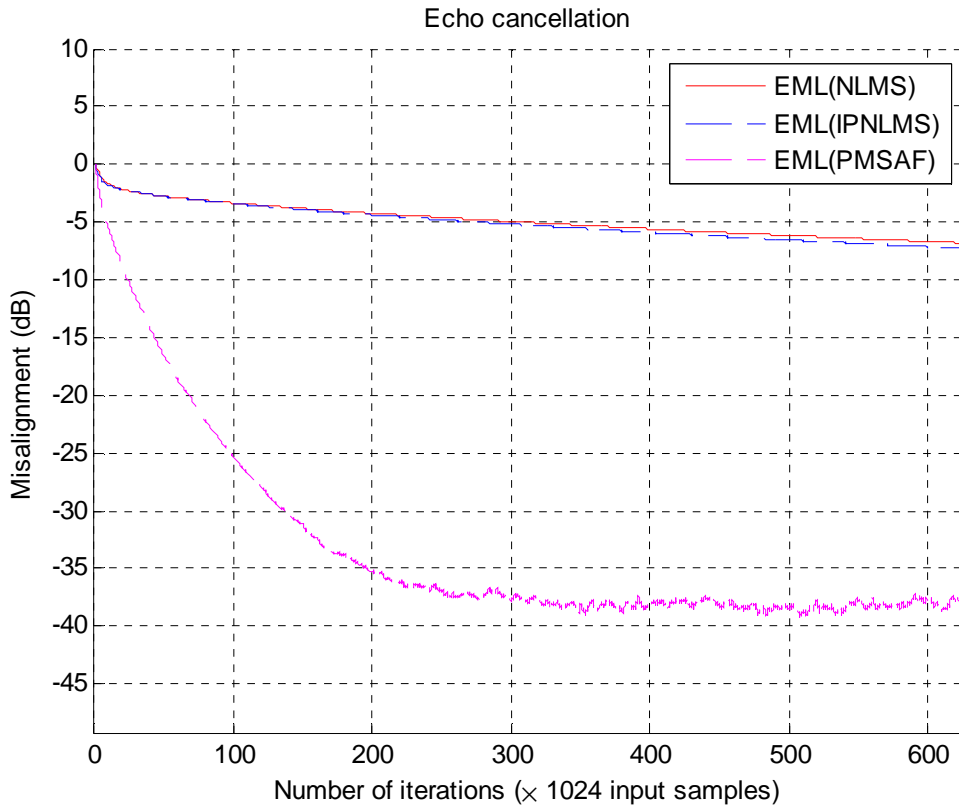




6.11 Sparse Index using 200 decaying constant (Dispersive Impulse response) and Color input (excitation signal)

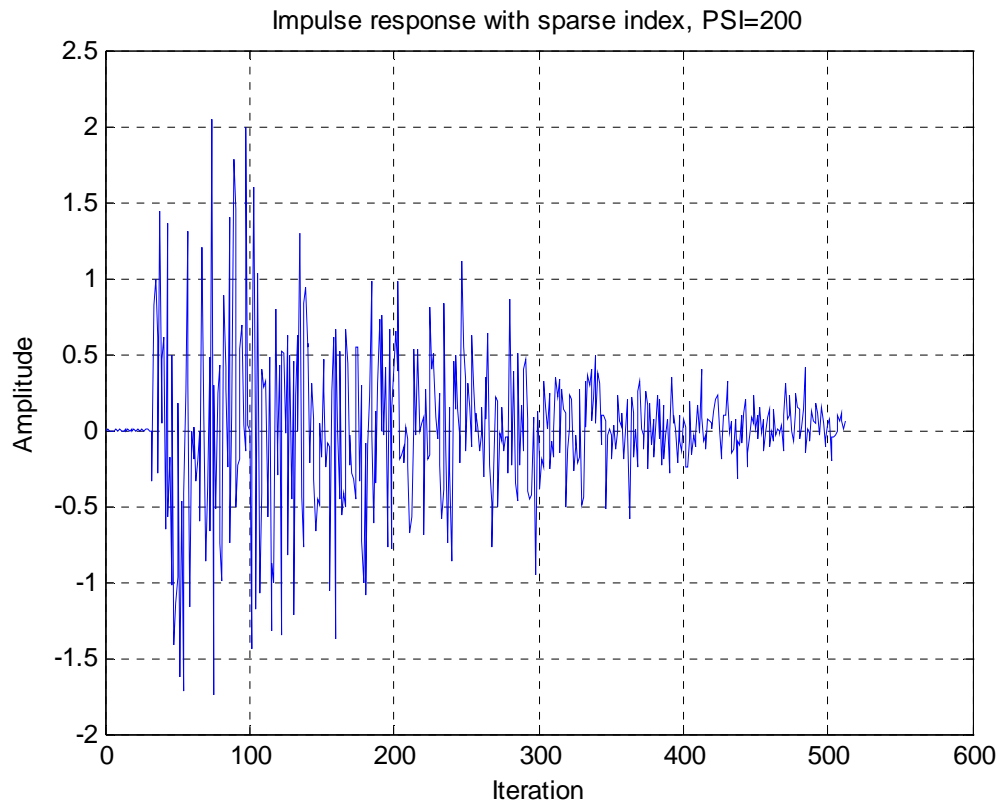
The below figures shows the output of the echo cancellation system. Fig a. is the sparse impulse response with 200 decay constant. Fig b. represent the system identification for FIR using PMSAF, Improved PNLMS and NLMS. Fig c. shows the misadjustments plot and Fig d. MSE learning curves.



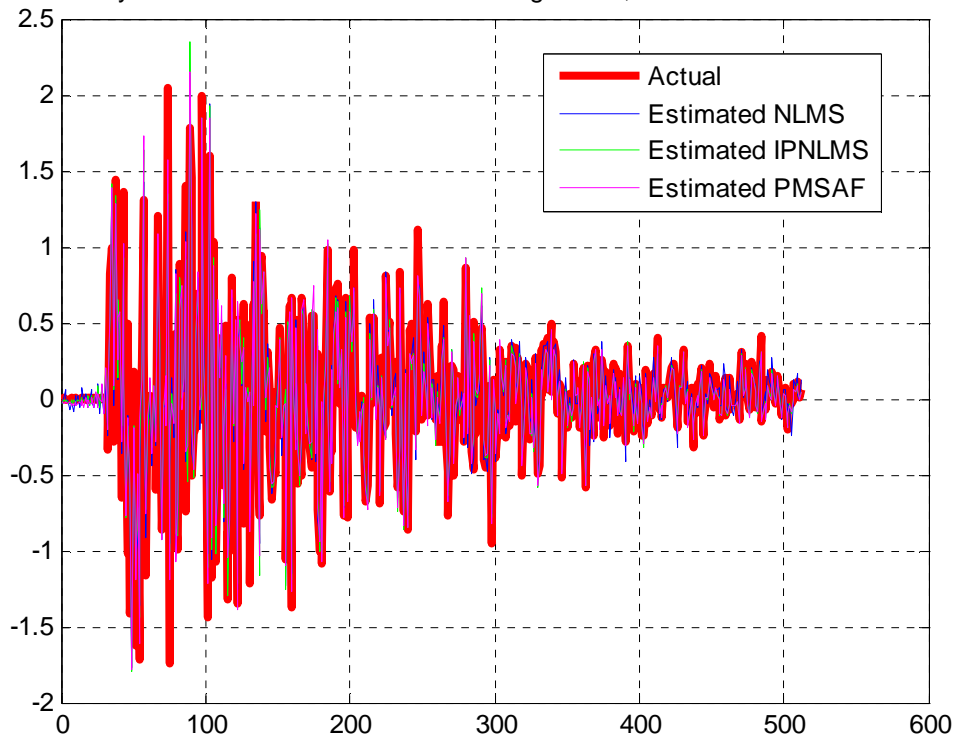


6.12 Sparse Index using 200 decaying constant (Dispersive Impulse response) and Speech signal (excitation signal)

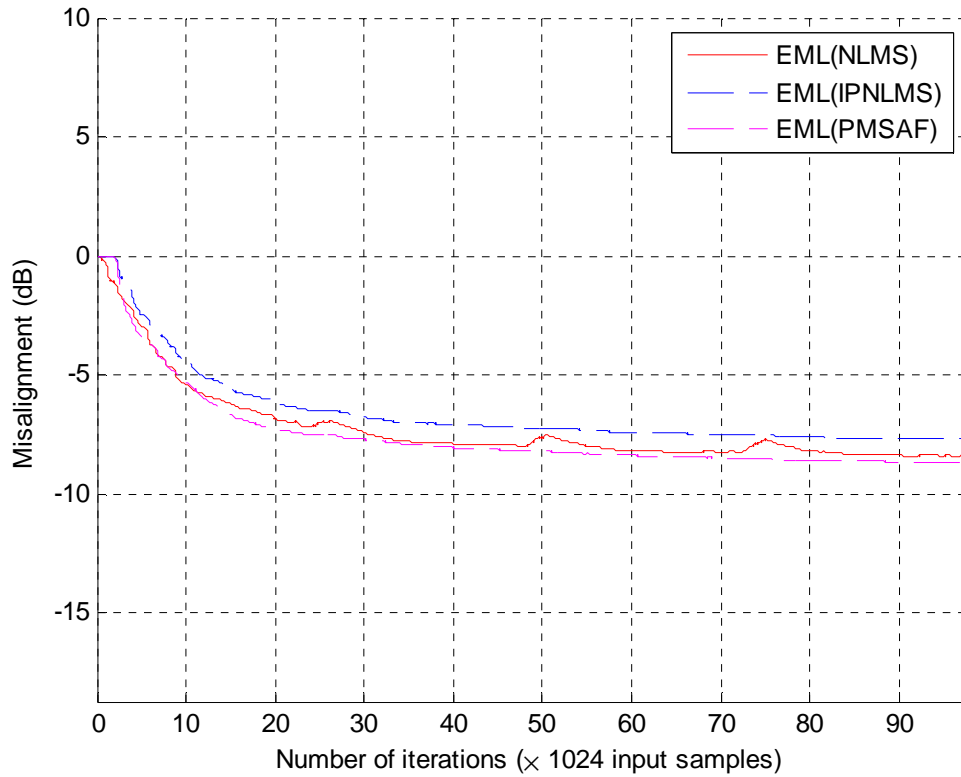
The below figures shows the output of the echo cancellation system. Fig a. is the sparse impulse response with 200 decay constant. Fig b. represent the system identification for FIR using PMSAF, Improved PNLMS and NLMS. Fig c. shows the misadjustments plot and Fig d. MSE learning curves.



System identification of FIR filter using NLMS, IPNLMS and PMSAF



Echo cancellation



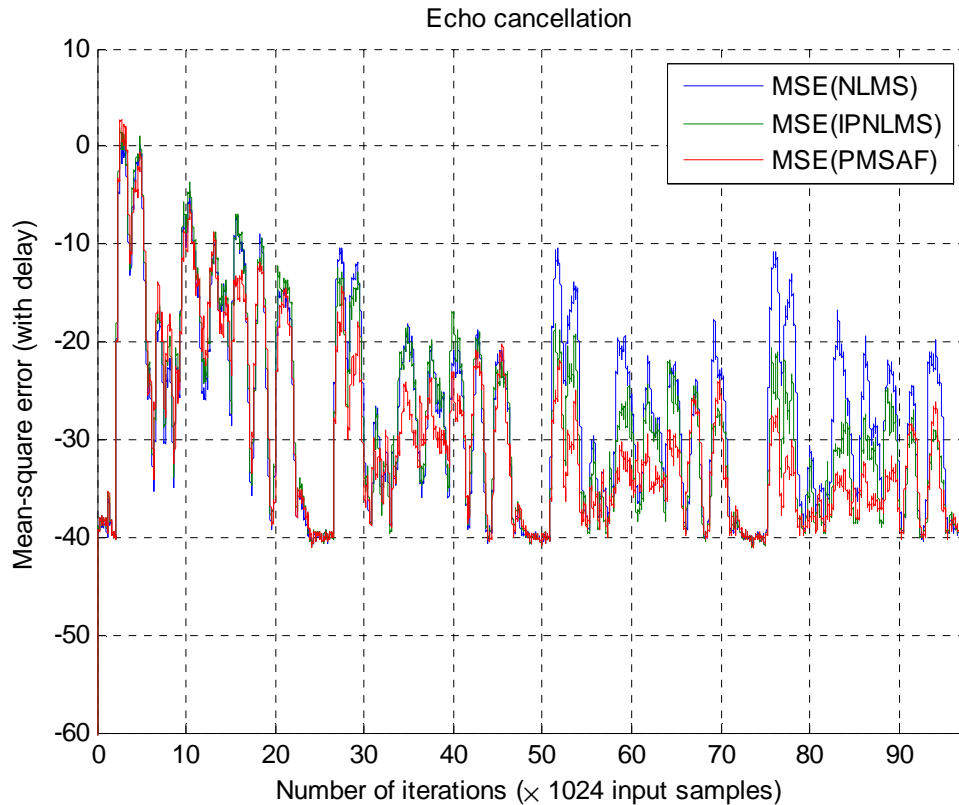


Table 6.1 shows the simulation result for the excitation signal (white noise, color input and speech signal), impulse responses (sparse (SI8, SI20, SI50) and dispersive (SI200)) for all the algorithms.

The mean square error curve for the sparse impulse response (SI8, SI20, SI50) with excitation signal (white noise) PMSAF and IPNLMS outperform the NLMS algorithm and no advantage using dispersive impulse response (SI200) under excitation signal (white noise).

The mean square error curve for the sparse impulse response (SI8, SI20, SI50) with excitation signal (color input) and also using dispersive impulse response (SI200) PMSAF outperform the IPNLMS, NLMS algorithm.

Similarly mean square error curve for the sparse impulse response (SI8, SI20, SI50) and dispersive impulse response (SI200) with excitation signal (speech signal) PMSAF algorithm continuously better as compare with IPNLMS and NLMS algorithm.

After the observation of these results we will well known the characteristics of PMSAF and Improved PNLMS for larger tap weights they uses larger step size and minimum adaptation near zero tap weights for achieving the small misadjustment and fast convergence.

	White Noise	Color Input	Speech Signal
SI8 (Sparse)	PMSAF & IPNLMS outperform NLMS	PMSAF outperform IPNLMS & NLMS	PMSAF consistently better
SI20 (Sparse)	PMSAF & IPNLMS outperform NLMS	PMSAF outperform IPNLMS & NLMS	PMSAF consistently better
SI50 (Sparse)	PMSAF & IPNLMS outperform NLMS	PMSAF outperform IPNLMS & NLMS	PMSAF consistently better
SI200 (Dispersive)	No advantage	PMSAF outperform IPNLMS & NLMS	PMSAF consistently better

Table 6.1: Comparison of all algorithms

Results (Part 2)

The second part of my thesis is to compare the MSE learning curves of NLMS algorithm with the MSAF algorithm with $N = 4, 8, 16, 32$ subbands under the white noise and colored AR (2) signals. The unknown system $B(z)$ identify the room acoustic path using a sample frequency of 8Kz. Length of weight vector $w(k)$ is identical to the impulse response vector b . Initially all tap weights are equal to zero. As shown in figure 4.1 white noise uncorrelated with the input signal is added to the output of unknown system $\eta(n)$ and 40dB SNR. The added noise disturbs the weight vector to identify exactly the unknown system b , non zero value of steady state mean square error bounded the power of noise $\eta(n)$.

The mean square error curves of MSAF and NLMS algorithms obtained by group of averaging over 100 independent trials and moving average filter 10 points used for smoothening. Pseudo-QMF modulated filter banks with filter length $L=8N$ used for analysis and synthesis part. Regularization parameter $\alpha = 0.0001$ and step size $\mu = 0.1$ used for both the algorithms.

6.13 MSE OF MSAF WITH N=4, 8, 16, 32 AND NLMS ALGORITHMS (White noise)

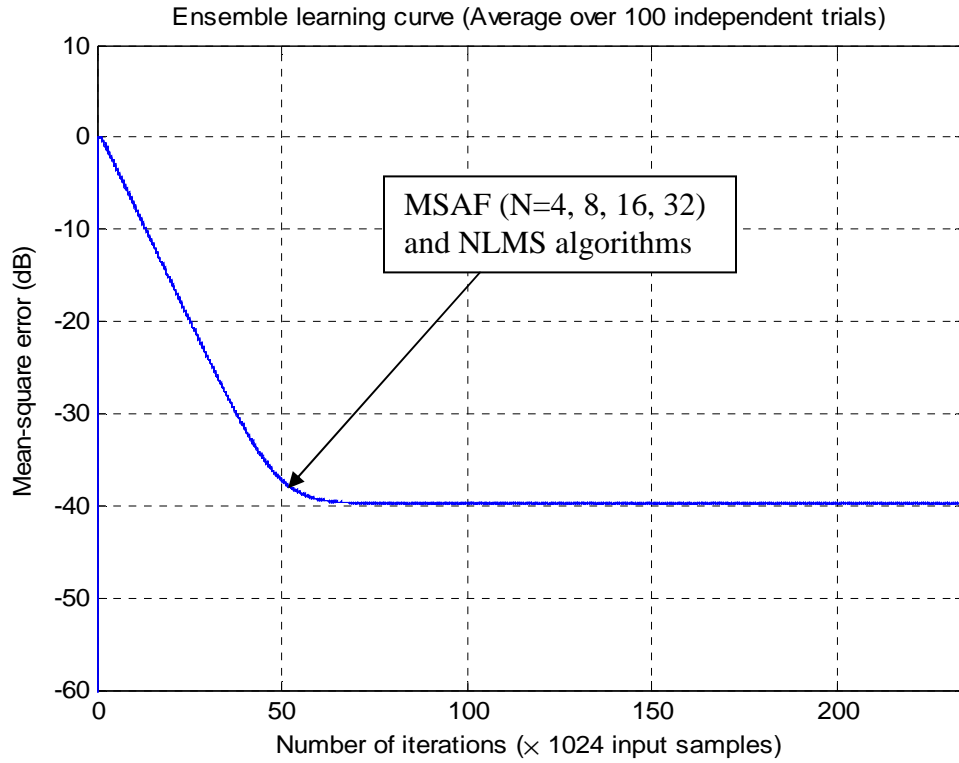


Figure 6.1: MSE learning curves of MSAF algorithm with N= 4, 8, 16, 32 and NLMS algorithm (white noise)

6.14 MSE OF MSAF WITH N=4, 8, 16, 32 AND NLMS ALGORITHMS (colored AR(2) signal)

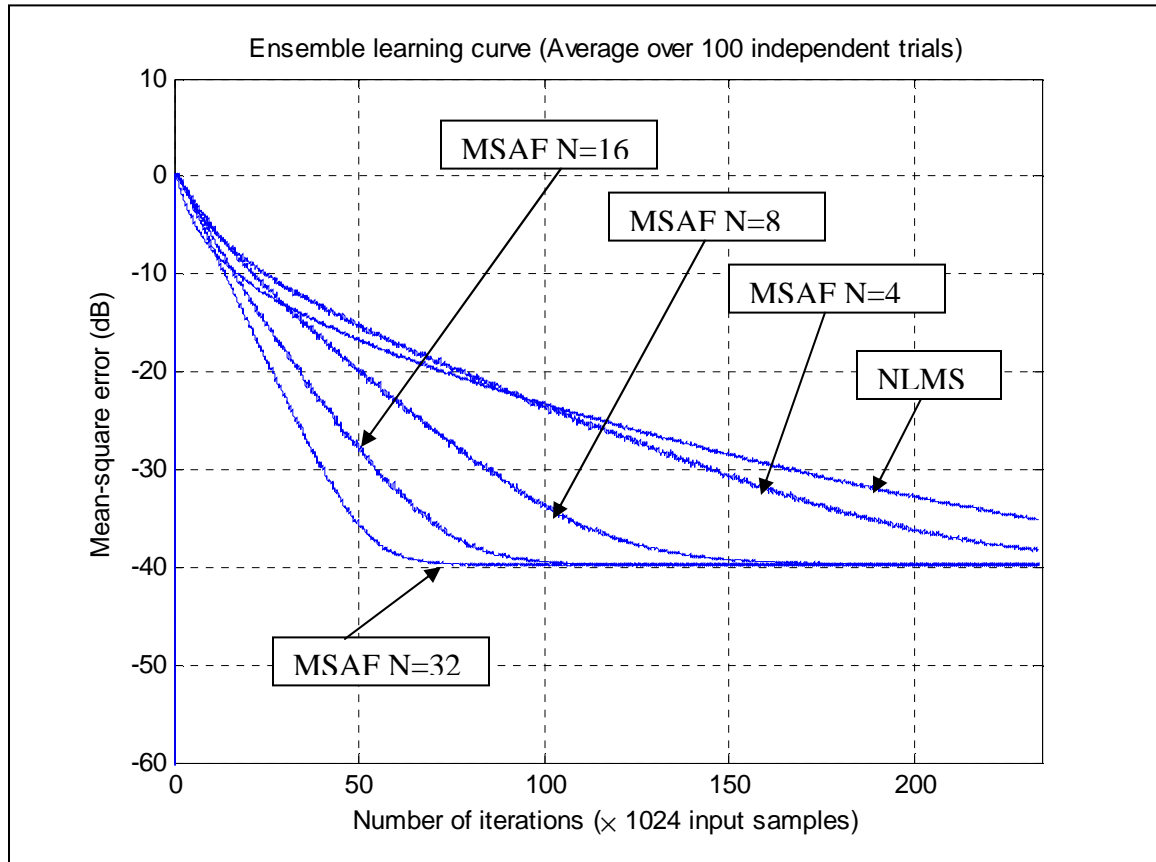


Figure 6.2: MSE learning curves of MSAF algorithm with N= 4, 8, 16, 32 and NLMS algorithm (colored AR(2) signal)

Figure 6.1 shows the simulation result for the white noise both algorithms NLMS and MSAF with different number of subbands have almost identical learning curve. The reason behind is that inherent decorrelation has no effect on the uncorrelated white noise for the MSAF algorithm.

Figure 6.2 shows the simulation result for the colored AR(2) signal both algorithm NLMS and MSAF. MSAF algorithm converges faster as compare with NLMS algorithm mainly due to inherent decorrelation. Which adapt the input signal previous to weight adaptation.

Conclusion and Future Work

7.1 Conclusion

Adaptive signal processing is the most important field in digital signal processing. Adaptive filters research work can be divided in to two categories; (1) developed advanced filter structure for improving the performance, computation complexity etc, (2) analyze developed adaptive filter.

PMSAF and IPNLMS algorithm behaves very well when the excitation signal (white noise), impulse response (sparse) and no advantage against the dispersive impulse response. While the excitation signal (color input or speech signal) PMSAF outperform and continuously better convergence rate as compare with IPNLMS and NLMS algorithms.

An identical mean square error curve for MSAF with different subband ($N = 4, 8, 16, 32$) and NLMS algorithm with input signal (white noise). MSAF with different subband ($N = 4, 8, 16, 32$) algorithm converges faster as compare with NLMS algorithm when the input signal (colored AR(2) signal).

7.2 Future Work

This thesis guides to many future research. The area that should focused on is that what are the filter banks and their involvement in Multiband subband adaptive filtering. The MSAF presented in this thesis is one with Pseudo-QMF modulated filter bank approach; further extension can be a generalized version of this algorithm to investigate the other types of filter bank like DFT modulated filter bank, DFT modulated polyphase filterbank.

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