<u>Development of Efficient Algorithms for Impulsive Noise Reduction</u>

by

Alina Mirza

Submitted to the Department of Electrical Engineering

in Partial Fulfillment of the Requirements for the Degree of

Doctor of Philosophy

at the

National University of Sciences & Technology, Pakistan

<u>PhD THESIS SUPERVISOR</u>

Dr. Shahzad Amin Sheikh

NATIONAL UNIVERSITY OF SCIENCES & TECHNOLOGY (NUST)

COLLEGE OF ELECTRICAL & MECHANICAL ENGINEERING

DEPARTMENT OF MECHANICAL ENGINEERING

In the name of ALLAH, the Most Merciful and the Most Beneficent

To my dear family

ABSTRACT

Impulsive noise is a category of acoustic noise which includes unwanted, instantaneous sharp sounds. Impulsive noise is a manmade noise and has catastrophic effects in high data rate applications and communication systems. All the non-Gaussian noises come under the category of impulsive noise. Impulsive noise produces burst errors, as a result information is significantly corrupted and band width is wasted. In this thesis we have proposed efficient algorithms for reduction of impulsive noise in OFDM and ANC realm. All the proposed algorithms are based on adaptive filtering philosophy.

In the first part of this research, State Space Recursive Least Square (SSRLS) algorithm based enhanced impulsive noise canceler is proposed. The suggested algorithm was tested on sinusoidal and Electrocardiogram signal and was successful in significantly reducing the impulsive noise. The same impulsive noise canceller again outperformed the existing techniques when it was implemented in OFDM system.

Second part of the thesis presents a new hybrid dual facetted technique for impulsive noise suppression in OFDM systems employing error correction code (Reed Solomon) and adaptive filters. Adaptive filtering achieves more accurate estimate of the original OFDM signal after impulsive noise cancellation. The results in terms of steady state mean square error (MSE) reduction, bit error rate (BER) improvement and signal to noise ratio (SNR) enhancement confirm the effectiveness of the proposed hybrid approach when compared with the recently reported techniques.

Moreover, a Filtered-x SSRLS (FxSSRLS), an SSRLS based practical adaptive solution for Active Noise Control (ANC) is suggested in this dissertation. The proposed FxSSRLS algorithm is more robust in eliminating high-peaked impulses than the recently reported algorithms for ANC applications. Moreover, the suggested solution exhibits better stability and faster convergence, without jeopardizing the performance of the proposed solution in terms of residual noise suppression in the presence of impulses.

Last but not the least, another efficient Filtered x Bhagyashri (FxBhagyashri) algorithm for impulsive noise mitigation in ANC is also proposed. FxBhagyashri algorithm becomes unstable in presence of impulsive noise, so two modifications in the FxBhagyashri algorithm i.e; Clipped FxBhagyashri (CFxBhagyashri) and Modified Filtered x Bhagyashri (MFxBhagyashri) algorithms are also presented in this research manuscript. Both modifications gave better results in impulsive noise reduction as compared to standard FxBhagyashri algorithm. It was also found that the proposed MFxBhagyashri algorithm can approach FxRLS algorithm in term of low steady state error with almost same computational complexity of FxLMS family algorithms. In the end of dissertation, the closed form expression for steady state analysis of Normalized Bhagyashri algorithm is presented on same lines as of Bhagyashri algorithm which serve as a motivation for the researchers who intend to work in this area.

ACKNOWLEDGEMENTS

I would like to thanks my Allah Almighty, for His countless blessings and divine direction throughout the course of my academic career. Very special thanks to my supervisor Dr Shahzad Amin Sheikh, for believing in me and accepting me as a PhD student. This work would not have been possible without his valuable guidance, advice and support over the years.

I would like to express my sincere gratitude to Dr Fahad Mumtaz Malik, and Dr Usman Ali for their guidance in my research. I am thankful to my father Dr Muhammad Ashraf Mirza who always motivated me to remain focus in the most difficult times of my studies and to my mother for her ever present support and prayers. I am indebted to my in-laws and most importantly my husband Ali Fahd and my sweet daughters Abeer Fatima and Wanya Fatima who have been very supportive and have shown extraordinary patience all the way along. I would like to pay my thanks to Muneer Ahmed Rajper, Publication Officer, Mehran University of Engineering and Technology and Dr Ejaz Muhammad, Head of department of APCOMS, for their motivation and extraordinary support during my research phase.

I am also grateful to my best friend Sofia Chaudary for unconditional love and care. Last not the least my colleagues Ayesha Zeb, Sumrin Mehak Kabir, Ume Hani and Javeria Habib, for their utmost cooperation and unconditional support.

I would also like to acknowledge National University of Sciences & Technology (NUST), Islamabad, Pakistan for the financial support they provided for my studies and research.

Table of Contents

List of Tables

List of Figures

List of Abbreviations

ANC = Active noise control

BER = Bit error rate

dB = Decibel

DR = Data reuse

DSL = Digital Subscriber Lines

FEC = Forward error correction codes

FFT = fast Fourier Transform

FxLMS = Filtered x least mean square algorithm

FxSSRLS = Filtered x state space recursive least square

i.i.d= Independent Identical Distribution

IFFT = Inverse fast Fourier Transform

ISI = Inter symbol interference

LMS= Least Mean Square

LTE = Long Term Evolution

MIMO= Multiple Input Multiple Output

MNR=Mean noise reduction

MSE =Mean square error

NLMS= Normalized Least Mean Square

NSS-FxLMS = Normalized step size filtered x least mean square algorithm

OFDM = Orthogonal frequency division multiplexing

PDF = Probability density function

PSD= Power Spectral Density

PSK= Phase Shift Keying

QAM= Quadrature Amplitude Modulation

QPSK= Quaternary Phase Shift Keying

RLS = Recursive least square

RLS= Recursive Least Square

RS = Reed.Solomon

SNR = Signal-to-noise ratio

SSRLS = State space recursive least square

SαS = Symmetric α-stable distribution

VSNLMS = variable step normalized least mean square

Chapter 1

Introduction

Impulsive noise normally exists in the form of pulses of short duration with very high amplitude. There are many sources of impulsive noise such as adverse channel environments, automatic start of generators, vacuum pumps, thundering etc [1-2]. Actually, a broad class of non-Gaussian noise lies under the category of impulsive noise.

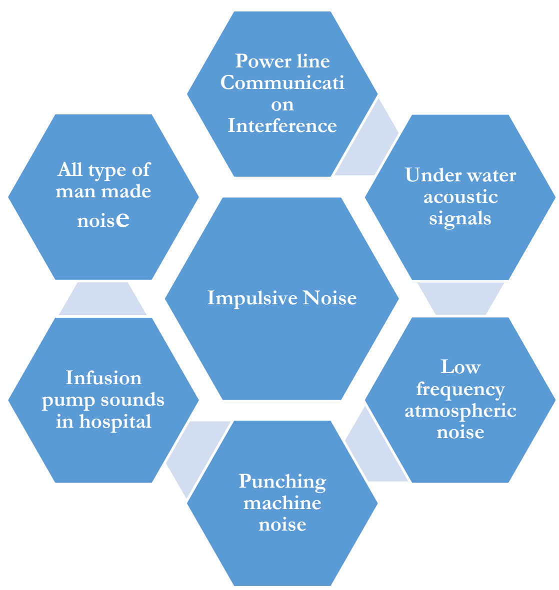


Figure 1.1: Different Sources of Impulsive Noise

Due to impulsive noise large amount of bandwidth is wasted in the communication channels. Moreover, it is one of the major reason of transmission impairments in wired communication systems and hearing loss in acoustic domain. So, there is a strong need to develop efficient algorithms for impulsive noise mitigation for both communication [3] and acoustic impulsive noise suppression [4].

1.1 Impulsive Noise Sources:

Impulsive noise is a category of acoustic noise which includes unwanted, instantaneous sharp sounds. Impulsive noise sources can be divided into two categories [6], [8].

1.1.1 Manmade Sources

All the manmade noises come under the category of impulsive noise. Different electrical and electronic devices and systems generate abrupt noise with high amplitude and short duration can be categorized as impulsive noise. For simplicity, manmade sources can be distinguished in

a) ***Indoor Sources*** include many household appliances producing frequent impulsive noise like dish washer, grinder, food mixer, washing machines, vacuum cleaners, hair dryers, drill machine and light switches etc. [5]

b) ***Outdoor sources****:* Combustion engine, car ignition, IV pump sounds in hospitals, stamping and punching machines, welding, high power grid lines etc are all sources of impulsive noise. [6]

1.1.2 Natural Phenomena:

Noise generated during natural phenomena like lightening, thundering, heavy rainfall, solar statistics etc can also be categorized as impulsive. This type of interference is also referred as atmospheric noise.

1.2 Types of Impulsive Noise

Impulsive noise can be broadly divided into the following types.

a) **Aperiodic Impulsive Noise (Asynchronous)**: Constitutes the impulses occurring at random times with short duration and high power. (i.e. impulsive noise can have a PSD 50 dB higher than the background noises [9])

b) **Periodic Impulsive Noise (Synchronous)**: are impulses with long interval occurring repeatedly after specific time intervals.

It is one of the biggest challenges for efficient communication- bandwidth applications and acoustic impulsive noise mitigation. The performance of communication systems is significantly degraded [9] - [11] as it can alter the complete data symbol by creating burst errors. Due to this fact, researchers are taking keen interest in developing methodologies for mitigating impulsive noise. The impulsive noise occurring in nature is characterized by its three random variables i.e. impulse width, amplitude and inter arrival time between impulses. The energy of single impulse is identified by impulse width and amplitude. Whereas, the impulse energy with frequency of impulses (the reciprocal of inter arrival time) calculates the power of impulsive noise.

1.3 Impulsive Noise Models:

Different statistical models are reported in literature for modelling impulsive noise. We will briefly review the three most widely used models of impulsive noise for better understanding of impulsive noise characteristics. These are:-

- Middleton Class A
- Bernoulli-Gaussian

- Symmetric Alpha-Stable distribution

1.3.1 Middleton Class A Noise

Middleton [13] developed statistical noise models which was best suited for both man-made and natural phenomena [14]–[16]. In [13], he presented three categories of noise models and their applications are summarized below in Table 1.1.

Table 1.1: Summary of Middleton Noise Types

	Class A	**Class B**	**Class C**
Bandwidth	Narrow	Broadband	Mix(Narrow & Broadband)
Application	Power line Communication OFDM systems	Atmospheric Car ignition	Cosmic radiations Extra-terrestrial solar

Most widely used way of modelling impulsive noise in communication systems is Middleton Class A. It adds both background and impulsive noise. The probability density function of Middleton Class A model is as follow:-

$$f(x) = e^{-A} \sum_{p=0}^{\infty} \frac{A^p}{p!\sqrt{2\pi\sigma_p^2}} \, e^{-\frac{x^2}{2\sigma_p^2}} \tag{1.1}$$

$$\sigma_p^2 = \frac{\frac{m}{A}+\tau}{1+\tau} \tag{1.2}$$

where σ_p^2 is the variance and factor A is the impulsive index. The small value of A means more impulsive noise, whereas large value of A means more Gaussian (less impulsive) noise. When A is ∞, the overall noise distribution is Gaussian [12]. The ratio among powers of background noise σ_{gg}^2 and impulsive noise σ_{ii}^2 is given by parameter τ.

$$\tau = \frac{\sigma_{gg}^2}{\sigma_{ii}^2} \tag{1.3}$$

The PDF of Middleton Class A noise is weighted sum of Gaussian PDF with zero mean. The mean and variance can be calculated as explained in [11].

1.3.2 Bernoulli-Gaussian Model

The second way of generating impulsive noise is Bernoulli-Gaussian [17]-[21]. In this method, the rate of occurrence of impulses is modelled by Bernoulli distribution c(p) and amplitude of impulses by Gaussian distribution. The probability mass function of Bernoulli distribution is given as:-

$$\boldsymbol{P_c[c(p)]} = \begin{cases} \propto & \mathbf{c(p) = 1} \\ \mathbf{1-}\propto & \mathbf{c(p) = 0} \end{cases} \tag{1.4}$$

The Bernoulli process mean is $\propto$ and variance is given by $\propto (1-\propto)$ [22]. The impulse amplitude is represented by Gaussian distribution of zero mean and σ_n^2 variance [22].

1.3.3 Symmetric alpha stable (SαS) Distribution

SαS distributions are also used for modelling impulsive noise in literature. The closed form expression for stable distribution does not exist. Therefore, impulsive noise is modelled by their characteristic equation given as

$$\varphi(t) = e^{-|t|^{\alpha}} \tag{1.5}$$

The parameters used for defining SαS distributions are given in Table 1.2 and its PDF is depicted in Fig. 1.2.

Table 1.2: Symmetric alpha stable distribution parameters

Parameter	**Symbol**	**Range**
Characteristic exponent	Α	$1 < \alpha \leq 2$
Skewedness of distribution	Β	$-1 \leq \beta \leq 1$
location of the distribution	Δ	Real number
scaling parameter	Γ	$\gamma > 0$

The shape of distribution is described by two parameters α and β, while statistics of Gaussian. Distribution are signified by γ and δ. The broadband impulsive noise is normally modelled by SαS distribution, i.e. band width of noise is larger than that of the receiver [12].

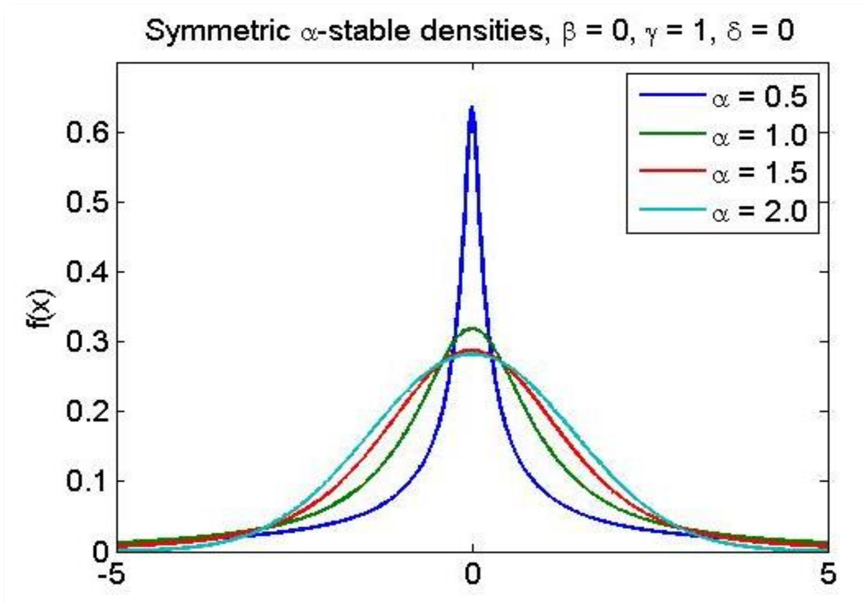


Figure 1.2: standard SαS process PDFs with different values of α

1.4 OFDM Model

Orthogonal Frequency Division Multiplexing is a variant of signal modulation that splits the modulated high data rate stream into many slow modulated narrowband closely spaced subcarriers and is less sensitive to frequency selective fading. The basic OFDM system is given in Fig.1.3

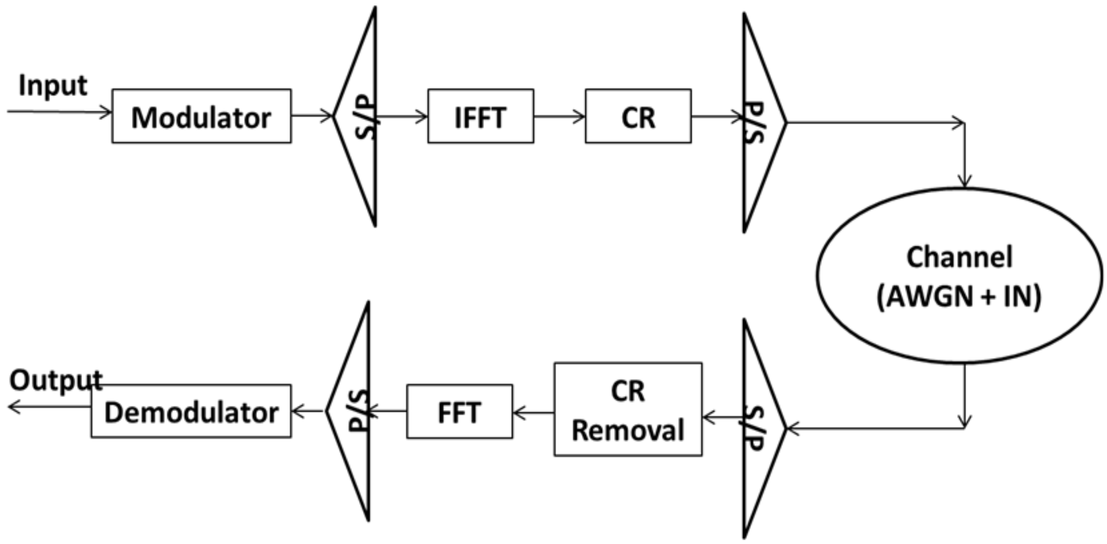


Figure 1.3: Generic Schematic Diagram of OFDM System

The input data bits are modulated into symbols that are passed through the serial to parallel block and converted into parallel format. The IFFT block manages the total number of subcarriers and orthogonality among them. The symbols are modulated on different subcarriers and are transformed in time domain using IFFT block. Inter Symbol interference is removed by guard interval use. The OFDM signal is transmitted over channel which is responsible for adding impulsive noise and Gaussian noise to signal. At receiver side, removal of cyclic redundancy is carried out, which is followed by FFT block. After that the signal is demodulated and original signal is retrieved.

1.5 Literature Review of Impulsive Noise Mitigation Methods in OFDM systems

Different mitigation techniques for impulsive noise exist in literature [17] - [25]. The most common methods used for suppressing impulsive noise are briefly viewed below: -

1.5.1 Time-domain Methods

The most commonly used nonlinear techniques are clipping, blanking and clipping/blanking. All the three techniques depend on the threshold. All the signal samples greater than threshold are assumed to be exaggerated by impulsive noise and nonlinearity suppression method are used to recover them. The nonlinear techniques used for mitigating impulsive noise determine both amplitude and phase of received signal but only modifies amplitude. All the three nonlinear techniques do not change the phase of received signal [20].

a) Clipping

In this technique, if the amplitude of the received signal is greater than clipping threshold T_c then threshold value is assigned to the receive signal. The mathematical expression for clipping is as follow.

$$y_k = \begin{cases} r_k & r_k \leq T_c \quad\quad k = 0,1,\dots\dots..N-1 \\ T_c e^{j arg(r_k)} & r_k > T_c \end{cases} \tag{1.6}$$

where r_k is the received signal and T_c is the Clipping threshold.

b) Blanking

In contrast to clipping method, in blanking the received sample values, above blanking threshold values, are assigned zero value. Normally blanking thresholds are greater than clipping threshold for same system environment [32]. The mathematical expression for blanking method is given as

$$y_k = \begin{cases} r_k & r_k \leq T_b \quad\quad k = 0,1,\dots\dots..N-1 \\ 0 & r_k > T_b \end{cases} \tag{1.7}$$

where r_k is the received signal and T_b is the Blanking threshold.

c) Clipping/Blanking

In this combination of above mentioned techniques, instead of one, two thresholds are introduced. The signal samples above blanking threshold will be given zero values. The samples lying between clipping and blanking thresholds will be assigned clipping threshold value. The remaining samples that fall below clipping threshold will remain unchanged. The mathematical equation is as below

$$y_k = \begin{cases} r_k & r_k \le T_c \\ T_c e^{j arg(r_k)} & T_c < \quad r_k \le T_b \\ 0 & r_k > T_b \end{cases} \quad k = 0,1, \dots \dots . . N-1 \tag{1.8}$$

where r_k is the received signal and T_b is the blanking threshold greater than clipping threshold T_c. Clipping/blanking method perform better than the individual clipping and blanking method [33].

1.5.2 Frequency-domain Methods

Frequency domain (FD) mitigation method was proposed by Zhidkov [32], [34-35] in OFDM systems. This technique is applicable to compensate impulsive noise in FD after OFDM demodulation and channel equalization. In this domain, the noise effect varies as per the mean of the signal's power spectrum. It involves the following steps;

- Estimation of FD representation of impulsive noise along with AWGN.
- A noise compensator that estimates the number of samples affected by the impulsive noise and reconstructs the impulsive noise vector using a peak detector.
- The estimated impulsive noise is then subtracted from the equalizer output.

Frequency-domain techniques can work well in reducing the impulsive noise effect, because impulsive noise appears random in the frequency domain while the signal is well-structured, whereas the opposite is true in the time domain [35]. The parameters in Fig 1.4 are well defined in [35].

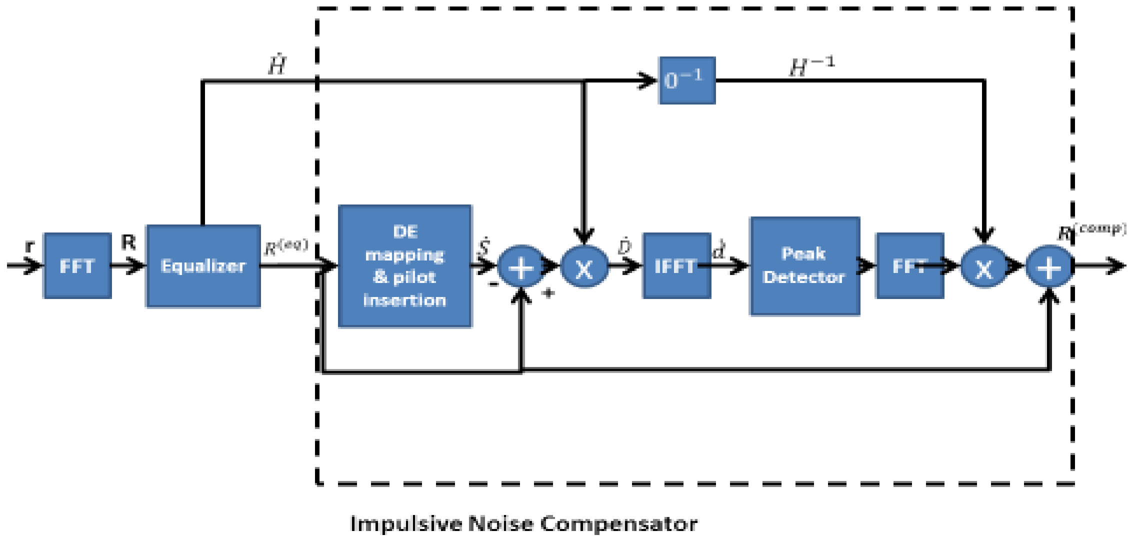


Figure 1.4: Basic block diagram of frequency-domain impulsive noise mitigation technique [32]

1.5.3 Time/Frequency Domain Method

K. A. Mawali [33] proposed noise mitigation technique based on both time and frequency domain in OFDM systems. The time domain mitigation techniques are applied to received OFDM signal before demodulation as compared to frequency domain technique, which are applied after OFDM demodulator. The combination of both time and frequency domains give better noise reduction than individual time and frequency domain methods. The Joint time/frequency technique block diagram is as follow: -

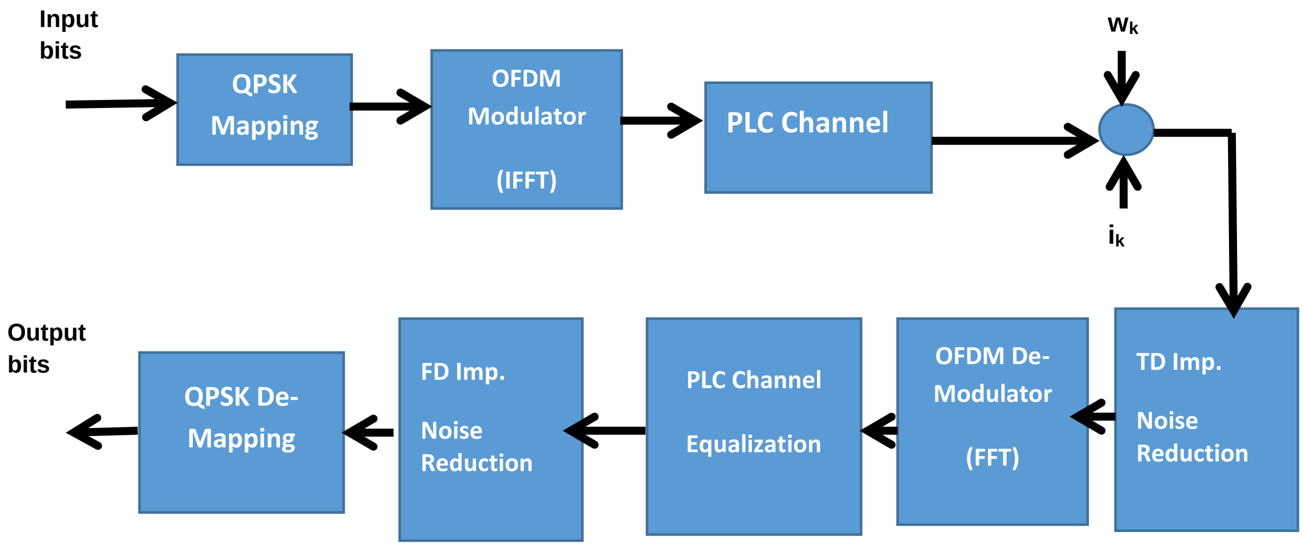


Figure 1.5: Basic block diagram of Joint Time/frequency-domain impulsive noise mitigation technique

1.5.4 Iterative Methods

In this method, impulses are assessed and then subtracted from the received signal. Noise estimation can be performed in both time as well as frequency domains. In iterative methods better impulsive noise estimate can be achieved with increased iterations. Haering and Vinck [36] proposed iterative methods for impulsive noise mitigation. Another iterative technique for impulsive noise is mentioned in [23], [32].

1.5.5 Error Correction Codes:

Error correction coding is opted as one of the basic part of communication systems for correcting errors caused by channel noise. They are also employed to reduce errors created by impulsive noise. The well-known class of coding used for combating impulsive noise are convolutional coding [37]-[38], Block Codes [39], Turbo coding [40]-[41], Reed Solomon [43-45] and low density parity-check [42]. Apart from these, other coding methods can also be suitable for communication systems.

1.5.6 Interleaving

Mostly, impulsive noise causes burst errors with duration longer than the length of symbol [10]. Normally, the burst errors are not removed by the error correction codes, which are designed for individual errors. Therefore, interleavers can be used to address burst error issue. Interleavers distribute the burst error by rearranging transmitted data bits and reduce the channel memory effect [10]. The decoder can now easily remove the individual errors instead of burst error.

1.6 Causes and Effects of Impulsive Noise

Within communication systems, normally non-Gaussian noises are encountered in nature. As discussed in section 1.1, there are many causes of impulsive noise. In everyday life, the impulsive noise is added usually in wireless communications such as radio transmission and mobile communication. It may also be added in high data rate communications. The impulsive noise adds random impulses to the signal making the signal data to be changed. Due to the occurrence of a random peak at a certain instant of time, the signal value cannot be approximated, as the approximation or prediction methods use the previous signal values, which may remain unchanged and thus the prediction may not be precise but remain probabilistic only.

1.6.1 Bandwidth Waste

The addition of impulsive noise causes transmission impairments in communications. The higher peaks caused by the impulsive noise have higher frequency ranges in frequency spectrum. The higher frequency to be afforded then costs more bandwidth. The higher frequency ranges are to be bought in order to avoid data loss. If the available bandwidth range is lesser than the one that is required after the impulsive noise has been added to the signal, then the signal samples having higher peaks may not get transmitted over that bandwidth range. So in this way, many signal samples would not be transmitted and the data or information is lost.

1.6.2 Amplitude Limit

All the conventional time domain techniques of impulsive noise mitigation discussed in section 1.5.1 depend on thresholds. Inappropriate value of threshold values can cause signal degradation. The careful selection of threshold value is needed for better reduction of impulsive noise. Receivers have a limiting property that is, the received signal is limited by the low pass filter and in this way the signal values get changed. Also the signal degradation caused by the impulsive noise affects BER of the signal. In audio signals, the addition of impulsive noise causes the signal amplitude to get changed thus changing the quality of the audio signals. Practically, in vehicle radios, the impulsive noise affects the signal badly.

1.7 Adaptive Filters

The traditional way to remove the noise from the signal is direct filtering: where noisy signal is passed to filter, which suppresses the noise and give noiseless signal at the output.

The specialised area that deal with designing such filters is called optimal filtering originated from the work of Wiener and was further enhanced by Kalman, Bucy and many others. In direct filtering both fixed and Adaptive filter can be used.

1. Fixed Filters-requires prior information about signal statistics.

2. Adaptive filters – in contrast to fixed filters, adaptive filters don't require signal statistics. The basic principle of adaptive filter consist of two processes

a) *Digital Filtering:* performs the desired signal processing i.e. Output signal is generated with respect to input signal.

b) Adaptive Algorithm: purpose is to adjust the weights of filter with time-varying environment. The error signal average square value is used as optimization criterion.

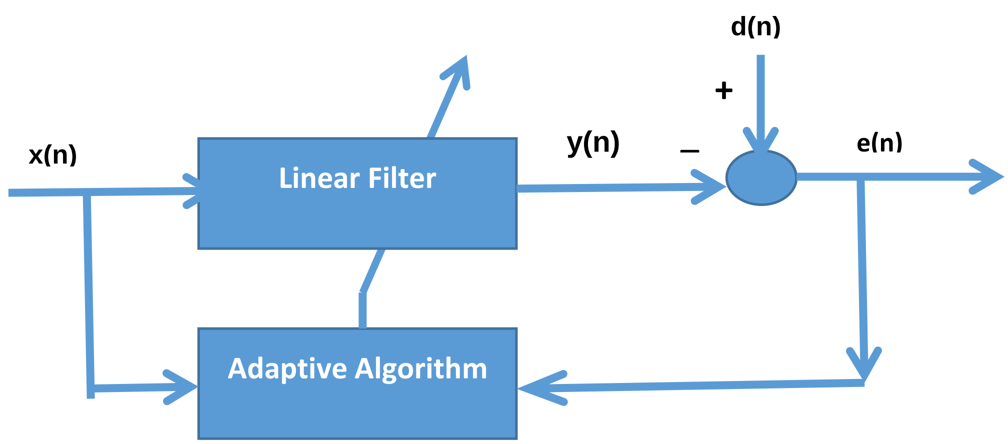


Figure 1.6: Basic Schematic of Adaptive Filter [46]

Where d(n) is the desired response, y(n) is the actual output of digital filter, x(n) is the reference input and e(n) is the error signal which is difference of d(n) and y(n). The role of adaptive filter is to adjust the digital filter tabs by minimizing the error e(n). Many recursive algorithms exist in literature. Therefore, following factors must be considered while choosing recursive algorithms

1. **Rate of convergence**. The number of adaptation cycles needed by the algorithm to converge close to the optimum Wiener solution in MSE with respect to stationary input. Fastest convergence ensures fast adaptation of algorithm with environment.

2. **Misadjustment** is deviation of MSE from Wiener soluion.
3. **Tracking** is the ability of adapting algorithm to track variations of signal statistics according to non-stationary environment.
4. **Robustness** is the characteristic that enables adaptive filter to deviate minimal in response to disturbance.
5. **Computational requirements** are the minimum number of operations within one adaptation cycle and memory size needed to store data.
6. **Structure factor** refer to hardware implementation of adaptive algorithm.
7. **Numerical properties** deal with the number of bits used for representing data.

   The adaptive filter's ability to track the variations of input statistics in non-stationary environment makes them the powerful tool for different engineering applications, i.e. communication, radar, seismology and biomedical engineering.

1.7.1 Adaptive Filter Basic Configurations

The basic class of adaptive filtering applications are as follow:

a) ***System Identification*****:** Fig. 1.7 represents the system identification configuration of adaptive filter, where it receives the same input $x(n)$ as the system. The adaptive filter output $y(n)$ is compared with desired response and output of the system $d(n)$ generating an error. That error $e(n)$ is used to adjust the weight $w(n)$ until error is minimized.

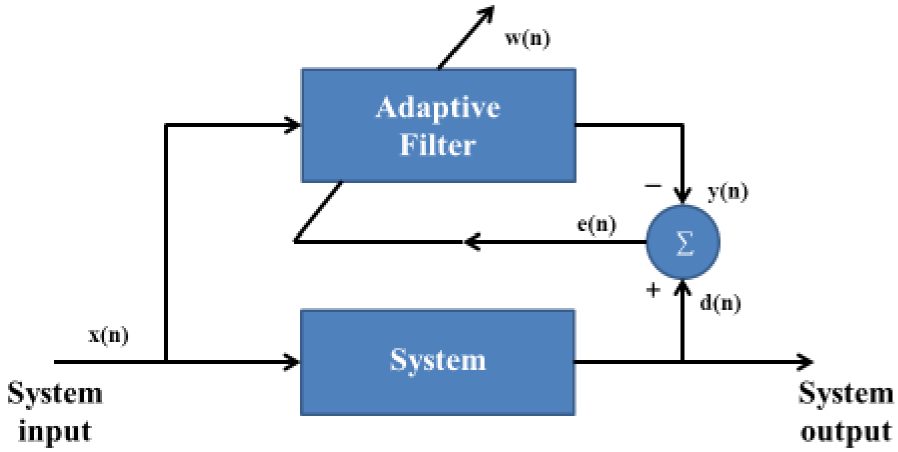


Figure 1.7: System Identification with adaptive filters [46]

b) ***Inverse Modelling:*** The inverse modelling has the aim of discovering and tracking the inverse transfer function of the system. This application consists of receiving one input $x(n)$ for the system with its output $u(n)$ connected to the adaptive filter. Then the comparison is made between the filter output $y(n)$ and the desired response $d(n)$ that consists of the delayed version of the input $x(n)$. The error $e(n)$, result of that comparison is then used to adjust the filter weights.

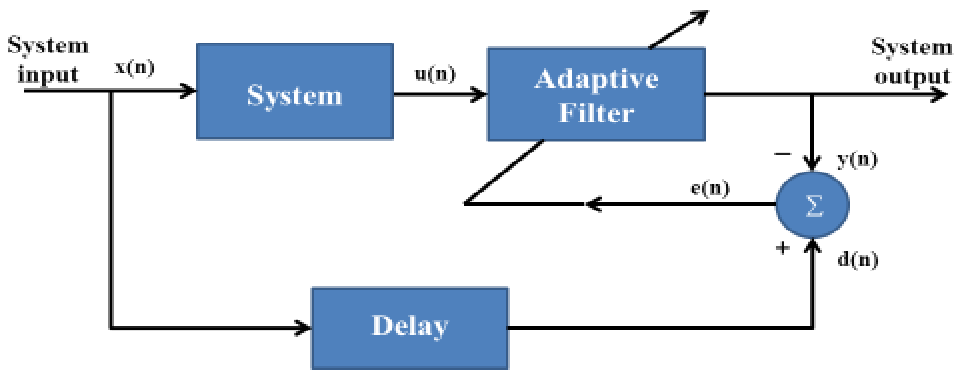


Figure 1.8: Inverse Modelling using adaptive filter [46]

c) ***Prediction:*** Fig 1.9 describes the working of the predictor adaptive filter. For giving the best prediction of a random signal, the adaptive predictor filter relies on applying the past values of the random signal $x(n)$, obtained by applying a delay to that signal provided to the adaptive filter input and comparing its output $y(n)$, with the desired response $d(n)$, that is nothing but, the actual random signal $x(n)$.

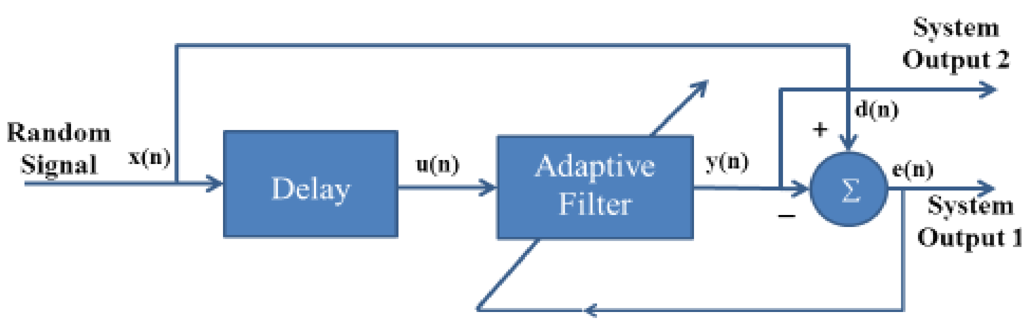


Figure 1.9: Adaptive Linear Prediction [46]

When the filter output is used to adjust the filter weights, the adaptive filter is called a predictor filter; when the result of the comparison between $y(n)$ and $d(n)$, called $e(n)$, is used to adjust the weights of the filter, it operates as a prediction error filter.

d) ***Noise Cancellation:*** The interference cancellation problem, which is selected for research in this thesis, is depicted in the Fig.1.10. The basic idea is following: a desired response $d(n)$, which is primary noisy signal $s(n) + n_2(n)$. It is compared with the output of the adaptive filter $y(n)$, that has a reference signal $n_1(n)$ at input, which is the correlated version of noise $n_2(n)$. The system output $e(n)$ is the difference between the filter output $y(n)$ and desired response $d(n)$. In an optimum situation, this $e(n)$ will be equal to the original signal without the interferences $s(n)$.

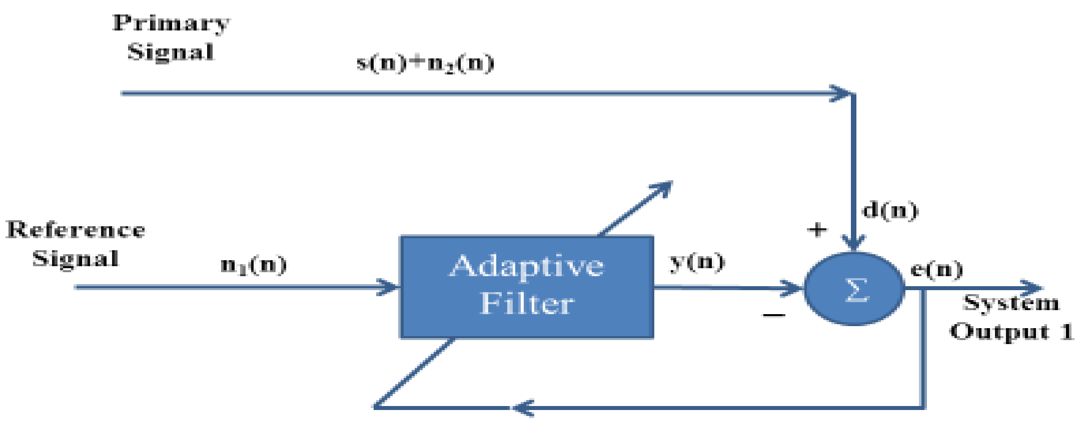


Figure 1.10: Adaptive Noise Canceller [46]

1.8 Active Noise Control

The working of active noise control is based on destructive interference of acoustic waves [47-49]. Basically, the mitigation of primary noise is performed in the region of error microphone. The anti-phase noise is provided by the adaptive controller which uses an adaptive algorithm.

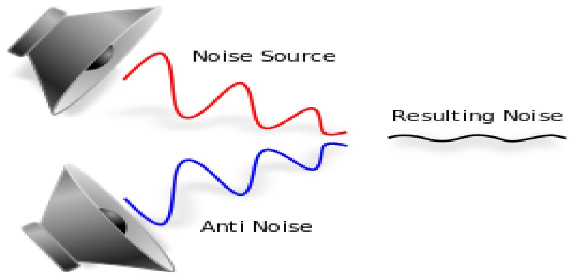


Figure 1.11: Basic Principle of ANC System [50]

Active noise control (ANC) has been extensively used by researchers over the last two decades, due to its superior performance in cancelling low frequency noise as compared to passive methods such as enclosures, barriers and silencers [51].

1.8.1 Types of ANC Systems

Active noise control systems are either Feed Forward or Feedback control [52]. In order to remove broadband noise, knowledge of primary noise source is mandatory to generate the anti-phase noise signal. The primary noise is cancelled in the region of error microphone and anti - noise signal is generated by the adaptive algorithm which derives the cancelling loudspeaker. In feed forward control the referenced noise input is sensed before passing to the secondary path and anti- noise signal is generated by the active noise controller. This method proved to be better than feedback ANC [53, 54] in case of reference input isolated from secondary anti-noise source. Feed forward ANC is further divided structurally into

- Broad band feed forward ANC.
- Narrow band feed forward ANC.

Fig.1.12 shows the schematics of feed forward ANC system using adaptive algorithm. The system consists of two microphones and a control system. The two microphones are used to obtain reference noise $x(n)$ and residual noise error signal $e(n)$ while the control system is used to generate an anti-noise signal $d(n)$. The output $y(n)$ of the adaptive control system drives the cancellation loudspeaker.

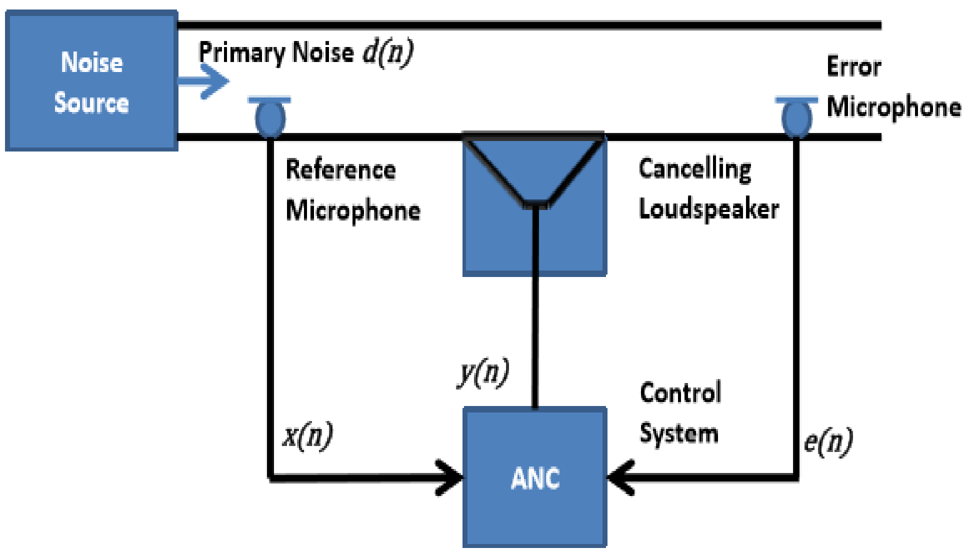


Figure 1.12: Basic principle of Broadband feed forward ANC system [51]

Feed Forward Narrow Band ANC

The schematics of feed forward narrow band ANC is shown in Fig 1.13. The non-acoustic sensor signal is synchronized with noise source and used to run the input signal consisting of fundamental frequency along with all harmonics of primary noise. This type of ANC generates the anti-noise signal and controls all harmonic noises by adaptively filtering reference signal. An error microphone is used to measure the residual acoustic noise and error signal adjust the adaptive filter coefficients recursively.

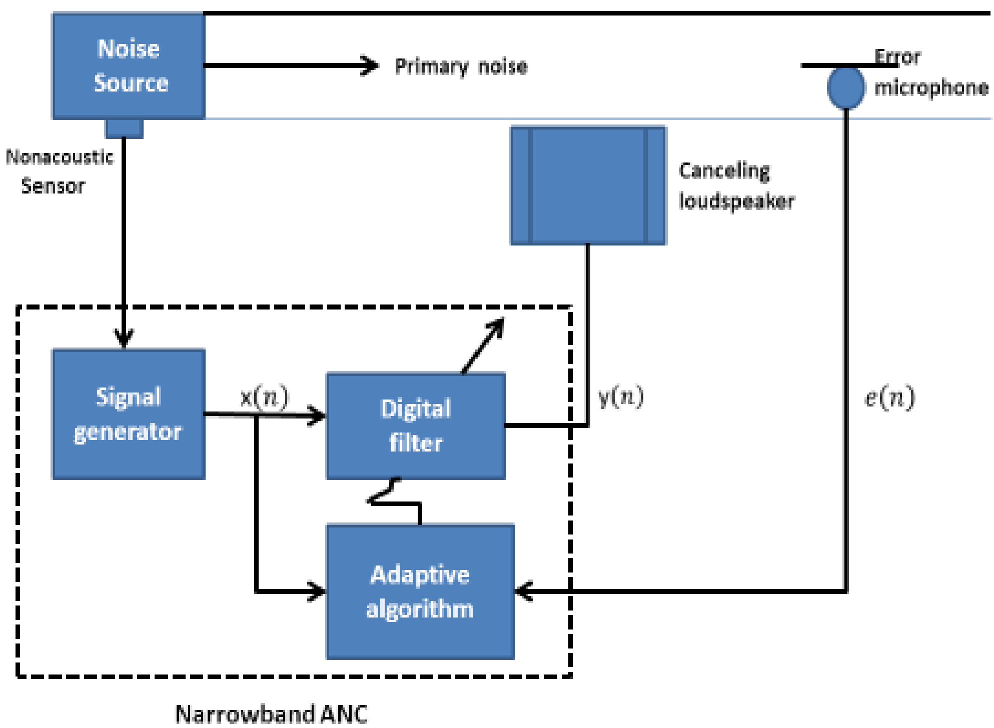


Figure 1.13: Basic principle of Narrowband feed forward ANC system [51]

1.8.2 Overview of Existing Adaptive Algorithm in ANC domains

In this section, some of the existing solutions for ANC of impulsive noise are briefly presented.

1.8.2.1 FxLMS and its variants:

In Figure 1.14, the primary path $P(z)$ is the acoustic path between both the microphones and secondary path $S(z)$ is the electro-acoustic path between cancellation speaker and error microphone. The reference noisy signal is filtered by the estimated secondary path $\hat{S}(z)$ for the filtered–x adaptive algorithm and $W(z)$ denotes the transfer function of the linear adaptive control filter. The residue noise $e\ (n)$ and the reference signal $x(n)$ are used together to adjust the coefficients of adaptive controller through its adaptive algorithm in order to achieve minimum error signal *e(n)*. Here the residual error signal and output of the filter is calculated as

$$e(n) = d(n) - y_s(n) \tag{1.9}$$

$$y(n) = \boldsymbol{w}^T(n)\boldsymbol{x}(n) \tag{1.10}$$

The most commonly used adaptive algorithm for ANC system is FxLMS [51], whose weight update equation is given below.

$$\boldsymbol{w}(n+1) = \boldsymbol{w}(n) + \mu e(n)\boldsymbol{x}'(n) \tag{1.11}$$

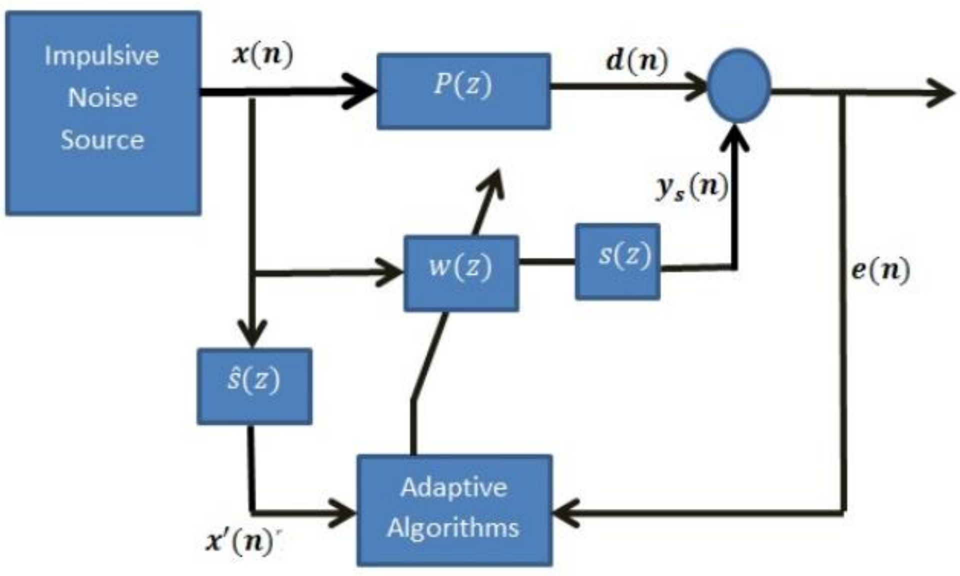


Figure 1.14: Block Diagram of ANC systems for Impulsive Noise

From (1.11), it is apparent that FxLMS algorithm based ANC system becomes unstable when the algorithm encounters large impulses in input samples of reference or error signal i.e. the weight coefficients may burst into a large value and thus making it strictly unsuitable for impulsive noise. To improve the robustness of the conventional FxLMS algorithm many variants have been proposed in the past. Among them, the most suitable algorithms for impulsive ANC are summarized in this section.

In [55], NSS-FxLMS algorithm uses the idea of time varying normalized step size to improve the robustness and stability of the FxLMS algorithm. The weight update equation is as follows

$$\boldsymbol{w}(n+1) = \boldsymbol{w}(n) + \mu(n)e(n)\boldsymbol{x}'(n) \tag{1.12}$$

$$\mu(n) = \frac{\hat{\mu}}{\delta + E_e(n) + \|\boldsymbol{x}'(n)\|_2^2} \tag{1.13}$$

Here in (1.13), when an impulse is encountered the adaptation of the algorithm is ceased. Thus, making it stable and robust enough for catering impulsive noise. The parameter delta δ in (1.13) is added to avoid zero denominator and it is a positive number. But freezing the adaptation makes the convergence of the algorithm slow. The problem of slow convergence of NSS-FxLMS algorithm [55] is resolved by merging it with DR adaptive algorithm [56] as presented in [57]. The improved stability of the DR-NSSFxLMS algorithm is achieved by using time varying normalized step size and better convergence speed is achieved by reprocessing the data. Referring to [57], the DR algorithm computes the error signal multiple times by reusing the input data. Therefore it requires prior estimate of the desired signal which is calculated as follows

$$d_1(n) = e(n) + y_s(n) \tag{1.14}$$

$$e_1(n,i) = d_1(n-i+1) - y_1(n-i+1) \tag{1.15}$$

$$y_1(n) = \boldsymbol{x}'^T(n-i+1)\boldsymbol{w_1}(n,i-1) \tag{1.16}$$

Where the weight update equation is same as of NSS-FxLMS algorithm. DR-NSSFxLMS algorithm gives better convergence and stability among the existing LMS family algorithms but at the cost of computational complexity.

The rate of convergence of RLS filter is an order of magnitude faster than that of simple LMS filter [2]. In [58], FxRLS based ANC for impulsive noise is presented and depicts fast convergence. The FxRLS algorithm weight update equation is defined in [51].

$$\boldsymbol{w}(\boldsymbol{n}+\mathbf{1}) = \boldsymbol{w}(\boldsymbol{n}) + \boldsymbol{k}'(n)e(n) \tag{1.17}$$

$$\boldsymbol{k}'(n) = \frac{(\lambda^{-1}\boldsymbol{Q}'(n-1)\boldsymbol{x}'(n))'}{\boldsymbol{x}'^{\boldsymbol{T}}(n)(\lambda^{-1}\boldsymbol{Q}'(n-1)\boldsymbol{x}'(n))'+1} \tag{1.18}$$

$$\boldsymbol{Q}'(n) = \lambda^{-1}\boldsymbol{Q}'(n-1) - \boldsymbol{k}'(n)(\lambda^{-1}\boldsymbol{Q}'(n-1)\boldsymbol{x}'(n))'^{\boldsymbol{T}}(n) \tag{1.19}$$

The FxRLS based ANC doesn't perform well when the underlying model of impulsive noise doesn't match the multiple linear regression model of FxRLS algorithm. In such situation, a new solution is proposed in the next section that is established on another filter of RLS family i.e. State space Recursive Least square (SSRLS) algorithm [59].

1.9 Motivations

In recent times, the demand for high speed multimedia applications has rapidly increased. It is one of the biggest challenges for efficient bandwidth communication applications. The performance of communication systems is significantly degraded [10], [11] by the impulsive noise as it can alter the complete data symbol by creating burst errors. Due to this fact, researchers have developed many algorithms for mitigating impulsive noise in OFDM systems as well as ANC domain and some of the most common techniques for both communication and ANC realm are presented above in this chapter. In this thesis, efficient algorithms for reduction of impulsive noise in sinusoidal, ECG signal, OFDM and ANC systems are proposed.

1.10 Thesis Organisation and Contribution of Dissertation

In this dissertation, efficient algorithms for impulsive noise reduction are proposed and implemented for OFDM and ANC applications. Adaptive filters can play a vital role in impulsive noise mitigation. The detailed description of proposed efficient algorithms is provided in chapter 2 to chapter 7.

In Chapter 2, an adaptive impulsive noise canceller for supressing impulsive noise from sinusoidal and Electrocardiogram (ECG) signals are proposed. The proposed noise cancellation technique is based on state space recursive least square (SSRLS) algorithm, which shows excellent tracking performance due to its state space model-dependent recursive parameters as compared to Normalized Least Mean Square (NLMS), Recursive Least Square (RLS) and Bhagyashri Algorithms.

In Chapter 3, an adaptive noise canceller for OFDM systems based on SSRLS algorithm is proposed. The presented adaptive noise canceller based on SSRLS gives low MSE, BER and fast convergence speed than the adaptive canceller based on NLMS, RLS and Bhagyashri adaptive algorithms.

In Chapter 4, a new hybrid technique based on combination of Reed Solomon error correction code and adaptive filter is proposed. Due to adaptive algorithm`s ability .to .track time variations of signal statistics in non-stationary environment, better reduction in impulsive noise is achieved and enhanced signal reception is attained by employing Reed Solomon error correction codes. The suggested scheme improves the quality of OFDM signal in terms of MSE, improved SNR and BER, when compared with recently reported scheme used. Moreover, the comparative analysis of proposed dual protection technique is tested in AWGN and Rician fading channel.

Furthermore, in Chapter 5 of this dissertation, Filtered-x SSRLS (FxSSRLS), an SSRLS based practical and adaptive algorithm for ANC is proposed. The suggested algorithm for ANC applications outperformed the existing algorithms in terms of mean noise reduction, convergence and stability.

Moreover, Chapter 6 presents another efficient Fx-Bhagyashri algorithm with its two modifications Clipped FxBhagyashri and Modified Fx-Bhagyashri algorithms in the ANC of impulsive noise. The both modifications gave better results in impulsive noise reduction as compared to standard Fx-Bhagyashri algorithm.

Chapter 7 presents the closed form expression for steady state analysis of Normalized Bhagyashri algorithm is performed on same lines as of Bhagyashri algorithm which can serve as a starting point for the researchers who intend to work in this area.

Chapter 8 gives the concluding remarks of dissertation and future recommendations.

In this dissertation, SSRLS based adaptive noise canceller is proposed for impulsive noise reduction and successfully tested on sinusoidal, ECG and OFDM system. Further hybrid technique based on error correction codes and adaptive filter is suggested that improve the overall performance of OFDM system. Moreover, few solutions in active control of impulsive noise are presented in the last part of thesis. The first solution based on Fx-Bhagyashri algorithm with its two modifications Clipped FxBhagyashri and Modified Fx-Bhagyashri algorithms are proposed which are tradeoff between FxLMS and FxRLS family. The Fx Bhagyashri and its modifications computational complexity is similar to FxLMS family algorithms. Further a robust solution i.e FxSSRLS is proposed which is an efficient algorithm in terms of convergence speed, steady state error and robustness at cost of high computational complexity.

CHAPTER 2

Impulsive Noise Suppressor based on SSRLS

2.1 Introduction

In chapter 1, the catastrophic effects of impulsive noise in communication systems as well as in Electrocardiography (ECG) signals are discussed. Therefore, for the proper diagnosis of cardiac diseases, there is a significant need of examining impulsive noise and recommend solutions to suppress it. For noise cancellation, various techniques exists for recovering the transmitted signal in literature [60, 61]. Among them the most suitable solution for mitigation of impulsive noise is adaptive filters. Adaptive filters are widely used in signal processing and control applications [1-2] due to their nature to adjust according to the unknown environment and low cost over the past decades.

Syed Ateeq ur Rehman in [62] carried out the performance comparison of least mean square (LMS), normalized LMS (NLMS) and Normalized signed LMS (NSLMS) algorithms to suppress Power-line Interference (PLI) from the ECG signal after its enhancement. The Normalized signed LMS (NSLMS) improves the speed and reduces complexity than that of LMS algorithm, making it useful for wireless biotelemetry ECG realizations. Another adaptive filter i.e. Recursive Least Squares (RLS) is proposed to reduce the ECG signal noises such as Power-line interference PLI and the Base Line wandering Interference. And it successfully removed artifacts preserving the ECG [63]. Nauman et al in [64] used SSRLS filter to remove 50 Hz PLI and it gives better results in comparison with the Notch filters with different attenuation levels in frequency domain. Different methods have been developed for retrieving sinusoidal components from the noisy signals as in [65] and [66]. Motivated by the performance of SSRLS in frequency domain for noise removal of ECG signals [64], in this chapter an impulsive noise canceller of sinusoidal and ECG signal based on SSRLS filter in time domain has been proposed. In addition comparison of SSRLS with existing techniques is carried out.

Section 2.2 gives the review of different adaptive filters employed in this research; section 2.3 describes the working principle of adaptive noise cancellation. The new technique based on SSRLS filter is presented in section 2.3.1. The proposed method came out to be very effective in impulsive noise cancellation of sinusoidal and Electrocardiogram (ECG) signal along with low mean square error. The comparative analysis supported with the simulation results is discussed in section 2.4. The conclusion of this chapter is presented in section 2.5.

2.2 Adaptive Algorithms

Many adaptive algorithms are reported in literature for noise removal [67], [68]. The adaptive algorithms used in this dissertation are summarized below.

A. Normalized Least-Mean-Square Algorithm

This algorithm belongs to the family of the linear stochastic gradient algorithms. This adaptive algorithm performs two operations. Firstly, there is no need of prior knowledge of signal statistics (e.g., covariance and cross-covariance). Secondly they track the variations in signal statistics by their tracking phenomena [69].

The main problem with LMS algorithm is that it suffer from the gradient noise amplification problem when the size of $x(n)$ is very large. To overcome this problem, Normalized Least square algorithm is developed. The correct choice of μ become difficult for large input $x(n)$, making the algorithm unstable [69]. The convergence is very slow and step size should be chosen carefully to guarantee algorithm stability. The tap weight of the NLMS has variable step-size parameter given by:

$$w(n+1) = w(n) + \mu(n)e(n)x(n) \tag{2.1}$$

$$\mu(n) = \frac{\hat{\mu}}{|x(n)|^2 + \delta} \tag{2.2}$$

where $\hat{\mu}$ is the optimum step size, $\mu(n)$ is the time varying normalized step size and δ is constant which is greater than 0.

B. Recursive least square Algorithm

The RLS adaptive filter [2], [70]-[71] was proposed in order to provide superior performance compared to those of the LMS algorithm and its variants [72]-[75], with few parameters to be predefined, especially in highly correlated environments. RLS adaptive filter is the one in which autocorrelation matrix estimation is used to de-correlate the current input data. It recursively finds the filter coefficients that is then used to minimize a weighted linear least squares cost function relating to the deterministic input signals [69]. Also, the RLS exhibits extremely fast convergence over all variants of LMS but with a cost of high computational complexity. The filter weights 'w' are updated in RLS algorithm by following equations.

$$w(n+1) = w(n) + k(n)x(n) \tag{2.3}$$

$$k(n) = \frac{\lambda^{-1}\varphi^{-1}(n-1)x(n)}{1+\lambda^{-1}\chi^{T}(n)\varphi^{-1}(n-1)x(n)} \tag{2.4}$$

$$\varphi^{-1}(n) = \lambda^{-1}\varphi^{-1}(n-1) - \lambda^{-1}k(n)\,x^{T}(n)\varphi^{-1}(n-1) \tag{2.5}$$

Where λ the forgetting is factor and φ^{-1} is the cross correlation matrix. The λ is initialized with 1 and φ^{-1} with δ^{-1}I .I is the identity matrix.

C. State Space Recursive Least Square algorithm (SSRLS)

SSRLS algorithm [59] is an important tool in the estimation theory due to its superior tracking performance as compared to existing techniques such as RLS, LMS etc. Its superior tracking performance in the presence of observation noise along with its state space representation makes it an excellent candidate for the estimation of deterministic signals. It is an extension of RLS algorithm. It is used to remove noise and its performance can be evaluated in a non-stationary environment (impulsive noise). The SSRLS can be presented by the following pair of equations. Analogous to the classical formulation of RLS [25], following symbols are defined.

$$\hat{s}[n] = \bar{s}[n] + K[n]\varepsilon[n] \tag{2.6}$$

$$\bar{s}[n] = A\hat{s}[n-1] \tag{2.7}$$

$$\varepsilon[n] = y[n] - \bar{y}[n] \tag{2.8}$$

$$\bar{y}[n] = C\bar{s}[n] \tag{2.9}$$

$$\Phi[n] = \lambda(A^{-T}\Phi[n-1])A^{-1} + C^{T}C \tag{2.10}$$

$$K[n] = \Phi^{-1}(n)C^{T} \tag{2.11}$$

Where $\varepsilon[n]$ is the prediction error, $K(n)$ is observer gain, $\overline{s[n]}$ is predicted input state, $s\widehat{[n]}$ is estimated state, $\bar{y}[n]$ is the predicted output state and $\Phi[n]$ is the correlation matrix.

D. **Bhagyashri Algorithm**

This filter cost function assumes that the error produced in adaptive systems is non-Gaussian [76]. The weight update equation of Bhagyashri algorithm is,

$$w_{n+1} = w_n + \mu.\tanh[\beta.e(n)] \tag{2.12}$$

$$\tanh[\beta.e(n)] = \begin{cases} \mathrm{sign}(e(n)) & \text{if } |e(n)| > 1/\beta \\ -e(n).|e(n)|\beta^2 + 2\beta.e(n), & \text{if } |e(n)| \le 1/\beta \end{cases} \tag{2.13}$$

$$w_{n+1} = \begin{cases} w_n + \mu.\,\mathrm{sign}[e(n)].\,x_n, & \text{if } |e(n)| > 1/\beta \\ w_n + \mu[2\beta - \beta^2.\,|e(n)|]\,e(n)x_n, & \text{if } |e(n)| \le 1/\beta \end{cases} \tag{2.14}$$

where β control the concavity in the cost function and sensitivity to large outliers in the value of $e(n)$and is defined as

$$\beta = \frac{3}{m+3\sigma} \tag{2.15}$$

The m and σ are the mean and standard deviation of error signal.

2.3 Adaptive Noise Cancellation

This research work focuses on new impulsive noise cancellation techniques. In this chapter, we have proposed a new solution to impulsive noise cancellation based on state space recursive least square (SSRLS). The block diagram used for this problem is shown in Fig.2.1.

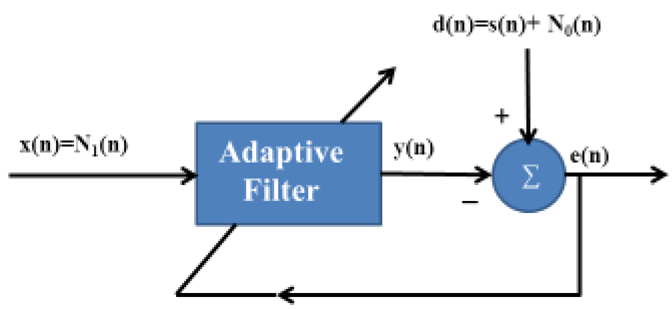


Figure 2.1: Schematic of Adaptive Noise Canceller [46]

The desired signal *d(n)* is compared with the input of the noise canceller which is a noisy source $N_1(n)$. An another noise source $N_0(n)$ corrupts the desired signal as shown in Fig. 2.1. The coefficients of the adaptive filter recursively vary to assure error signal e(n), which is produced by the difference of desired signal d(n) and the adaptive filter output y(n), to be the noiseless version of the signal s(n).

The adaptive systems have general characteristics i.e. an input signal is received by the adaptive filter and compared with a desired response, generating an error. This error modifies the filter coefficients. These filters assume that error obtained by adaptive system follow Gaussian distribution.

2.3.1 SSRLS as Adaptive Noise Canceller

The state space recursive least square filter gives excellent tracking capabilities depending on model accuracy. Acceleration model is selected for tracking the correlated version of impulsive noise as it can better track sharp transitions as compared to the other predefined state space models of SSRLS [59]. When SSRLS tracks the impulsive noise signal, it is subtracted from the noisy ECG signal to get better estimate of ECG signal. Fig 2.2 depicts the working of SSRLS as adaptive noise canceller.

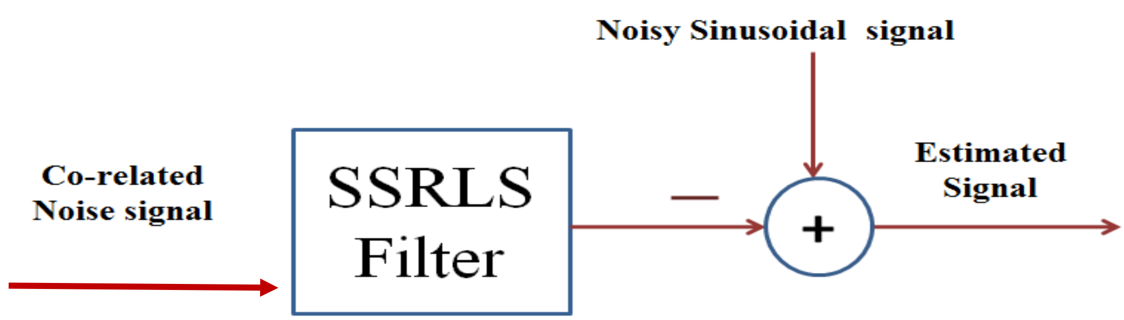


Figure 2.2: Proposed SSRLS based Adaptive Noise Canceller

2.4 Simulation Results

In this chapter, we have tested proposed impulsive noise suppressor on the sinusoidal signal and an ECG signal. The characteristics of sinusoidal signal considered for the experimentation are amplitude 1 and frequency 0.075 Hz and is perturbed with the impulsive noise and then four different types of adaptive filters are used to recover the sinusoidal signal. The Adaptive filters used are NLMS, RLS, SSRLS and Bhagyashri adaptive filters. The impulsive noise is generated by following the algorithm mentioned in [77] and depicted in Fig.2.3. The parameters used for simulating impulsive noise are tabulated below:

Table 2.1: Parameter set for simulation of Impulsive Noise

Parameters	**Symbol**	**Value**
Sampling Frequency	F	10
Total time	T	100s
Average Time between samples	β	1s
Mean of log amplitude	A	10dB
Standard deviation of log amplitude	B	5dB
Mean of Additive Gaussian Noise	M	0.1
Standard deviation of Gaussian Noise	σ	0.4

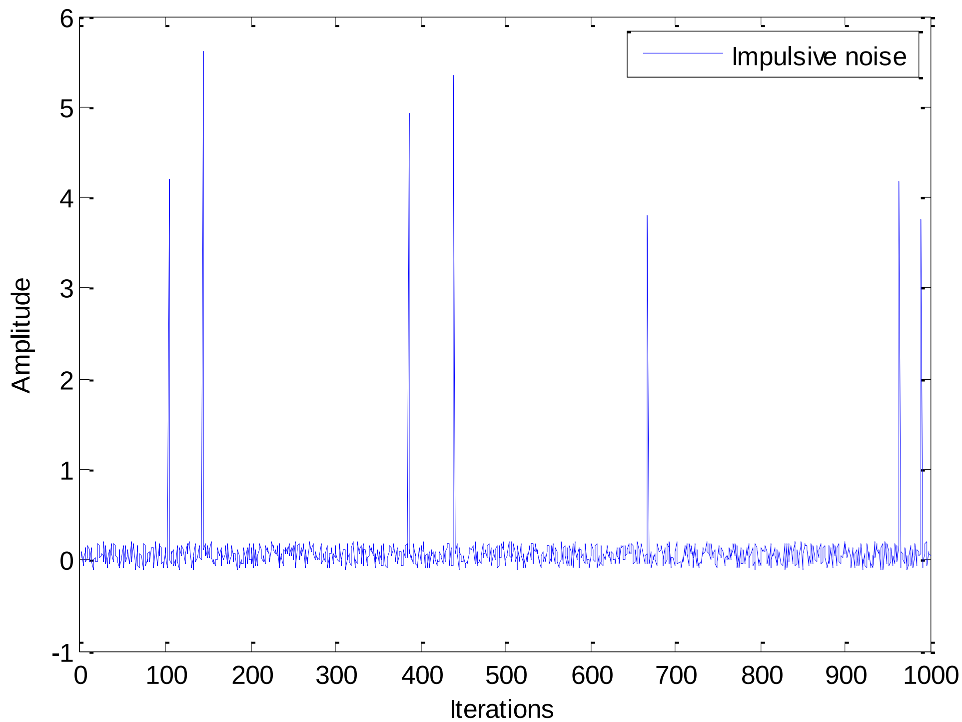


Figure 2.3: Time Realization of Impulsive Noise Signal

The sinusoidal signal distorted by the above generated impulsive noise is depicted in Fig. 2.4. The signal is filtered to guarantee the correlated $\boldsymbol{n_1(n)}$ and $\boldsymbol{n_2(n)}$ noise signals.

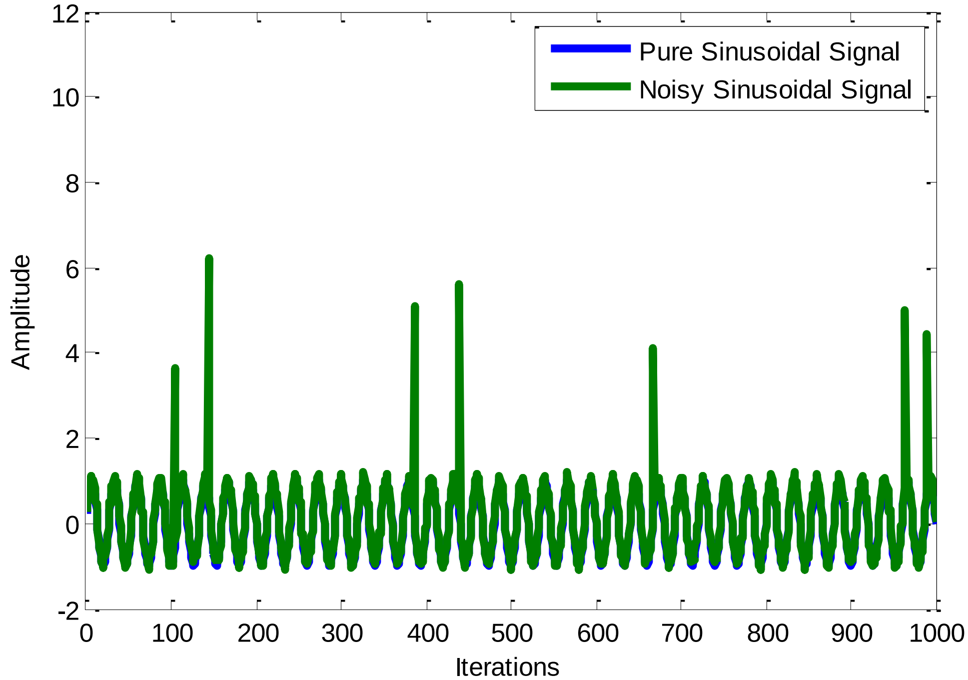


Figure 2.4: Original and noisy input sinusoidal signal

The objective of algorithm is to make output $y(\boldsymbol{n})$ of the filter, equal to the reference noise signal $\boldsymbol{n_2}(\boldsymbol{n})$. Having this equivalence, it is easy to deduce that the error is equal to the desired signal $\boldsymbol{s}(\boldsymbol{n})$.

$$e(n) = d(n) - y(n) = s(n) + n_2(n) - n_2(n) = s(n) \qquad (2.16)$$

The system output error signal $\boldsymbol{e}(\boldsymbol{n})$ should contain the original signal $\boldsymbol{s}(\boldsymbol{n})$ in an optimum sense. The step size parameter of Bhagyashri Algorithm is selected as 0.0002, the forgetting factor for RLS is 1 and for SSRLS is 0.01.The system output error signal $\boldsymbol{e}(\boldsymbol{n})$ should contain the original signal $\boldsymbol{s}(\boldsymbol{n})$in an optimum sense. The error signals obtained by above mentioned adaptive filters are collectively shown in Fig 2.5, while removing impulsive noise from the sinusoidal signal.

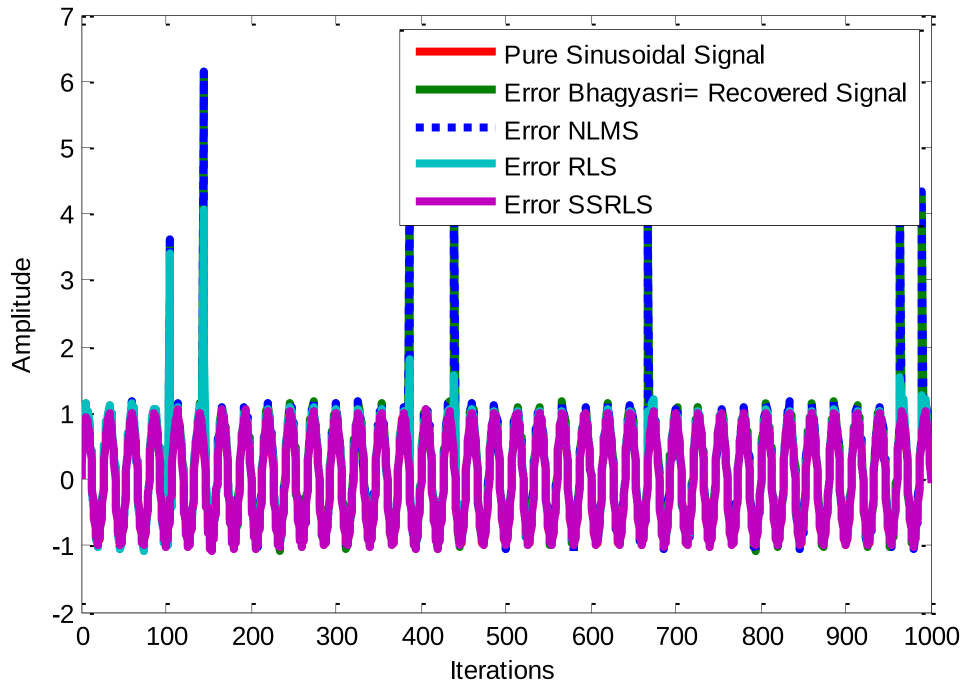


Figure 2.5: Comparison of suppression of Impulsive Noise through Adaptive Filters

The results from Fig 2.5 represent that the larger peaks of impulsive noise from the noisy sinusoidal signal are removed by the SSRLS algorithm, while other three investigated algorithms fail to remove the noise with large amplitudes. For the convenience of readers, the error plots of four algorithms are also compared with the original signal in following Fig. 2.6- 2.9.

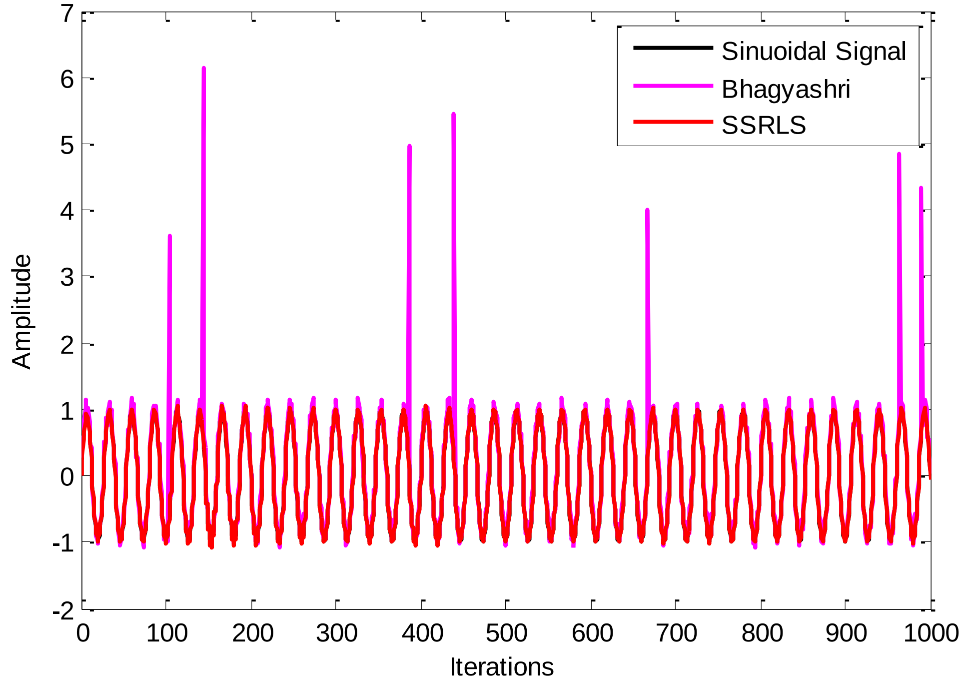


Figure 2.6: Comparison of Recovered sinusoidal signal using Bhagyashri and SSRLS Filters

Fig. 2.6 shows the signal recovered by the Bhagyashri algorithm that fails to completely remove the high peaks from the sinusoidal signal caused due to the impulsive noise. There is also a comparison with the signal recovered by the SSRLS filter. The SSRLS filter removes nearly all the higher peaks from the sinusoidal signal.

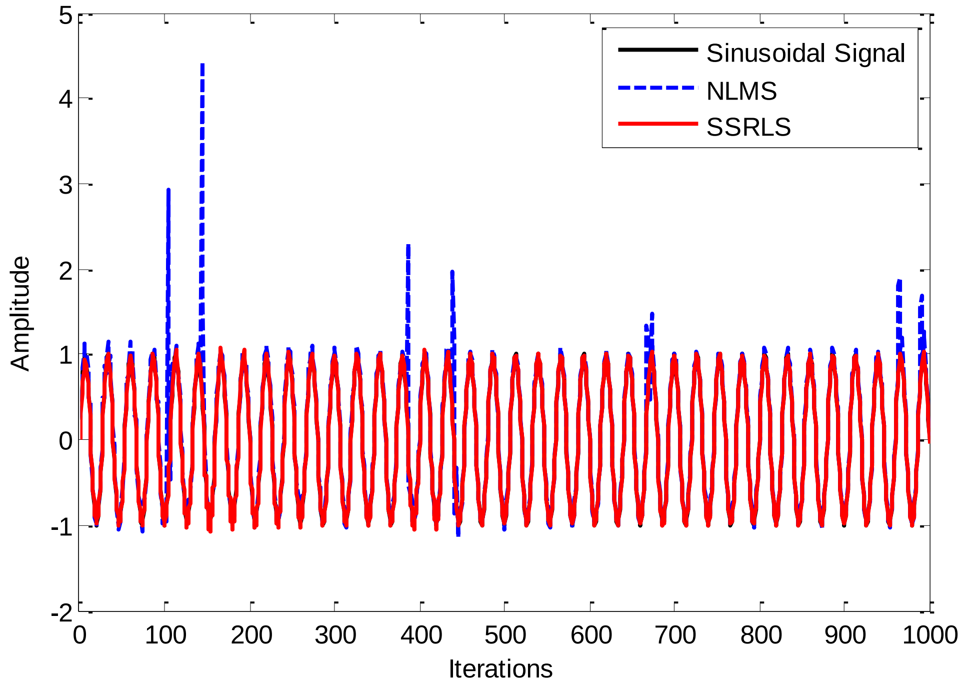


Figure 2.7: Comparison of Recovered Sinusoidal signal using NLMS and SSRLS Filters

Fig. 2.7 compares the signals recovered by using NLMS and SSRLS filters. The NLMS filter could not remove all the peaks while SSRLS performs quite better.

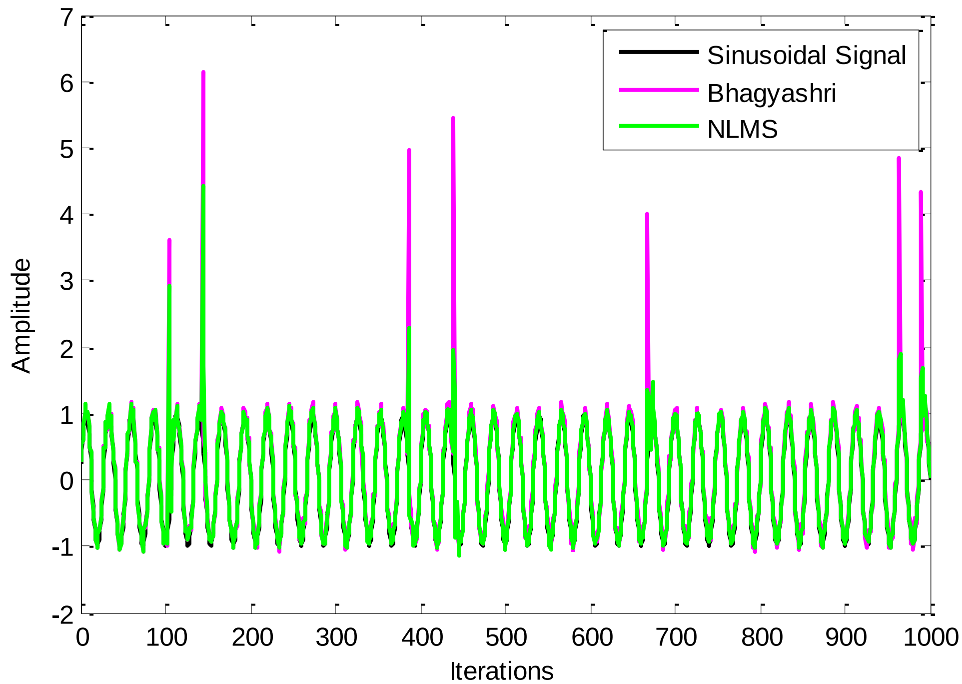


Figure 2.8: Comparison of Recovered Sinusoidal signal using NLMS and Bhagyashri Filters

Similarly, there is a comparison of the sinusoidal signal recovered by the Bhagyashri adaptive filter and NLMS filter. It is clearly illustrated in Fig 2.8 that NLMS adaptive filter exhibit slight improvement than the Bhagyashri filter.

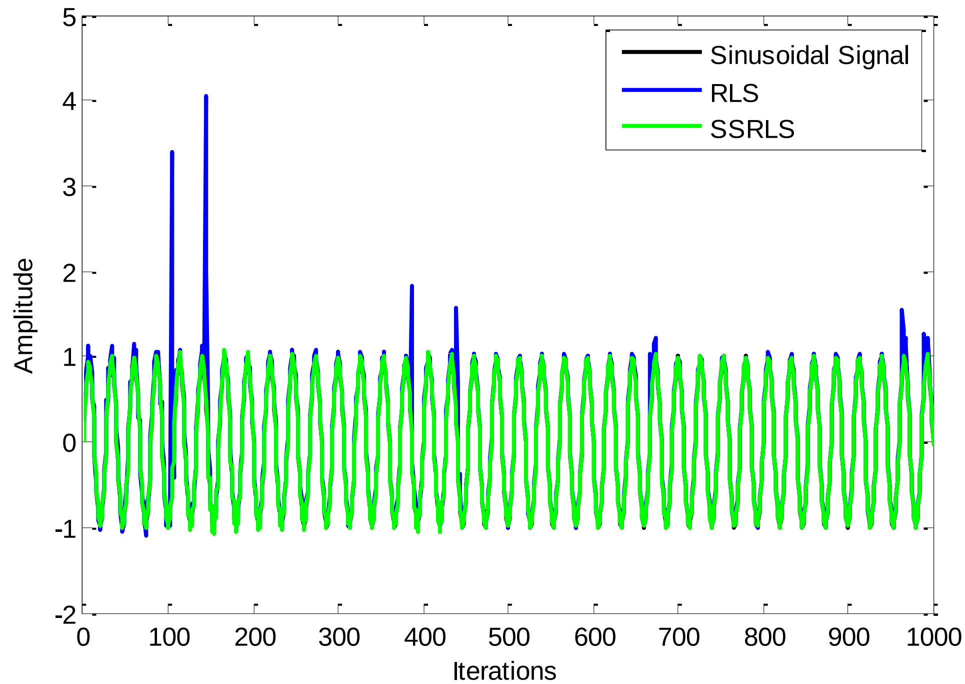


Figure 2.9: Comparison of Recovered Sinusoidal signal using RLS and SSRLS Filters

Fig. 2.9 compares the signals recovered by RLS filter and SSRLS filter. The RLS removes the high peaks but still fails to remove all the peaks caused due to the impulsive noise. The SSRLS performance is quite satisfactory as compared to all discussed adaptive filters i.e.; Bhagyashri, NLMS, RLS and SSRLS.

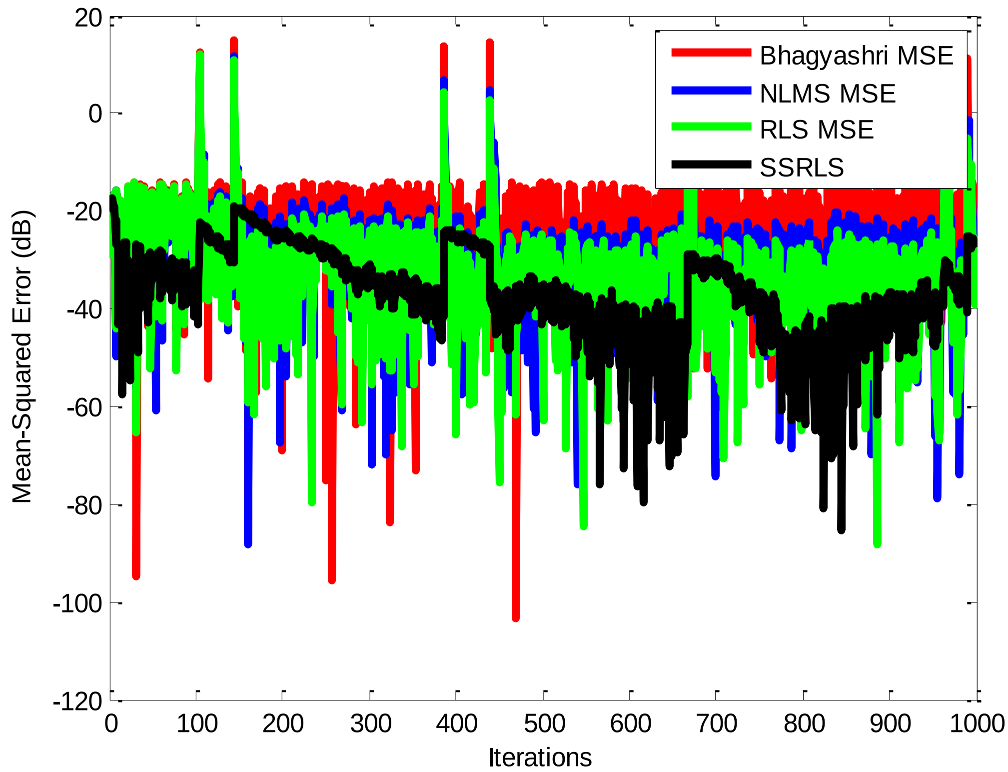


Figure 2.10: Comparison of MSE (dB) of adaptive filters while recovering Sinusoidal signal

The mean square error in terms of decibel simulation results also confirms that SSRLS give lowest MSE while cancelling impulsive noise as depicted in Fig 2.10. The conclusion drawn from Fig 2.5 and Fig 2.6 is that SSRLS filter outperforms both Bhagyashri filter and RLS in impulsive noise cancellation. Another performance metric mean square error (MSE) in term of bar chart, where the averaging of MSE values of 100 iteration set for each filter is depicted in Fig 2.11. It is obvious that MSE performance of SSRLS is far better than Bhagyashri algorithm and much better than RLS algorithm.

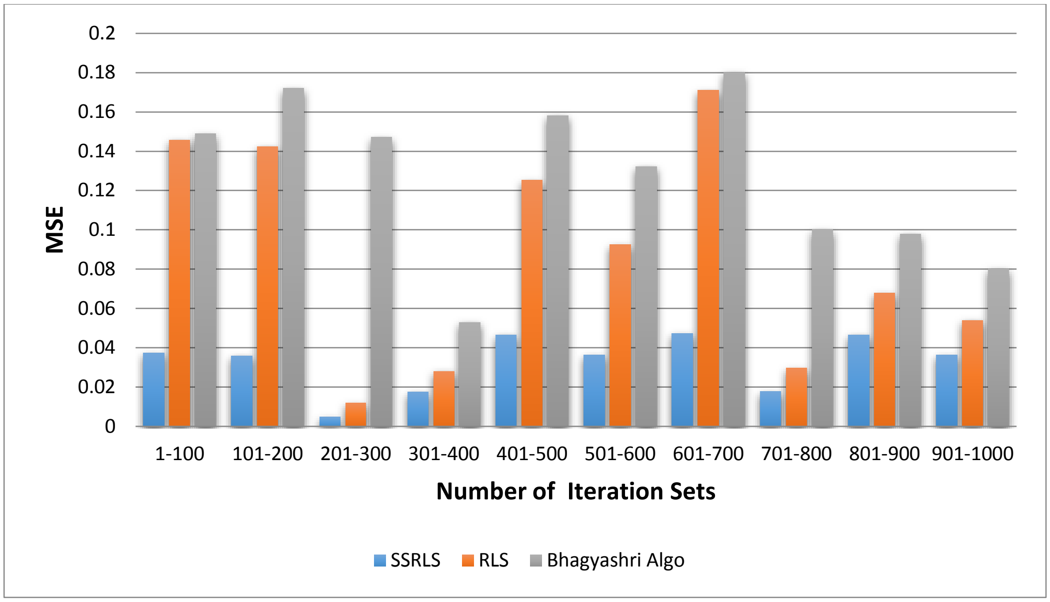


Figure 2.11: Comparison of average MSE (dB) of adaptive filters for sinusoidal signal

After verifying that SSRLS successfully removes the impulsive noise from the noisy sinusoidal signal. It is further analyzed on Electrocardiogram (ECG) signal.

Electrocardiogram (ECG) signal is a real time continuous signal that is recorded directly from the human body. When the ECG signal is recorded, there is a chance of the addition of random peaks into the signal due to man-made mistakes. These randomly introduced higher peaks are considered to be the impulses added to the signal. Also, the noise may affect the diagnostic of person's heart condition, therefore, the noise reduction techniques are applied to remove all types of noise from the ECG signal and purify it while keeping the information retained. In this section of the chapter, the noise removal techniques discussed in the previous section are applied over the ECG signal and the comparisons are held accordingly.

For this part of the simulations, the pure ECG signal is obtained from the MIT-BIH database which is made up of ambulatory ECG recordings of 47 patients at BIH Arrhythmia Lab from 1975 to 1979. All of these recordings are digitized at 360Hz per channel with 11-bit resolution over a

10mV range. Almost half of signal present in database is available at Physio Bank freely [77].This selected ECG signal is named as “GoldStandard” signal in which three beats of signal are extracted for simplicity. MIT-BIH Arrhythmia database is a part of the Physio Bank, which contains the collection of digital recordings of biomedical signals and related data. The community doing biomedical research uses this data for experimentation and analysis. The ECG signal used in this research is available freely at Physio-bank website. Fig. 2.12 illustrates the Pure ECG signal having sampling frequency of 360 Hz and its peak to peak amplitude normalized at 1. This signal has been taken from MIT-BIH database [77]. The comparison of original ECG signal and impulse noise affected ECG signal in time domain is illustrated in Fig. 2.13.

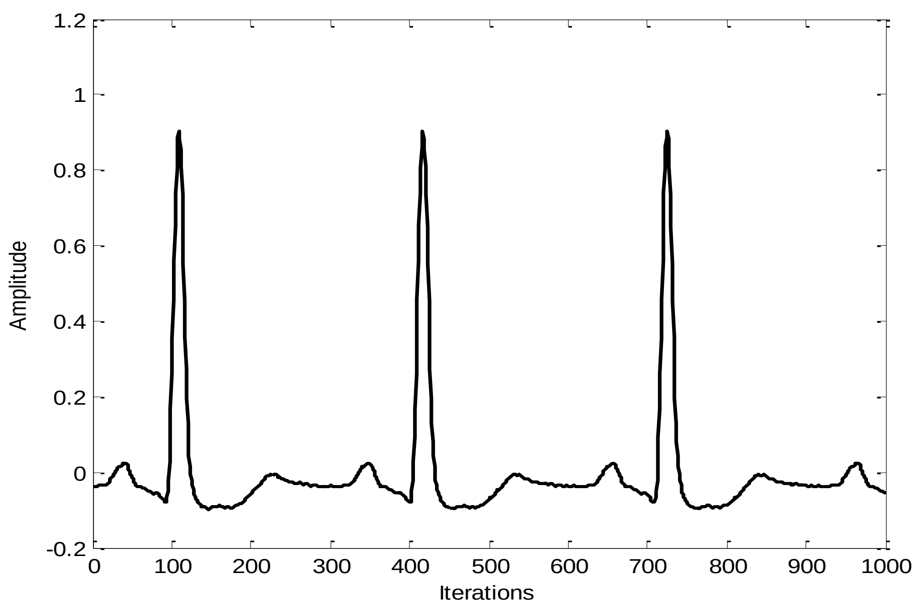


Figure 2.12: Pure ECG signals with Peak to Peak Amplitude 1

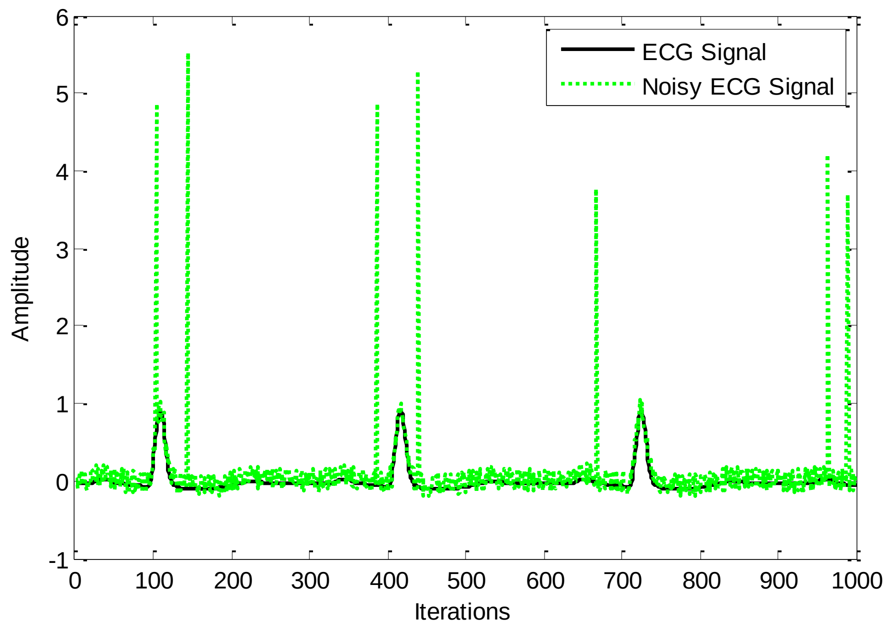


Figure 2.13: Original and Noisy ECG Signals

Fig. 2.13 clearly shows the large negative impact of impulsive noise on the original ECG.

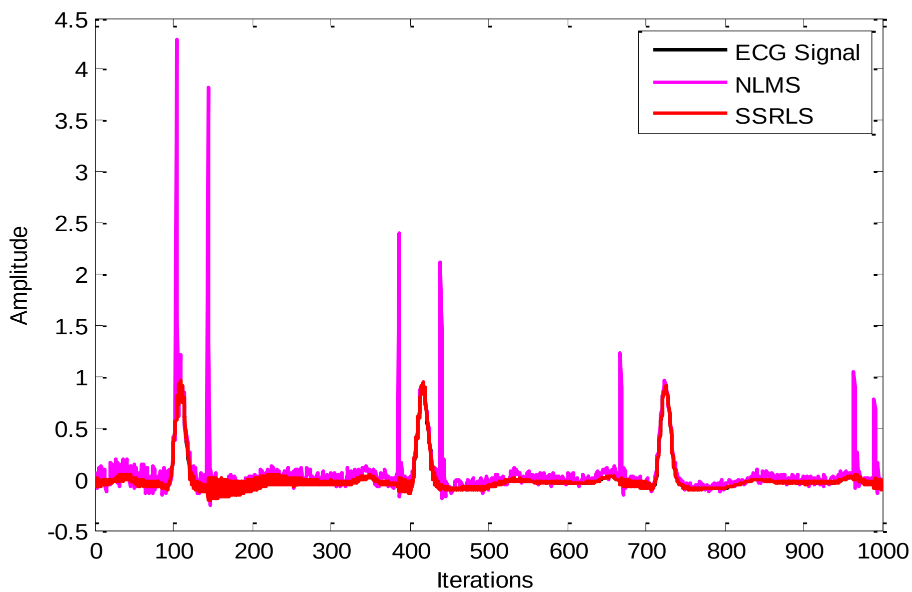


Figure 2.14: Comparison of Recovered ECG signal using NLMS and SSRLS Filters

Fig. 2.14 represents the comparison of the signal recovered using NLMS and SSRLS adaptive filters. The high peaks caused due to the impulsive noise can be clearly seen that are left over by the NLMS adaptive filter. While that of SSRLS, we can see that similar to the performance for sinusoidal signal, the ECG signal has been recovered using the SSRLS filter.

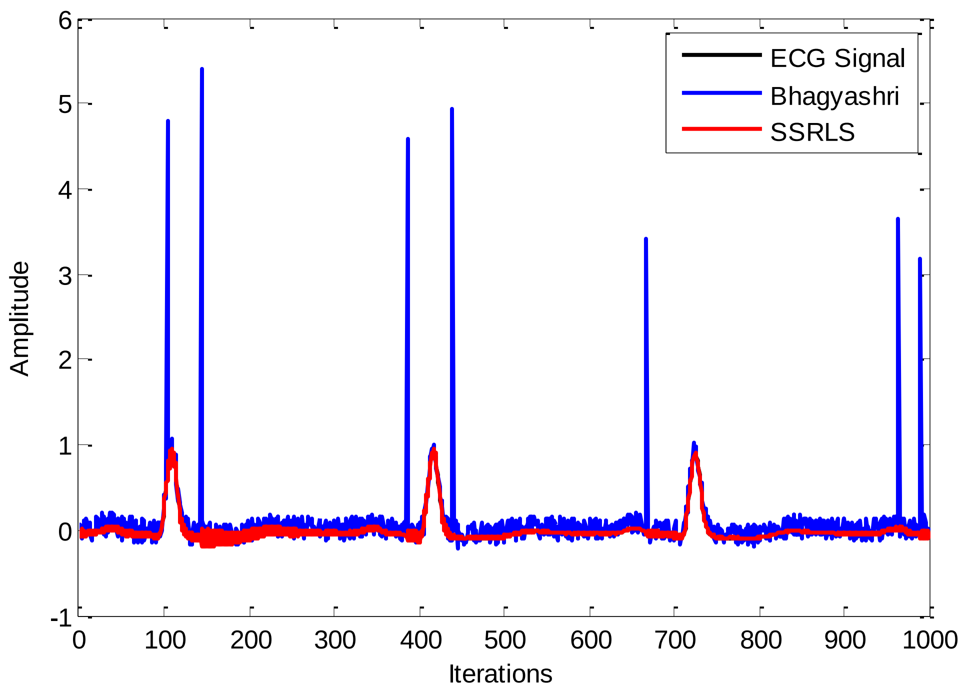


Figure 2.15: Comparison of Recovered ECG signal using Bhagyashri and SSRLS Filters

Fig. 2.15 compares the signals of Bhagyashri filter and SSRLS filter. The signal that has been recovered using Bhagyashri filter failed to remove the high peaks of the impulsive noise and even the random noise is also left over. On the other hand, the SSRLS filter has successfully removed the noise leaving almost clean ECG signal.

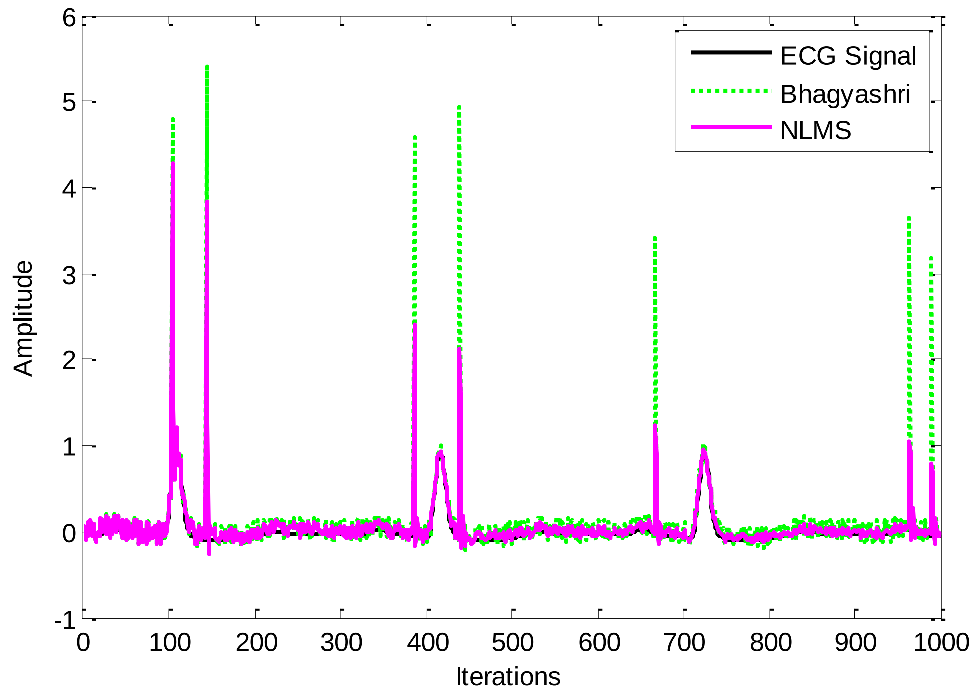


Figure 2.16: Comparison of Recovered ECG signal using NLMS and Bhagyashri Filters

The above figure compares the signals recovered using NLMS and Bhagyashri adaptive filters. Both the adaptive filters could not completely mitigate higher peaks from Noisy ECG signal as discussed earlier in the previous section of this chapter.

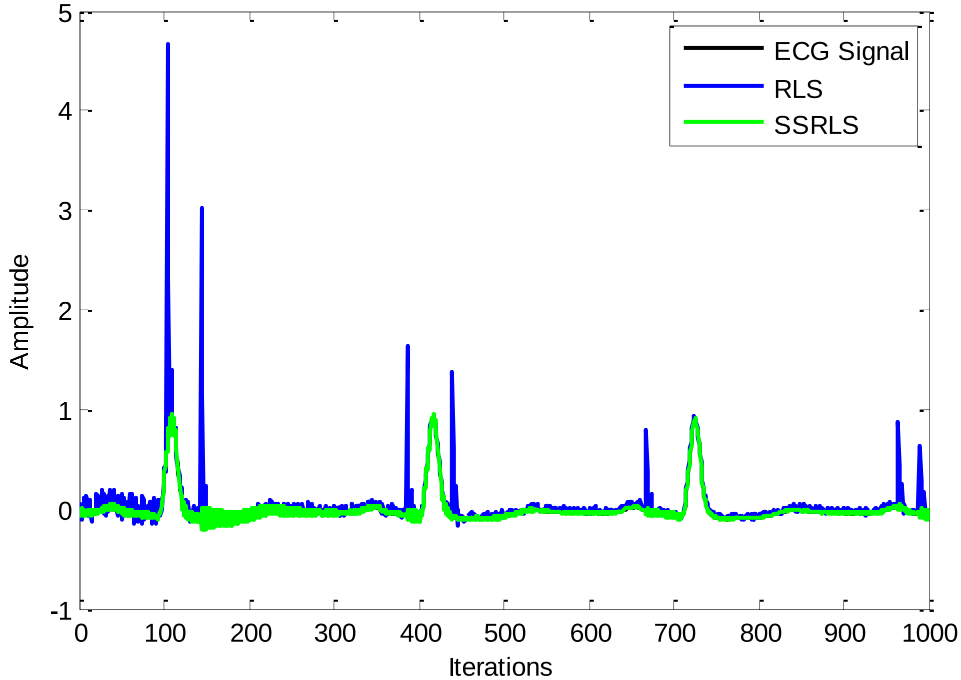


Figure 2.17: Comparison of Recovered ECG signal using RLS and SSRLS Filters

From the results we can conclude the SSRLS and RLS filters of least square family are reducing impulsive noise from the ECG signal in a better way than Bhagyashri proposed adaptive algorithm and NLMS filter respectively. Also SSRLS is outperforming RLS in removing impulsive noise from ECG signal. Moreover, the results clearly state that SSRLS algorithm has suppressed almost all the high amplitude of noisy ECG signal, while other three investigated algorithms fail to remove the noise with large amplitudes..

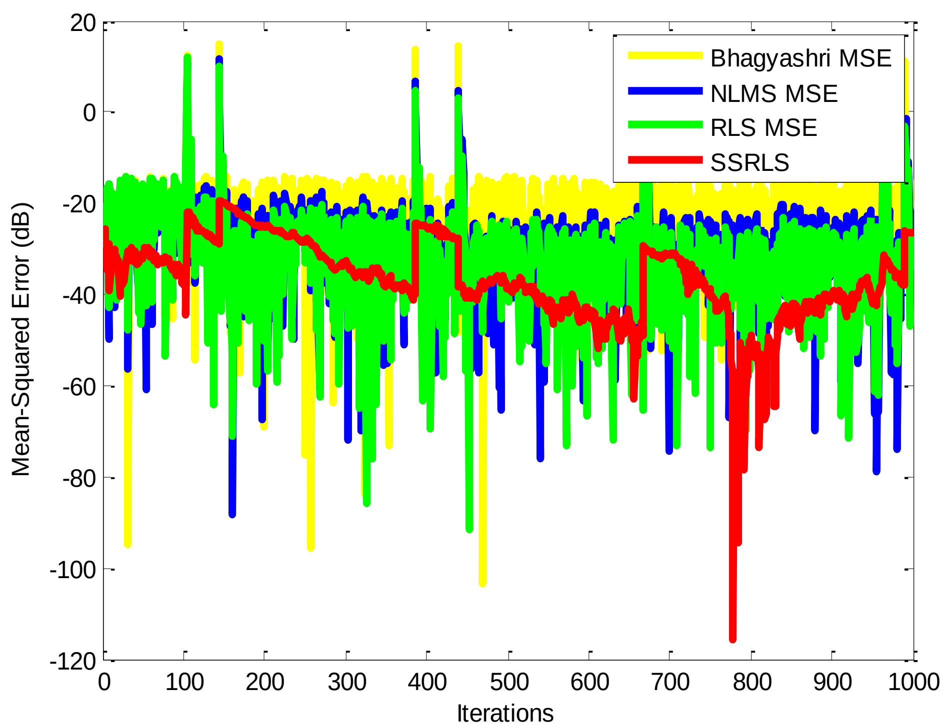


Figure 2.18: Comparison of MSE (dB) of adaptive filters

Fig. 2.18 represents the simulation result of mean square error in terms of decibel, which also confirms that SSRLS gives lowest MSE in cancelling impulsive noise. The MSE of SSRLS filter is below -20dB whereas Bhagyashri and RLS MSE are below 18dB. The above plot shows that the value of MSE of Bhagyashri algorithm and RLS algorithm both goes up to positive scale while that of SSRLS remains in negative scale indicating that it provides minimum error. Moreover, the result clearly states that SSRLS algorithm has suppressed almost all the high amplitude of noisy ECG signal.

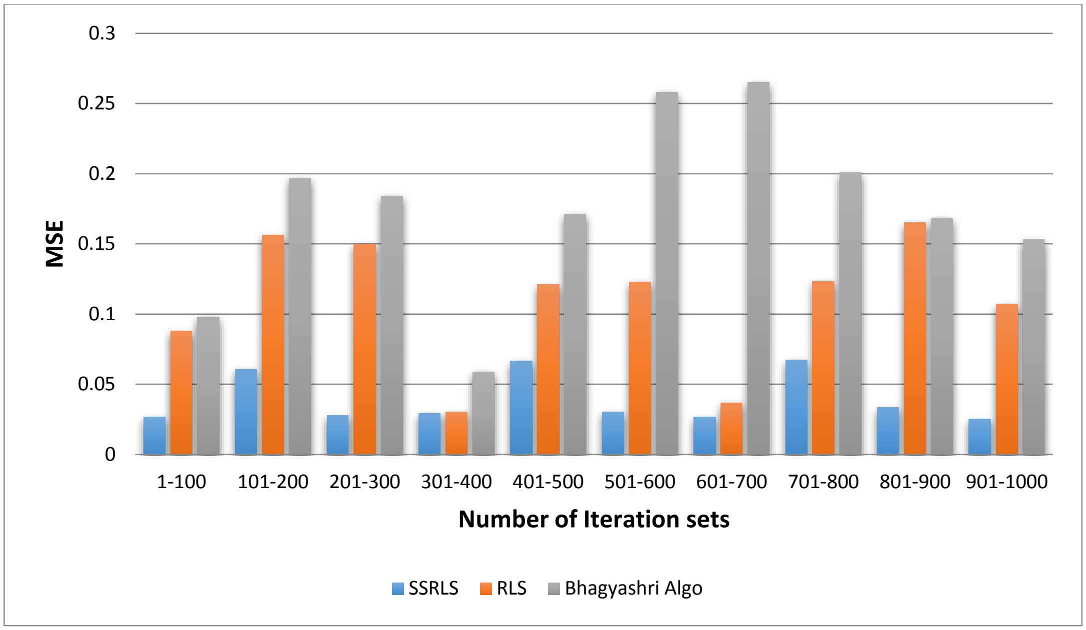


Figure 2.19: Comparison of average MSE (dB) of adaptive filters for ECG signal

Fig. 2.19 shows the average MSE for each 100 iterations for ECG signal in term of bar chart, where x-axis represent the 10 set of 100 iterations and y axis represent the average value of MSE of each 100 iteration of three investigated filters. It is obvious that SSRLS MSE performance is far better than Bhagyashri Algorithm and much better than RLS filter.

2.3.1 Comparison of Proposed Solution with Median Filter

In this subsection, the proposed solution based on SSRLS is further analyzed on the ECG signal and compared with the non-linear median filter, which is commonly used for removing the impulsive noise from signals. The median filter work by calculating the median of immediate neighbours in window after sorting them in ascending order. The window slides over the entire signal.

As mentioned before, the ECG signal used in this research is available freely at Physio-bank website. For readers` convenience, Fig. 2.20 (a) illustrates the Pure ECG signal having sampling frequency of 360 Hz and its peak to peak amplitude normalized at 1. This signal has been taken from MIT-BIH database [10]. The impulse noise generated by the statistics of Table 2.1 is depicted in Fig. 2.20 (b) and the affected ECG signal in time domain is illustrated in Fig. 2.20 (c).

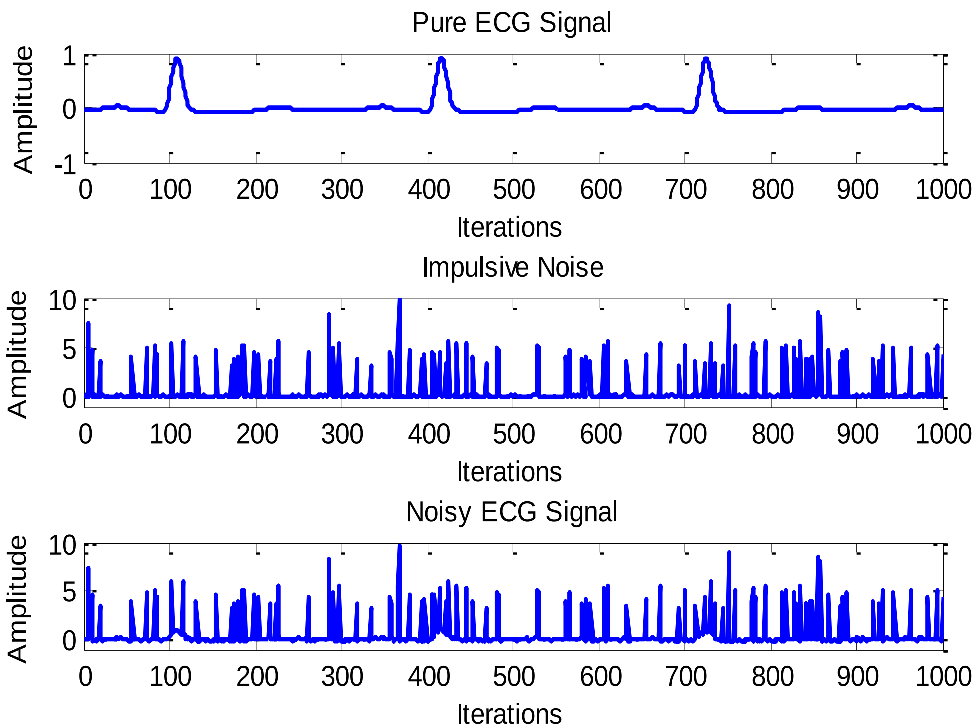
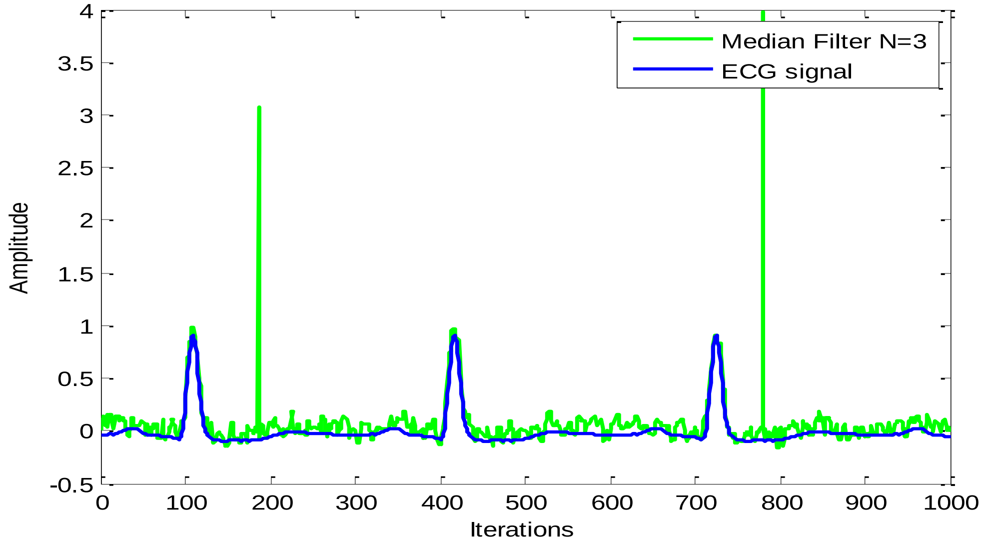
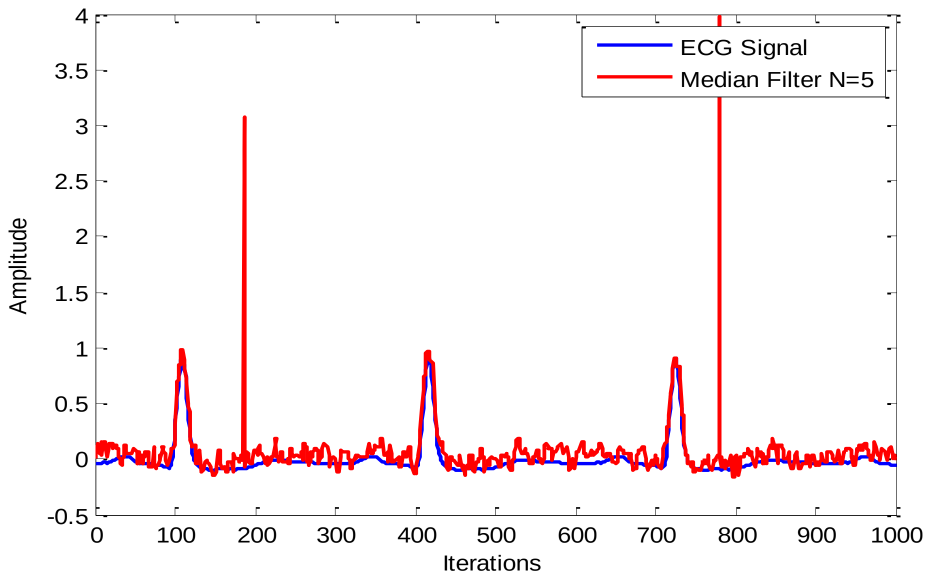


Figure 2.20 (a) ECG Signal (b) Impulsive Noise Generated (c) Noisy ECG Signal

When the noisy ECG signal is passed to the median filter of order N=3, almost all the small peaks are suppressed by the median filter except two large peaks at 200 and 800 iterations as can be seen from results of Fig. 2.21.



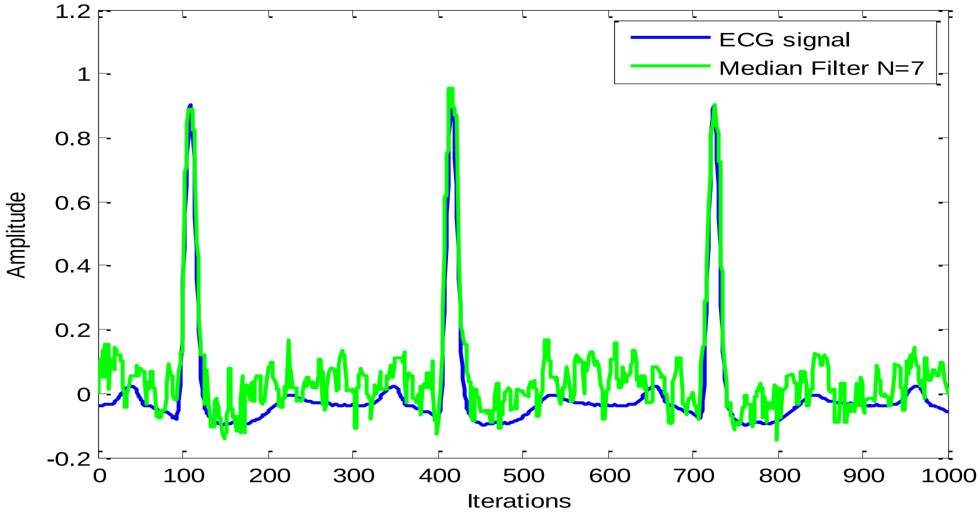
(a)



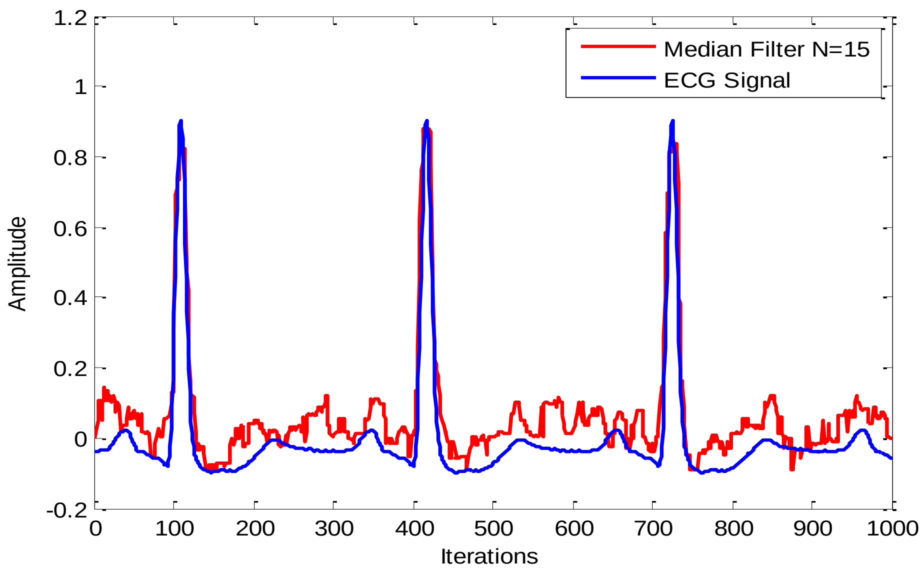
(b)

Figure 2.21: Comparison of Recovered ECG signal using Median Filters with order (a) N=3 and (b) N=5

From Fig. 2.22, we can conclude that the median filter with increasing order N removes the large peaks from ECG signal, but it fails to recover the original ECG signal.



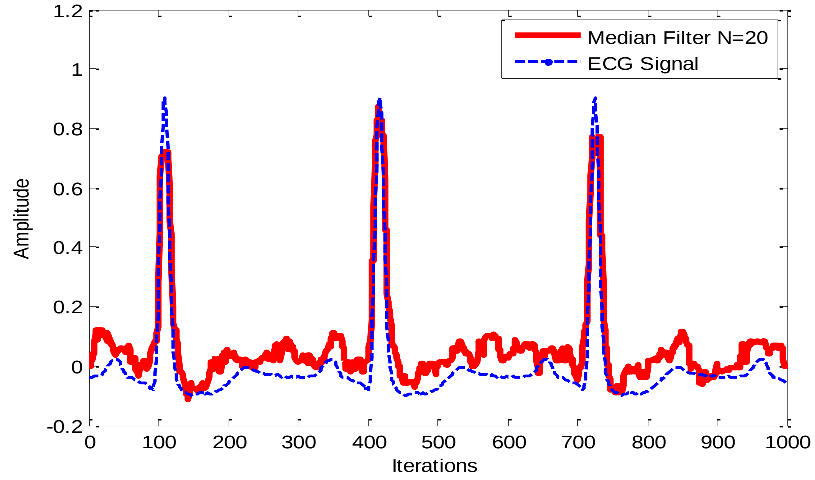
(a)



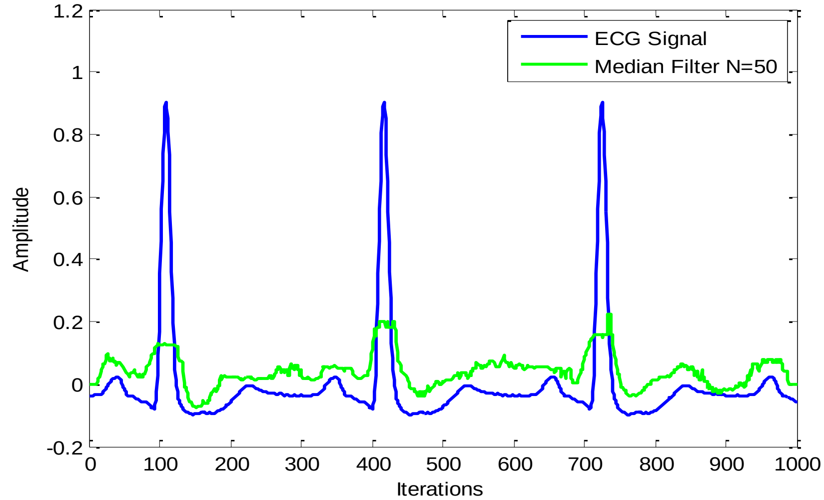
(b)

Figure 2.22: Comparison of Recovered ECG signal using Median Filters with order (a) N=7 and (b) N=15

We can clearly see from Fig. 2.23, that median filter with its high filter order suppresses peaks of impulsive noise as well as ECG signal. Therefore, median filter is not a good choice for suppressing impulsive noise from the ECG signal.



(a)



(b)

Figure 2.23: Comparison of Recovered ECG signal using Median Filters with high order (a) N=20 and (b) N=50

At the end, comparison of proposed solution with median filter is shown in Fig. 2.24, which depicts the effectiveness of SSRLS based proposed solution as compared to median filter in recovering the ECG signal.

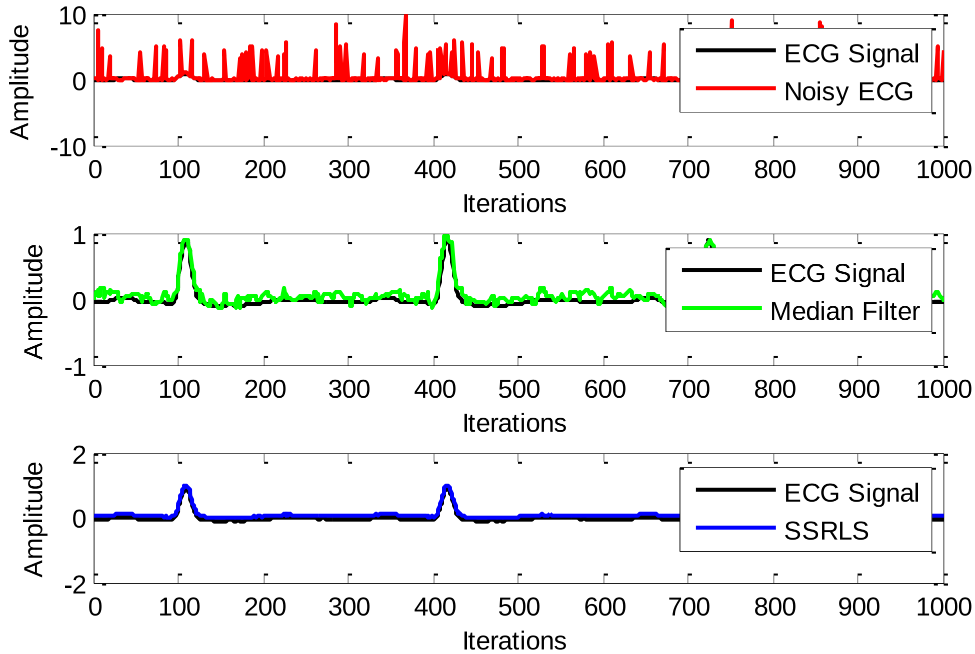


Figure 2.24: Comparison of Recovered ECG signal using Median and SSRLS Filter

2.5 Summary

In this chapter, an adaptive noise cancellation technique has been proposed that is based on state space recursive least square (SSRLS) algorithm. Due to state space model-dependent recursive parameters of the proposed technique show significant suppression of impulsive noise from sinusoidal and ECG signal; when compared with some existing techniques in literature. The suggested solution guarantees efficient noise cancellation in non-stationary environment due to the superior performance of SSRLS in terms of lowest MSE, which is verified by the simulation results.

CHAPTER 3

Impulsive Noise Canceller for OFDM System

3.1 Introduction

Orthogonal frequency division multiplexing is a variation of signal modulation that splits high data rate stream into numerous moderate balanced narrow band firmly divided subcarriers and is less delicate to frequency selective fading. OFDM systems are usually corrupted by non-Gaussian impulsive noise, which have disastrous effects in OFDM transmission. The performance of OFDM systems is degraded due to the existence of impulsive noise in the received signal because of its wide frequency content [36]. Researchers are investigating solutions for mitigating this type of noise and to improve system performance. Different techniques are addressed in literature that endeavours to suppress impulsive noise from the original transmitted signal.

The conventional technique for impulsive noise suppression is median filter with some signal degradation [5]. The simplest time domain approaches like clipping [79, 80] and nulling [60] are used to mitigate impulsive noise effect by removing the received OFDM signal peaks above certain threshold values. The bit error rate characteristic of OFDM systems is further enhanced by the combination of clipping and nulling as presented in [20]. However, the techniques proposed in [20], [60], [79-80] cut off many noise samples after thresholding and as a result bit error rate of OFDM systems is degraded. Therefore, Hirakawa et al. [81] presented another sample replacement scheme for suppressing multiple impulses from the received OFDM signal. When the additional point of impulsive noise is a centre point between OFDM samples in time domain, the performance of replacing sample scheme is degraded. This problem is solved by replica signal subtraction scheme [82], but it cannot reduce the influence of impulsive noise under the existence of multiple impulse events for class A noise. Two more schemes, replica signal [83] and iterative replica signal [84], are reported to solve the underline problem and improve the OFDM systems performance. The frequency domain technique for impulsive noise suppression is presented by Zhidkov et al. in [32]. Further, impulsive noise characteristics are exploited in both time and frequency domain in [33] i.e. Impulsive noise is cancelled in time domain, information signal detected in frequency domain and detected signal is transformed back to time domain to start next iteration. Liu et al [85] presented another iterative impulsive noise location and value search algorithm, which is based on exploiting the important relationship between impulsive noise and symbol constellation.

Adaptive filters are the best solution for impulsive noise suppression due to their capability to track signal statistics time variations in non-stationary environment [69]. Researchers opted least mean square filters in OFDM based PLC systems in [86], for suppression of periodic impulsive noise. The NLMS, RLS, VSNLMS adaptive filters based receiver techniques for minimizing impulsive noise effect on OFDM systems performance under AWGN [87, 88] and Rayleigh fading channel [89] are used. In [90], Khedkar et al. also improved the OFDM systems performance by suppressing the intercarrier symbols effect using trained LMS adaptive filter based technique. An impulsive noise canceller based on SSRLS for sinusoidal and ECG signal in time domain is presented in [91], [92]. Another new technique clipping and adaptive filters in AWGN Channel for impulsive noise reduction is proposed in [93]. This chapter presents an impulsive noise suppressor for OFDM system by motivational results obtained in [91-93].

In section 3.2, the basic concept of OFDM is reviewed and its advantages over single carrier modulation schemes are briefly discussed. The solution for impulsive noise cancellation of OFDM systems is presented in section 3.3. The proposed solution significantly reduces the impulsive noise in OFDM system because of its adaptive algorithm based on state space model. The comparative analysis of suggested technique with the existing techniques in literature is performed in section 3.4 and chapter 3 concludes in section 3.5.

3.2 Basic Concepts of OFDM

OFDM is a frequency-division multiplexing (FDM) technique, in which orthogonal sub carrier signals are splited into several parallel data streams. The conventional modulation schemes are used to modulate all the low data rate sub-carriers. The OFDM uses many orthogonal subcarriers which help in eliminating ISI between OFDM symbols, providing more resistance to multipath fading and achieving high SNR improvement. Therefore, OFDM is suitable for many digital communication applications like digital television, digital audio broadcasting (DAB), wireless local area network (WLAN), power line networks, DSL internet access and 4G mobile communications.

Digital wired and wireless systems operate at high SNR with high spectral efficiency but their performance is degraded by impulsive noise and cross talk. Various techniques are reported in literature, which improves the performance of digital communication systems in terms of low bit error rate and mean square error by mitigation impulsive noise from transmitted OFDM signal. In this chapter, we have also proposed an effective impulsive noise suppressing technique for OFDM

3.3 Proposed Impulsive Canceller in OFDM System

The transmission over a dispersive channel is carried out in OFDM. The schematics diagram of proposed OFDM system is shown in Fig. 3.1.

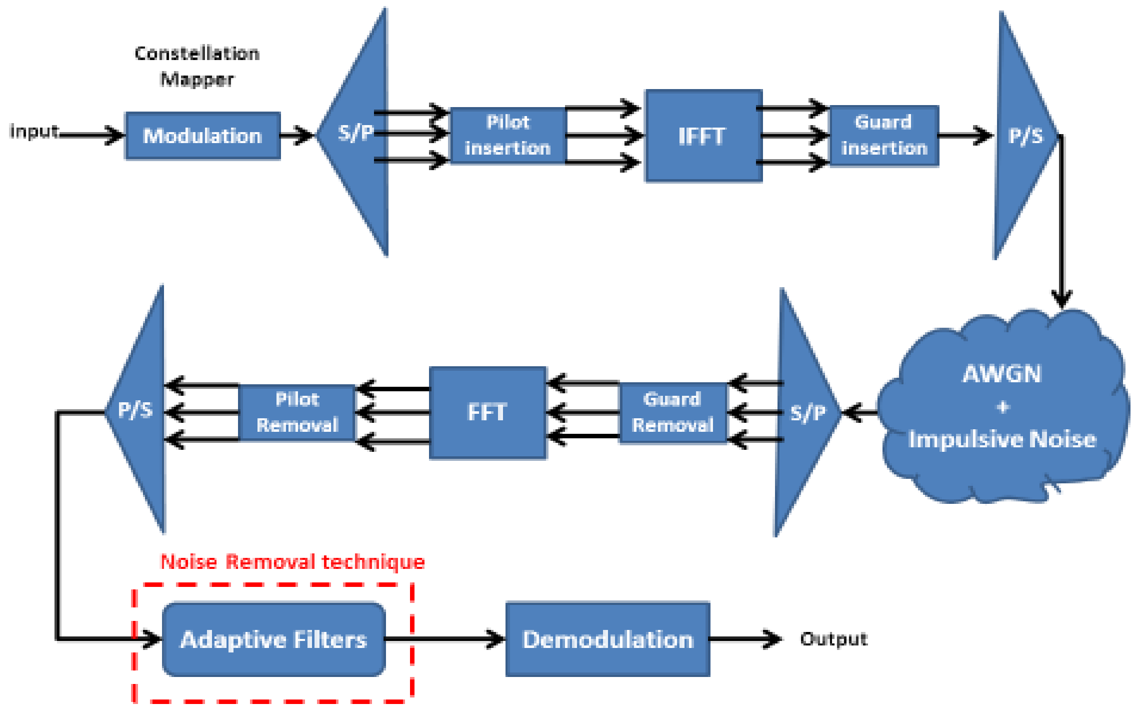


Figure 3.1: Proposed OFDM system

In OFDM the high data rate streams are split into low data rate streams in parallel and modulated separately on different orthogonal sub-carriers. The introduction of pilot insertion and cyclic redundancy at the transmitter reduces the complexity to only FFT processing on the receiver side. These subcarriers are multiplexed and passed through the channel, which is responsible for adding impulsive noise and white Gaussian noise in the transmitted OFDM signal. At the receiver side, the signal is demodulated and passed through the adaptive filter for mitigation of impulsive noise in the OFDM signal. The adaptive filters used in the proposed technique for OFDM systems are reviewed in section 2.2 of chapter 2. The basic benefit achieved by the adaptive filters before demodulation is that it track the received signal statistics with time and help in reducing impulsive noise from received signal.

3.4 Simulation Results

The parameters for simulating the OFDM system are tabularized below.

Table 3.1: Parameter set for simulation of OFDM system

Parameters	**Values**
Modulation technique	QPSK
Number of subcarriers	52
Size of cyclic prefix	16
FFT-length	64
Number of bits generated	5000

The performance of different adaptive filters in impulsive noise cancellation of OFDM signal are compared by computer simulation using MATLAB version 12 in this section.

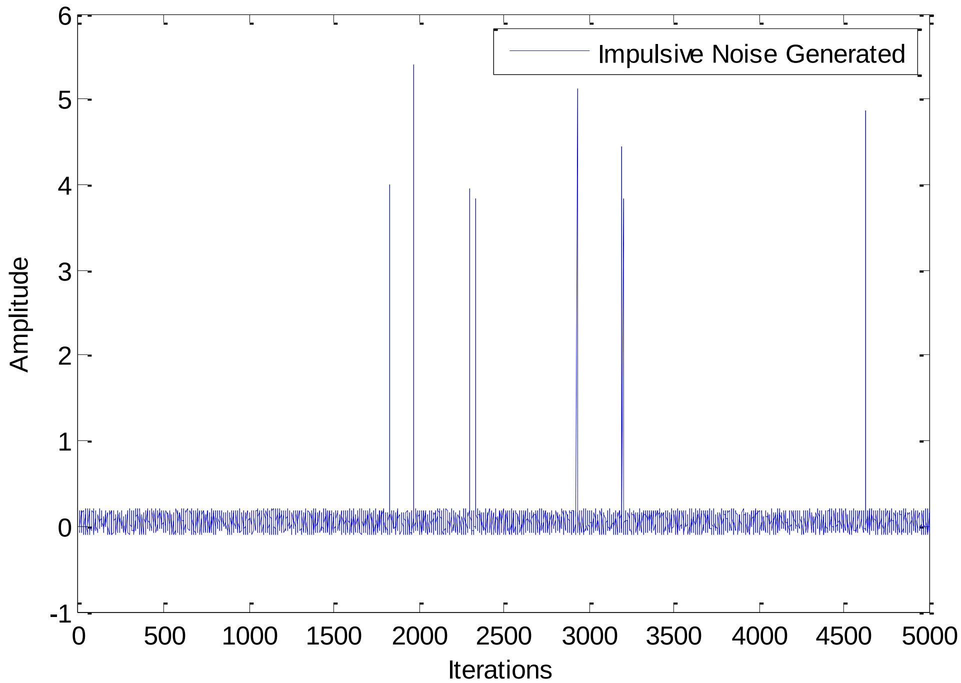


Figure 3.2: Impulsive Noise Signal

The generated binary data is passed through the channel responsible for adding impulsive noise and white Gaussian noise. The noisy data is depicted in Fig. 3.3 in comparison to the original data.

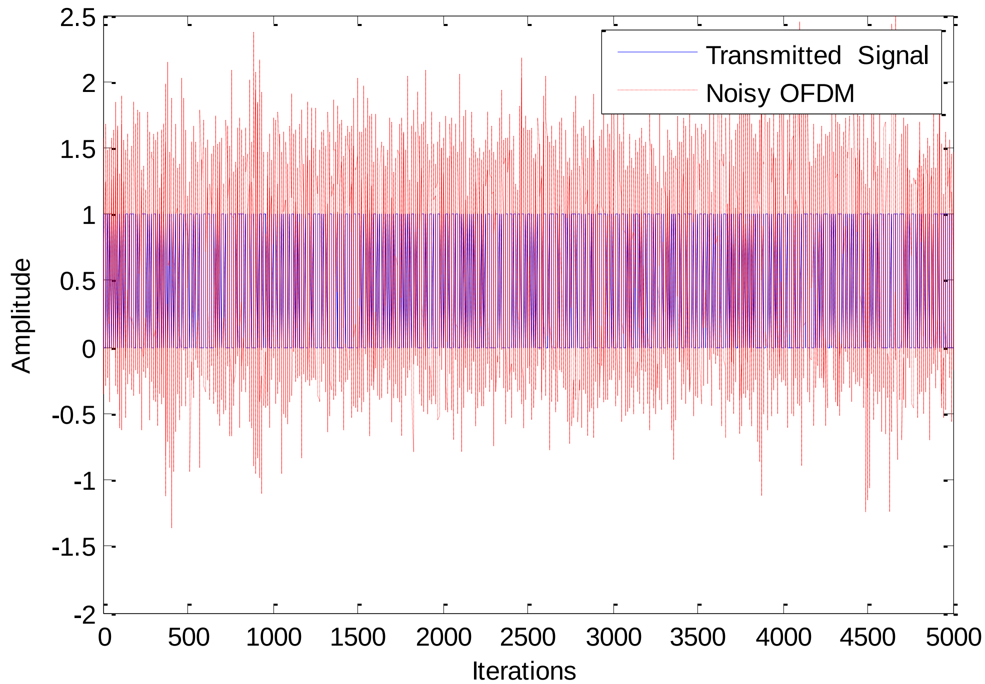


Figure 3.3: Original and Received Signal

The system output error signal $e(n)$ should contain the original signal $s(n)$ in an optimum sense. The step size parameter for NLMS Algorithm is chosen to be equal to 0.005 and forgetting factor for RLS is 1 and for SSRLS is 0.01. The error signals obtained by above mentioned adaptive filters are compared with one another in Fig. 3.4-3.6.

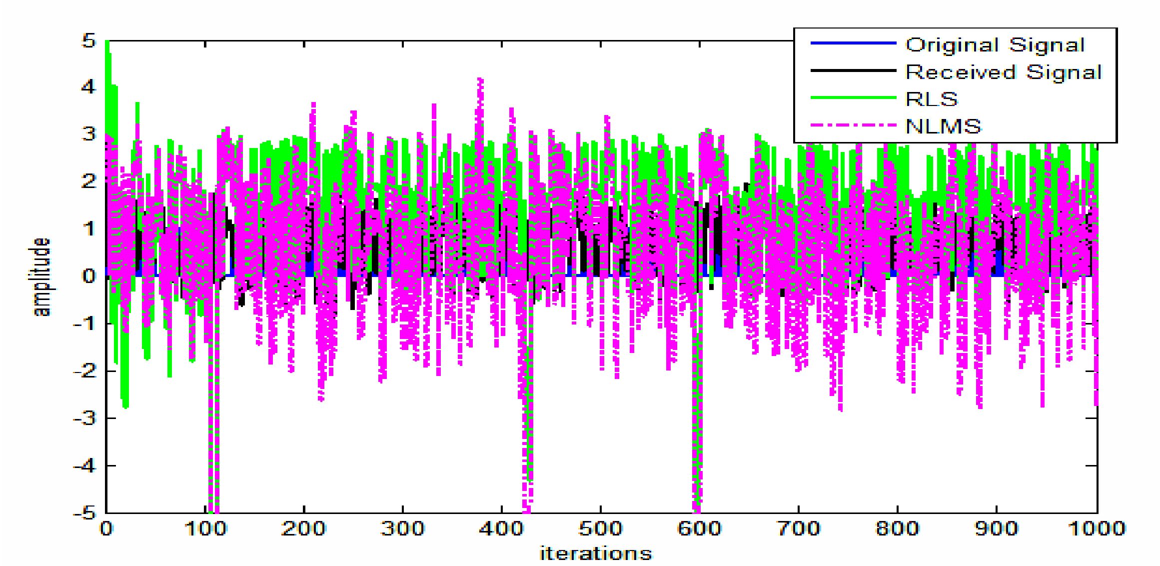


Figure 3.4: Comparison of original data, received data and recovered data using NLMS and RLS Filters

Fig.3.4 represents that the largest peaks of impulsive noise from the noisy binary signal are not properly removed by the RLS and NLMS algorithm. The RLS filter is removing impulsive noise better than NLMS. The error plots of above mentioned algorithms are also compared with the original signal and received signal.

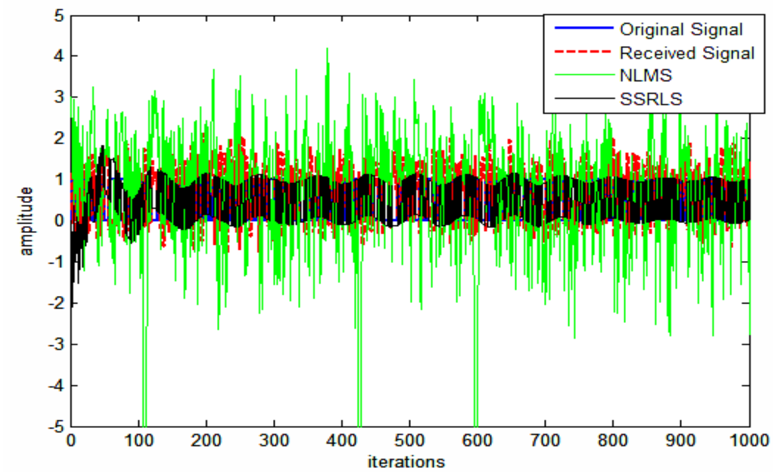


Figure 3.5: Comparison of original data, received data and recovered data using NLMS and SSRLS Filters

The results of Fig. 3.5 illustrate that superior performance of SSRLS in suppressing impulsive noise from the noisy OFDM signal as compared to the NLMS adaptive algorithm. The error plots of above mentioned algorithms are also compared with the original signal and received signal.

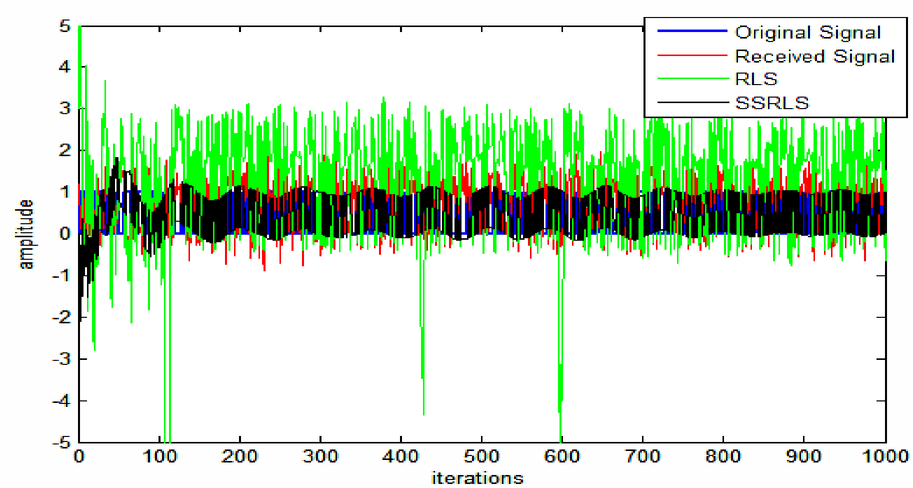


Figure 3.6: Comparison of original data, received data and recovered data using RLS and SSRLS Filters

Similarly the comparison of SSRLS and RLS filter error plots while cancelling impulsive noise from the OFDM signal are shown in Fig. 3.6. It is clear from the above simulation results that SSRLS exhibit better performance in cancelling the largest peaks of impulsive noise from the OFDM signal, while other two investigated algorithms fail to remove the noise with large amplitudes.

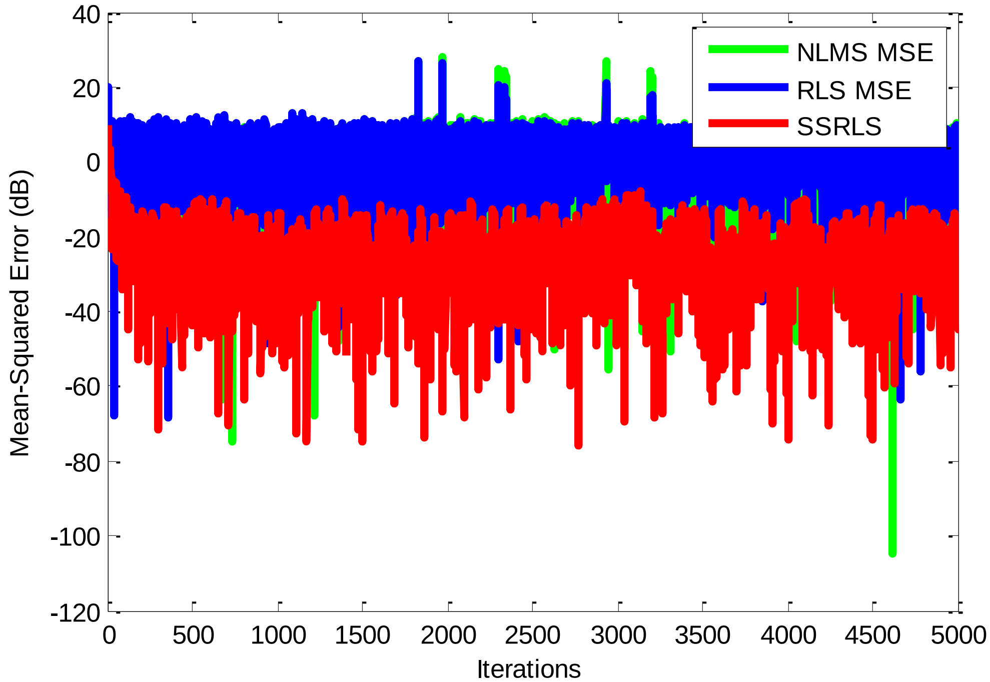


Figure 3.7: Comparison of MSE (dB) of adaptive filters

The mean square error in terms of decibel simulation results also confirms that SSRLS give lowest MSE while cancelling impulsive noise as depicted in Fig. 3.7. The conclusion drawn from Fig. 3.4-3.7 is that SSRLS filter outperforms both NLMS filter and RLS in impulsive noise cancellation of OFDM signal.

3.5 Summary

OFDM is widely employed in high data rate applications and is corrupted by impulsive noise. In this chapter of thesis, an adaptive impulsive noise suppressor for OFDM system has been proposed that is based on SSRLS algorithm. It gives the better tracking due to its state space model-dependent recursive parameters. The proposed technique have better tracking characteristics and its effectiveness is demonstrated by the simulation results in MSE sense while impulsive noise cancellation in OFDM signal.

CHAPTER 4

Hybrid Technique for Mitigation of Impulsive Noise in OFDM Systems

4.1 Introduction

It has been described in the previous chapter that OFDM communication systems have attracted much attention in past decades and are successfully implemented in the wired systems including Digital;Subscriber Lines (DSL) [94],;power line communications [95] and cellular communication standards like LTE/LTE-A and WiMAX [96].

Forward error correction (FEC) codes are also used for mitigation of impulsive noise in literature [24], [38], [97-98]. The basic principle of FEC is based on introducing redundancies to the information to be transmitted. Reed Solomon (RS) codes are used in reversible steganography on OFDM channel for securing data in wireless communication by Praveen kumar et al. in [99]. Researchers presented an impulsive noise reduction method by combining iterative impulsive noise cancellation along with space time block codes [100]. Another hybrid technique comprising of clipping and adaptive filter is implemented by Alina et al. in [101] for impulsive noise removal. Jia et al. [101-102] used a dual protected scheme based on time domain pre-processing mean filter in combination with Reed Solomon (RS) coding in OFDM and ZigBee communication link that limits the effects of impulsive noise. Motivated by the idea of researchers in [99-102], a new hybrid technique based on RS coding and adaptive filter in OFDM systems for impulsive noise cancellation is proposed in this research.

In the section 4.2, a new hybrid dual protected technique for mitigation of impulsive noise is presented which is followed by comparative analysis along with the simulation results in section 4.3. The summary of chapter 4 is presented in section 4.4.

4.2. Proposed Hybrid Technique

In this section, we have proposed a new dual protected technique for cancellation of impulsive noise in OFDM communication systems employing Reed.Solomon (RS).coding and adaptive filter. In the first part of simulation, the Reed Solomon error correction scheme is used in combination with modified NLMS (NSSLMS) filter from the Least Mean Square family of adaptive algorithms as a dual protection strategy. RS code can remove the burst errors but the RS decoder error correction capability fails in presence of large;impulsive;noise. To avoid such situation, at the receiver side least mean square adaptive filter is applied before RS decoder for minimizing the impulsive noise;effects from OFDM signal. Adaptive filter creates a more accurate estimate of the original OFDM signal after impulsive noise cancellation. The residual impulsive noise is then managed by the RS decoder in the second stage of proposed technique. The proposed hybrid technique is depicted in Fig. 4.1.

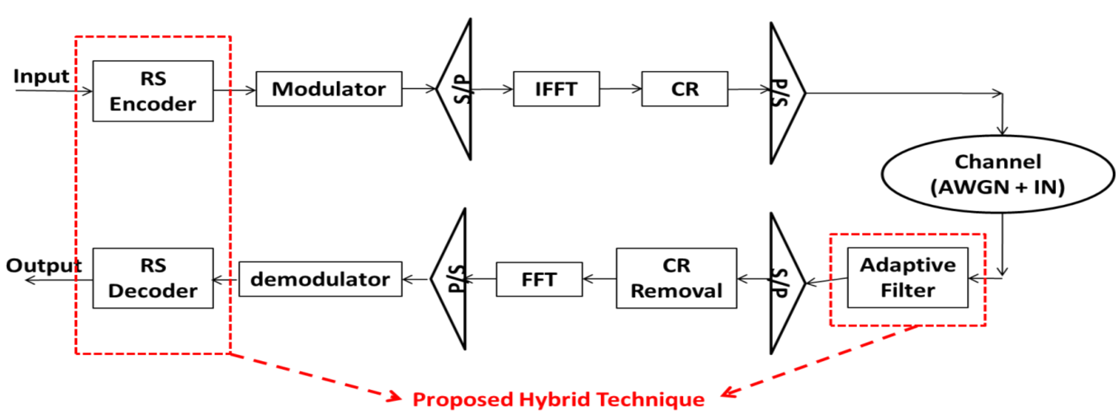


Figure 4.1: Schematic of Proposed Hybrid Technique

4.2.1 Application of NLMS Filter as Noise canceller

NLMS filter belongs to the Least Mean Square family of adaptive algorithms. The most widely used adaptive filter is NLMS because of its simplicity and robustness. In this application, we have used NLMS filter as an adaptive noise canceller.

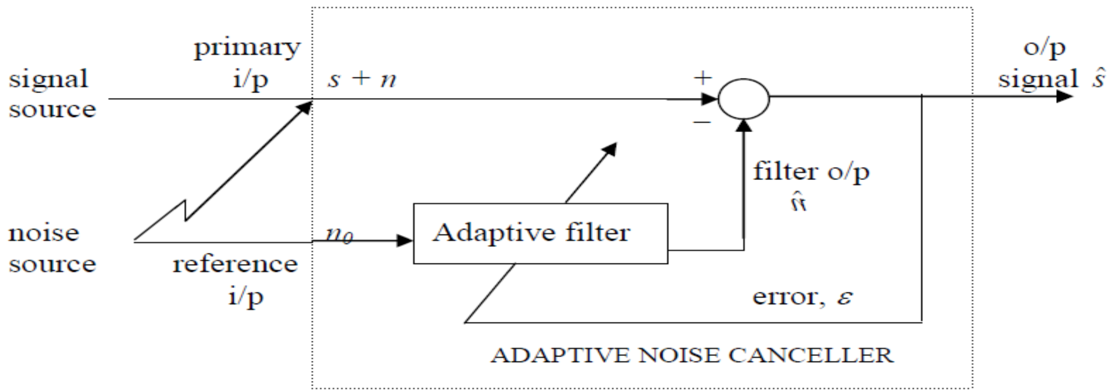


Figure 4.2: Adaptive filter noise cancellation configuration [46]

An Adaptive Noise Canceller (ANC) with primary and reference inputs is shown in Fig. 4.2. The primary input receives a signal $s(n)$ from the signal source that is corrupted by the presence of noise $n(n)$ uncorrelated with the signal. The reference input receives a noise $n_0(n)$ uncorrelated with the signal but correlated in some way with the noise $n(n)$ [103]. The noise $n_0(n)$ passes through filter to produce an output $\hat{n}(n)$ that is a close estimate of $n(n)$ present in primary input. This noise estimate is subtracted from the received corrupted signal $r(n)$ to produce an estimate of the signal $\hat{s}(n)$ at the output of ANC system.

$$e(\mathrm{n}) = \mathrm{r(n)} - \hat{\mathrm{n}}(\mathrm{n}) = \mathrm{s(n)} + \mathrm{n(n)} - \hat{\mathrm{n}}(\mathrm{n}) = \hat{\mathrm{s}}(\mathrm{n}) \tag{4.1}$$

Thus the system error signal $e(n)$ should contain the original signal $s(n)$ in an optimum sense. The output $\hat{n}(n)$of M-tap adaptive filter is given by

$$\hat{n}(n) = w(n)^T n_0(n) \tag{4.2}$$

The weight update equation of NLMS algorithm is given as

$$w(n+1) = w(n) + \mu(n)e(n)n_0(n) \tag{4.3}$$

$$\mu(n) = \frac{\hat{\mu}}{|n_0(n)|^2 + \delta} \tag{4.4}$$

where $\hat{\mu}$ is the optimum step size of algorithm, $\mu(n)$ is the time varying normalized step size and $e(n)$ is the error between the OFDM signal and Noisy OFDM signal. The following modified normalized step size LMS (NSSLMS) algorithm for noise cancellation in OFDM systems with modified step size is given as

$$\mu(n) = \frac{\hat{\mu}}{|n_0(n)|^2 + E_e(n) + \delta} \tag{4.5}$$

$$E_e(n) = \lambda E_e(n-1) + (1-\lambda)e^2(n) \tag{4.6}$$

where $E_e(n)$ is power of the residual error signal $e(n)$ and λ is the forgetting factor ($0.9 < \lambda < 1$). When LMS algorithm is excited by a signal having large variations such as impulsive noise, the residual error signal may also have large variations. Keeping in view, an inverse relation between step size parameter and power of residual error signal is therefore established in eq (4.5) [69]. When an impulse is encountered, the step size parameter reduces accordingly and the adaptation of the algorithm is ceased. Thus making it stable and robust enough for catering impulsive noise.

4.2.2 Application of Reed Solomon Decoding process:

The remaining impulsive noise and AWGN from the received OFDM signal will be removed by the second step of the proposed scheme i.e., the Reed Solomon decoder, which is applied after the demodulation block. Reed Solomon decoder is used to remove the burst errors because it replaces the whole byte irrespective of the number of bits in error [104]. The *b*-bit RS codes (*v*,*k*), where *v* is the number of data symbols, *b* is the number of code symbols for each coding block, that is (v,*k*) = (2^b-1,2^b-2*t*-1), where *t* is the length of error correcting capability and 2t is the length of parity symbol. The syndrome computation is the parity check performed on output of FFT in OFDM systems, in order to remove error produced by noise. It is calculated as:

$$\hat{S} = \hat{R}\hat{H}^T = \left(\hat{C} + \hat{E}\right)\hat{H}^T = \hat{E}\hat{H}^T = (\widehat{s_1}, \widehat{s_2}, \dots, \widehat{s_{v-k}}) \tag{4.7}$$

The received code word is $\hat{R}$, $\hat{C}$ is the original transmitted code word, $\hat{E}$ is the error vector given by $\hat{E} = (\widehat{e_1}, \widehat{e_2}, \dots, \widehat{e_v}\ )$, and $\widehat{H}^T$ is the parity check matrix transpose. The syndrome is dependent on error, not on the transmitted code word. Let's assume that there are *t* errors in the code word at locations $X^{f_1}, X^{f_2}, \dots, X^{f_t}$ with error values $Y_{f_1}, Y_{f_2}, \dots, Y_{f_t}$where indices *i=1,2,….t* refer to the error number and *f* represents error location. The error polynomial can be represented as

$$\hat{E}(x) = Y_{f_1}X^{f_1} + Y_{f_2}X^{f_2} + \dots + Y_{f_t}X^{f_t} \tag{4.8}$$

In order to determine each location X^{f_l} and its error value $Y_{f_l}$where *l=1,2,…,t*, an error location number is computed by $\varepsilon_l = \alpha^{f_l}$, where α is representation of Galois field elements. Next, α^c is substituted into the received polynomial, where *c =1,2,...,2t*. Then the *2t* syndrome symbols are obtained:

$$s_c = \hat{R}(a^c) = \sum Y_{f_l}\,\varepsilon_l{}^c \tag{4.9}$$

For finding the error values Y_{f_l}, and the locations X^{f_l}, the error location polynomial $\gamma(x)$ is:

$$\gamma(x) = (1-\varepsilon_1 x)(1-\varepsilon_2 x)\ldots.(1-\varepsilon_t x)$$

$$= \prod_{l=1}^{t}(1-\varepsilon_l x) = \gamma_t x^t + \gamma_{t-1}x^{t-1} + \cdots + \gamma_1 x + \gamma_o \tag{4.10}$$

Where the solution $1/\varepsilon_1, \ldots\ldots, 1/\varepsilon_t$, are the roots, indicating the error location $\varepsilon_1, \varepsilon_2 \ldots. \varepsilon_t$. The Berlekamp Massey (BM) iterative method is employed to find the given syndrome polynomial S.

$$\hat{S}(x) = 1 + \widehat{s_1}x + \widehat{s_2}x^2 + \cdots + \widehat{s_{2t}}x^{2t}$$

$$\omega(x) = \hat{S}(x)\gamma(x)$$

$$\omega(x) = 1 + (\widehat{s_1} + \gamma_1)x + (\widehat{s_2} + \widehat{s_2}\gamma_1 + 2\gamma_2)x^2 + \cdots + (\widehat{s_t} + \gamma_1 + \widehat{s_{t-2}}\gamma_2 + \gamma_t)x^t$$

$$\omega(x) = 1 + \omega_1 x + \omega_2 x^2 + \omega_t x^t \tag{4.11}$$

For the BM iterative processing, a step difference function b_i is calculated by:-

$$\hat{S}(x)\gamma^{(i)}(x) = \omega^{(i)}(x)b_i x^{i+1}(\mathrm{mod}\ x^{i+2}) \tag{4.12}$$

Where i is the i^{th} iteration and b,$\gamma(x)$ *and* $\omega(x)$ are calculated as below:-

$$b_i = \widehat{s_{i+1}} + \sum_{c=1}^{\partial\omega^{(i)}(x)} \widehat{s_{i+1-c}}\,\omega_c{}^{(i)}$$

$$\left\{\begin{array}{l} \gamma^{(i+1)}(x) = \begin{cases} \gamma^{(i)}(x) + b_i b_j{}^{-1}x^{i-j}\gamma^{(i)}(x), & b_i \neq 0 \\ \gamma^{(i)}(x), & b_i = 0 \end{cases} \\ \omega^{(i+1)}(x) = \begin{cases} \omega^{(i)}(x) - b_i b_j{}^{-1}x^{i-j}\omega^{(i)}(x), & b_i \neq 0 \\ \omega^{(i)}(x), & b_i = 0 \end{cases} \end{array}\right. \tag{4.13}$$

Where ∂ indicates a partial derivative operation. The roots in eq (4.10) are found by the chien-search algorithm and the error location polynomial after 2t iterations,

$$\gamma(\mathrm{x}) = \gamma^{(2\mathrm{t})}(\mathrm{x}) \tag{4.14}$$

The error value is then evaluated by the Forney Algorithm:-

$$\mathrm{y}_{\mathrm{f}_1} = -\frac{\omega(\varepsilon_{\mathrm{l}}^{-1})}{\gamma\prime(\varepsilon_{\mathrm{l}}^{-1})} \tag{4.15}$$

Decoding with error correction is done when the error polynomial is obtained.

In the second half of this chapter, we have used adaptive filters Recursive least square, Bhagyashri in our proposed hybrid technique and performed their comparison with already proposed RS-NLMS based hybrid technique. The detail of parameters is shown in Table 4.1.

Table 4.1: Detail of Parameters for Proposed Hybrid Technique

Variables	**Description**
μ	Step size of NLMS algorithm
$\mu(\boldsymbol{n})$	Time varying normalized step size
$\boldsymbol{e}(\boldsymbol{n})$	Error signal
$\boldsymbol{\beta}$	Concavity control in the cost function of Bhagyashri algorithm
$\boldsymbol{m}$	Mean of error signal
$\boldsymbol{\sigma}$	Standard deviation of error signal
$\boldsymbol{k}$	Gain of RLS algorithm
$\boldsymbol{\Phi}$	Cross correlation matrix.

The weight update equations of investigated adaptive algorithms are given in Table 4.2.

Table 4.2: Summary of Steps of Adaptive Algorithms used for Simulation

Adaptive Algorithm	**Weight Update Equation**	**Step Size/Gain update Equation**
NLMS	$w(n+1) = w(n) + \mu(n)e(n)n_0(n)$	$\mu(n) = \dfrac{\mu}{\lvert n_0(n)\rvert^2 + \delta}$
Bhagyashri	$w(n+1) = w(n) + \mu.\tanh[\beta.e(n)]$	$\tanh[\beta.e(n)] = \begin{cases} \mathrm{sign}(e(n)) & \text{if } \lvert e(n)\rvert > 1/\beta \\ -e(n).\lvert e(n)\rvert\beta^2 + 2\beta.e(n), & \text{if } \lvert e(n)\rvert \leq 1/\beta \end{cases}$ $\beta = \frac{3}{m+3\sigma}$
RLS	$w(n+1) = w(n) + k(n)x(n)$	$k(n) = \dfrac{\lambda^{-1}\Phi^{-1}(n-1)x(n)}{1 + \lambda^{-1}x^T(n)\Phi^{-1}(n-1)x(n)}$ $\Phi^{-1}(n) =$ $\lambda^{-1}\Phi^{-1}(n-1) - \lambda^{-1}k(n)x^T(n)\Phi^{-1}(n-1)$

4.2.3 Flow chart of Proposed Hybrid Technique

The summarized algorithm for proposed dual protected technique in OFDM communication systems is as follows:

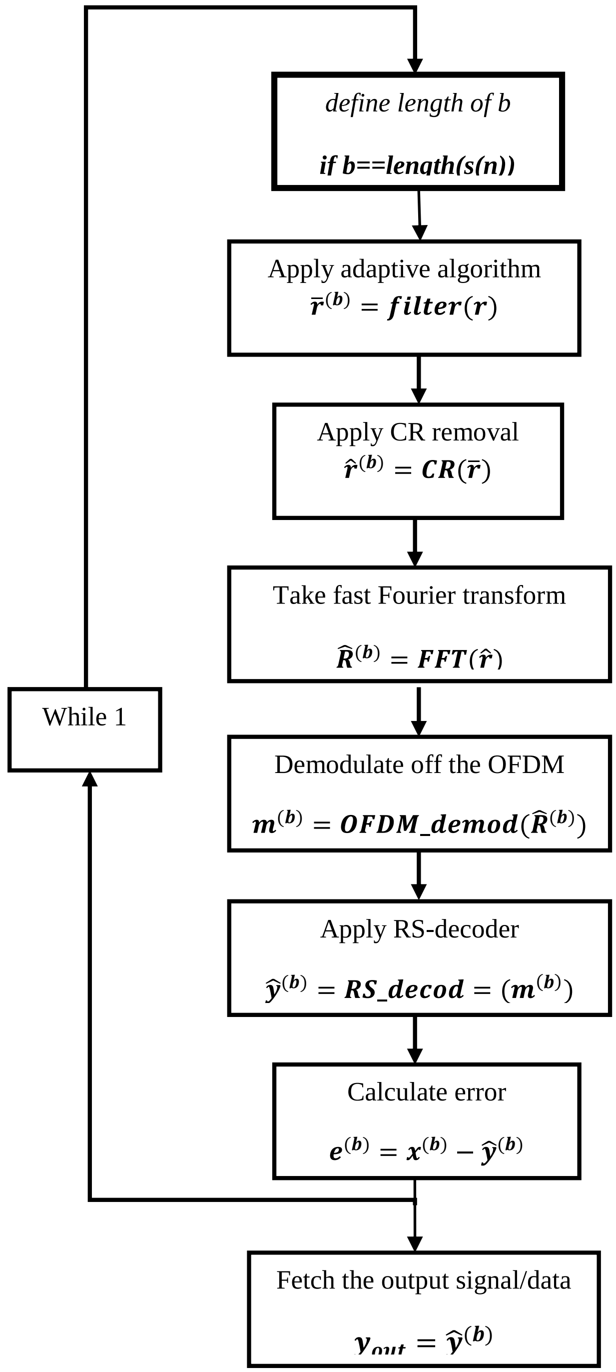
Here:

- x(n) is system input
- s(n) is OFDM signal
- r(n) is noisy OFDM
- $\bar{r}(n)$ is output of adaptive filter
- $\hat{y}(n)$ is system output.

Initial values:

$b = 0$

$r^{(0)} = r$



4.3 Simulation Results

OFDM system affected by impulsive noise is implemented using the MATLAB platform. The performance of proposed technique is compared with those of already reported techniques in literature [93] in both AWGN and Rician channel. The parameters used in simulating the OFDM system are tabularized below.

Table 4.3: Simulation Parameter Set For Proposed Hybrid Technique

OFDM System		**Impulsive Noise**	
Parameters	**Values**	**Parameters**	**Value**
Modulation technique	QPSK	**Sampling frequency**	8Hz
Size of cyclic prefix	2	**Total time**	4681s
FFT-length	8	**Samples intermediate average time**	1s
Number of bits generated	32767	**Log amplitude mean value**	3dB
		Standard deviation of log amplitude	2dB
		Mean of AWGN	0
		Standard deviation of AWGN	0.8

The binary random data is generated and passed to the RS encoder. After encoding and modulation, the signal is transmitted by OFDM transmitter which.is.illustrated in.Fig. 4.3.

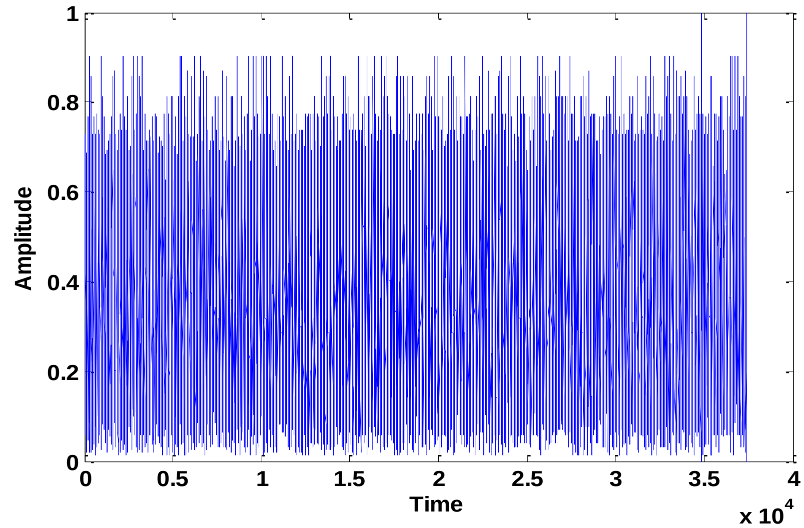


Figure 4.3: Transmitted OFDM Signal

This OFDM signal is then propagated from the channel containing AWGN and impulsive noise. The impulsive noise is generated by the algorithm mentioned in [77] and illustrated in Fig. 4.4(a).

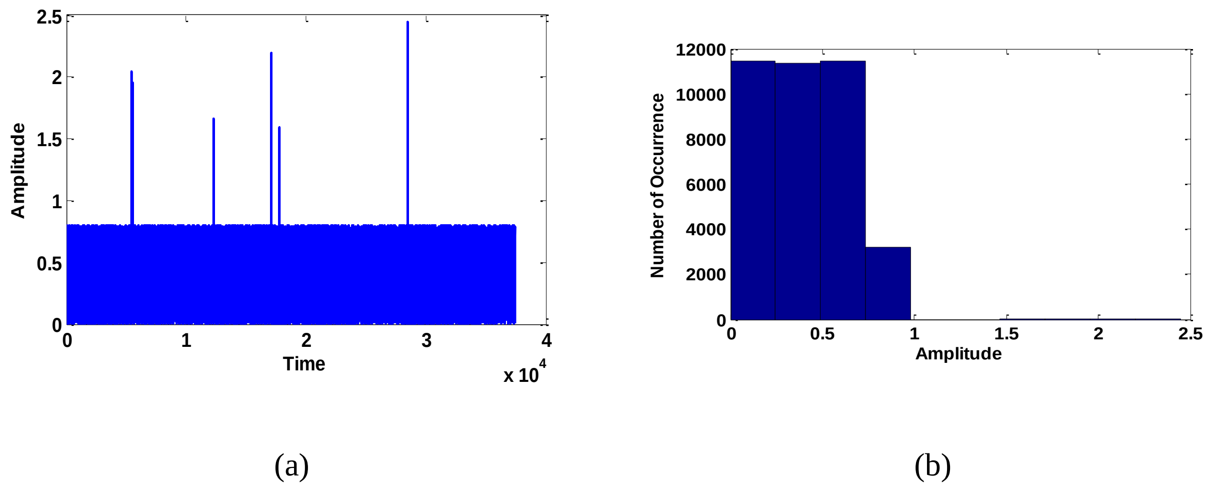


Figure 4.4: (a) Time Domain Impulsive Noise Signal b) Histogram of Generated Impulsive Noise

The histogram of the generated impulsive noise in Fig. 4.4(b) shows that noise pulses with amplitude less than 0.75 have very high rate of occurrence as compared to the pulses that have amplitude from 0.75 to 1. However, the high peaked impulses with amplitude between 1.5 and 2.5

occur rarely. When the OFDM signal propagates through the channel containing AWGN and impulsive noise, it gets perturbed. The noisy OFDM signal is shown below:

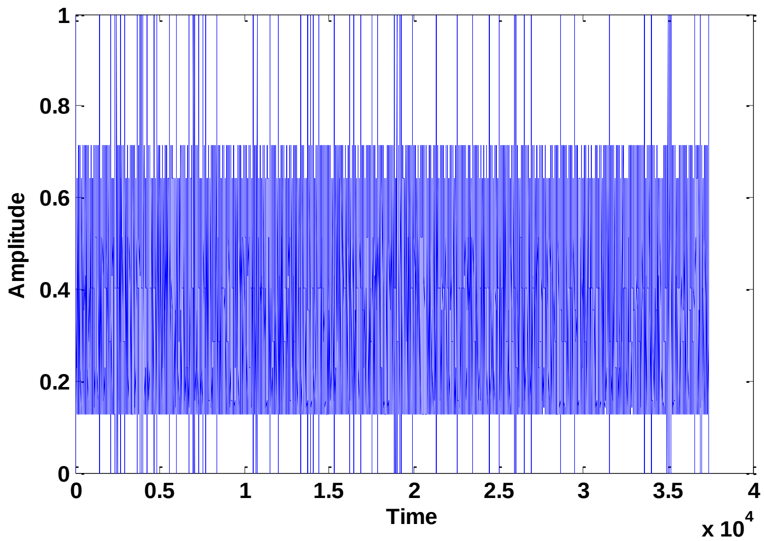
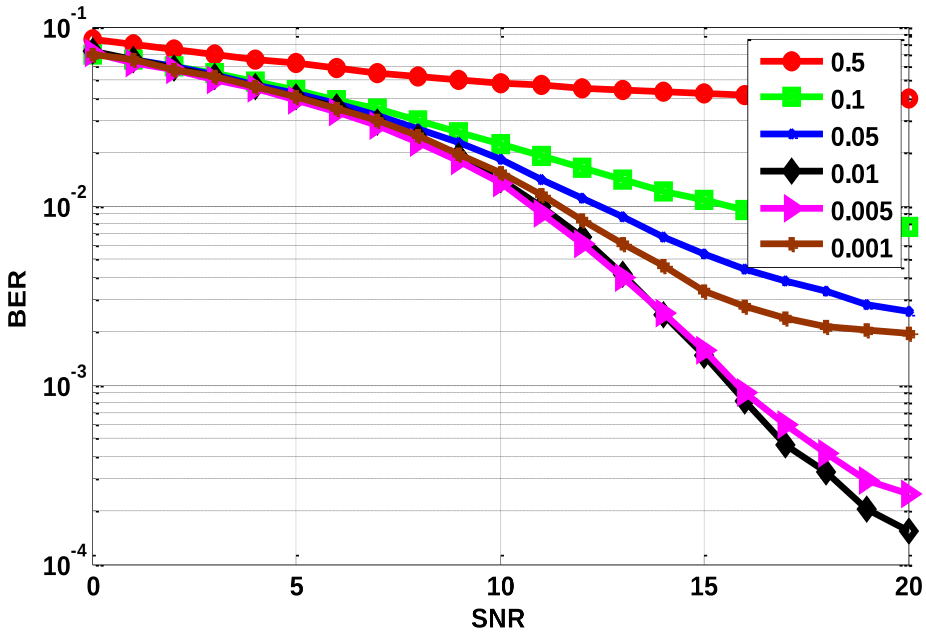
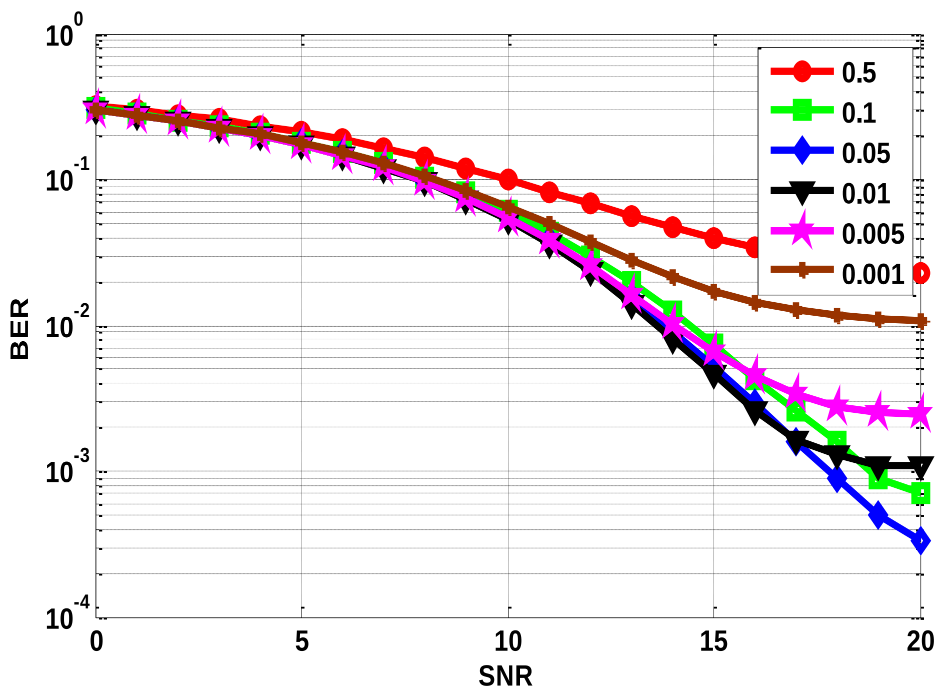


Figure 4.5: Noisy OFDM signal with AWGN and Impulsive Noise

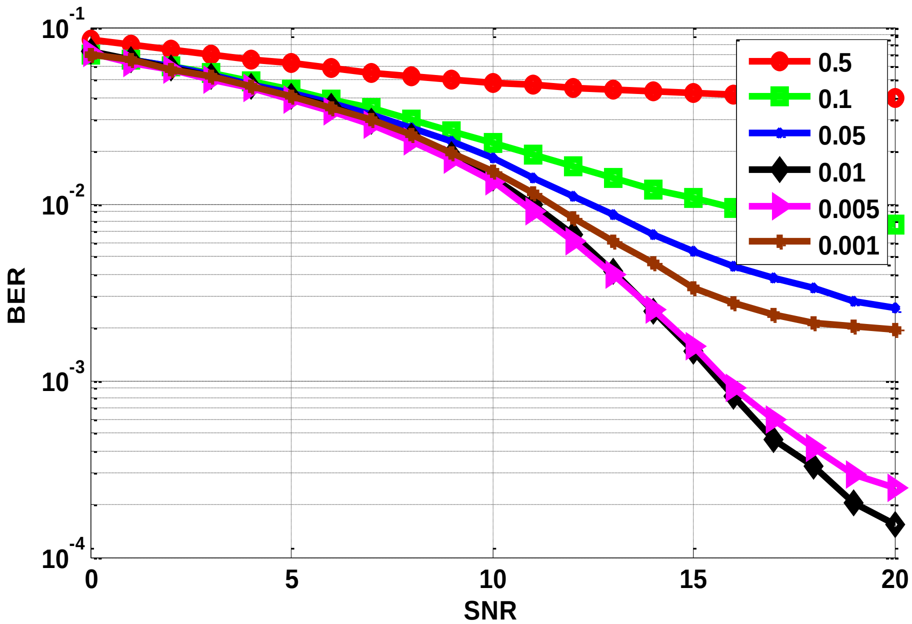
This noisy received signal is filtered through proposed NSSLMS filter and then OFDM receiver operates in reverse order for sorting encoded symbols in original sequence. After demodulation Reed Solomon decoder is applied for further reducing the impact of noise in the original signal. The performance of both NLMS and newly proposed NSSLMS filter in combination with RS codes is compared regarding BER, MSE and SNR improvement. Extensive simulations are carried out to study the effect of step size on NLMS and proposed NSSLMS filters by varying different modulation schemes. These values are used as a guideline to tune the step size for the rest of the method. Fig. 4.6 and Fig 4.7 shows the BER curves obtained with proposed RS-NLMS and RS-NSSLMS algorithms in AWGN channel for various values of step size for BPSK, QPSK and 16 QAM constellations.



(a)

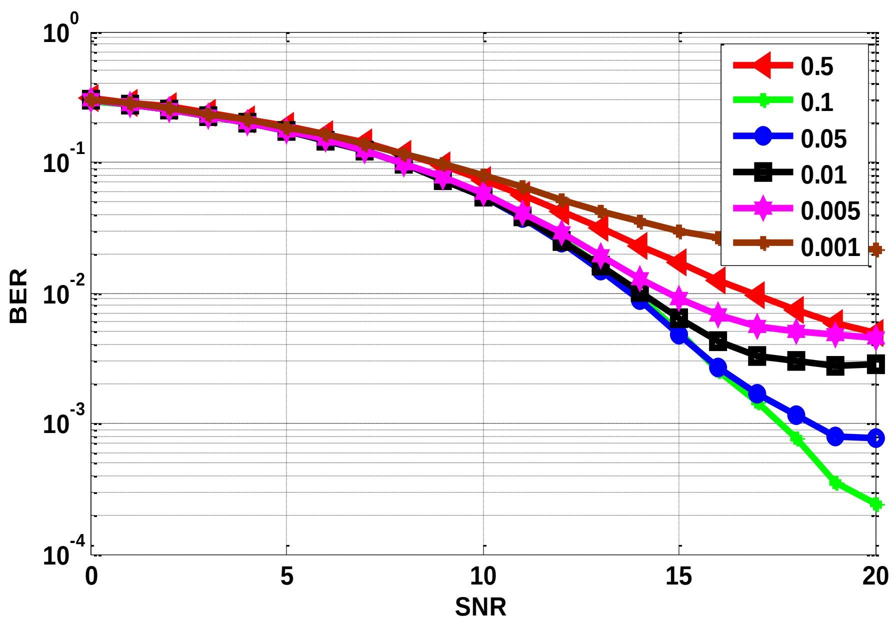


(b)

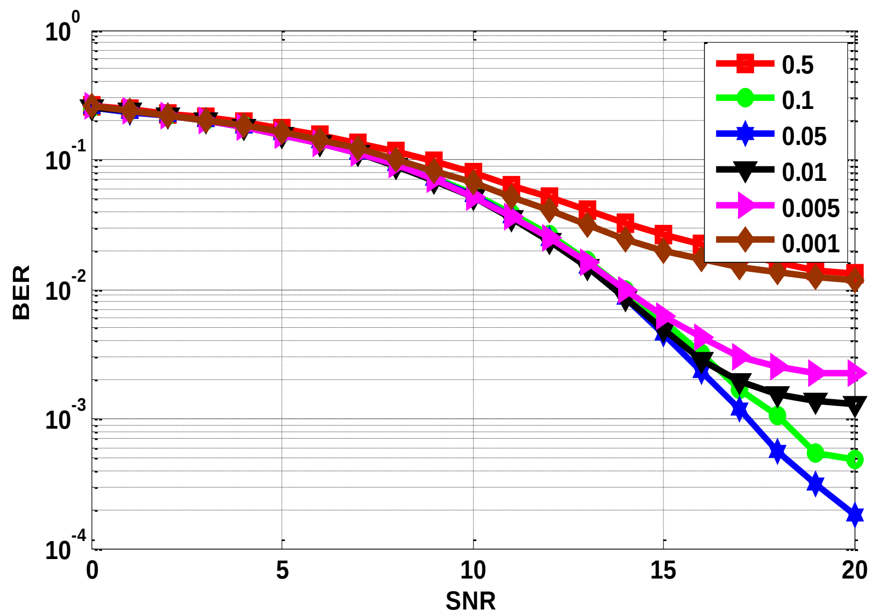


c)

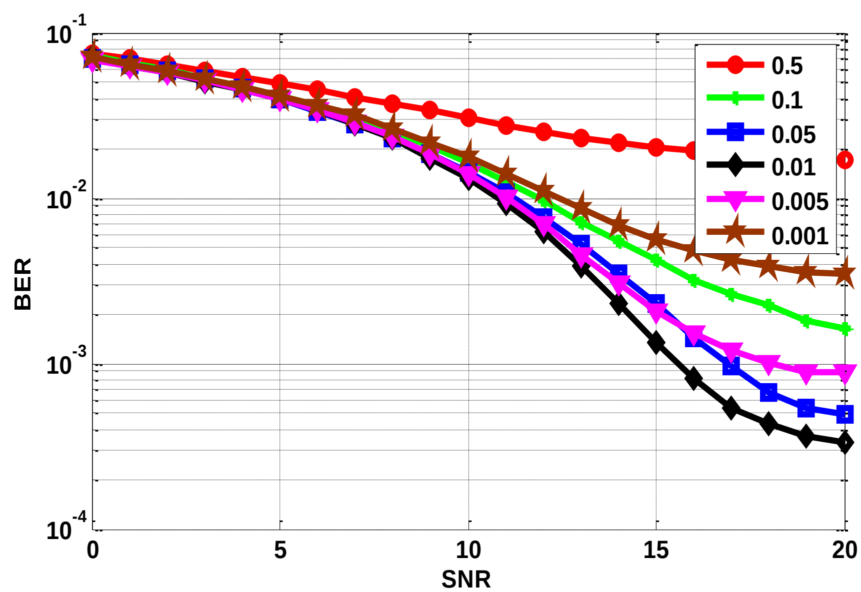
Figure 4.6: BER curves of proposed RS-NLMS algorithm in AWGN channel for various values of step sizes for (a) BPSK, (b) QPSK, (c) 16-QAM constellation



a)



(b)



(c)

Figure 4.7: BER curves of proposed RS-NSSLMS algorithm in AWGN channel for various values of step sizes for (a) BPSK, (b) QPSK, (c) 16-QAM Constellation

From these experiments, the selected values of parameter step size are shown in Table 4.4.

Table 4.4: Optimum step sizes for different modulations

Modulation	RS-NLMS Algorithm	RS-NSSLMS Algorithm
BPSK	0.05	0.1
QPSK	0.01	0.05
16QAM	0.01	0.01

The performance comparison of proposed RS-NLMS and RS-NSSLMS algorithms for AWGN channel and Impulsive noise (IN) with their best step sizes is shown in Fig. 4.8.

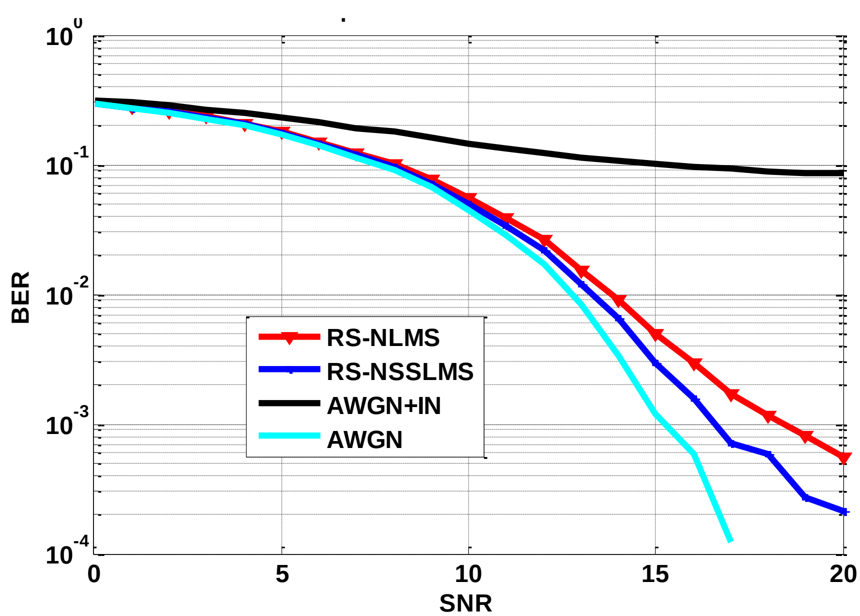


Figure 4.8: Comparison of BER for proposed RS-NLMS and RS-NSSLMS algorithms in AWGN

It is noticed that the suggested NSSLMS filter gives better BER performance than that of NLMS filter when used in our proposed hybrid technique. It can be seen that the BER of proposed RS-NSSLMS algorithm is closest to AWGN BER curve for SNR up to 20 dB.

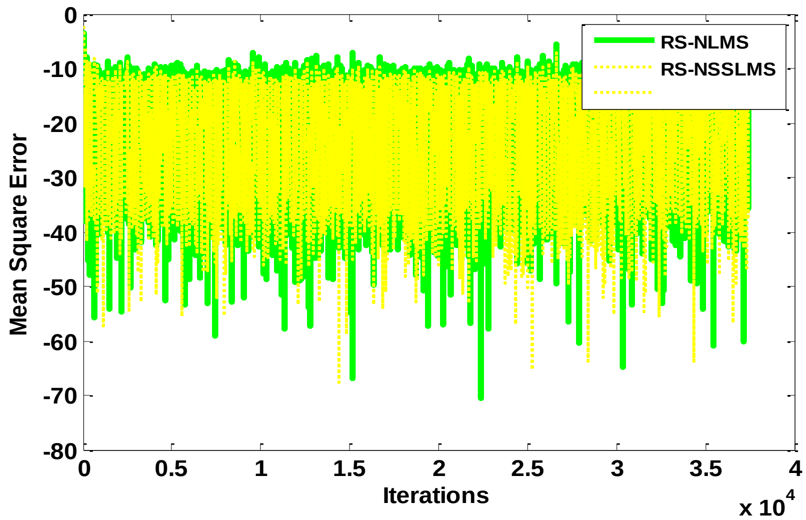
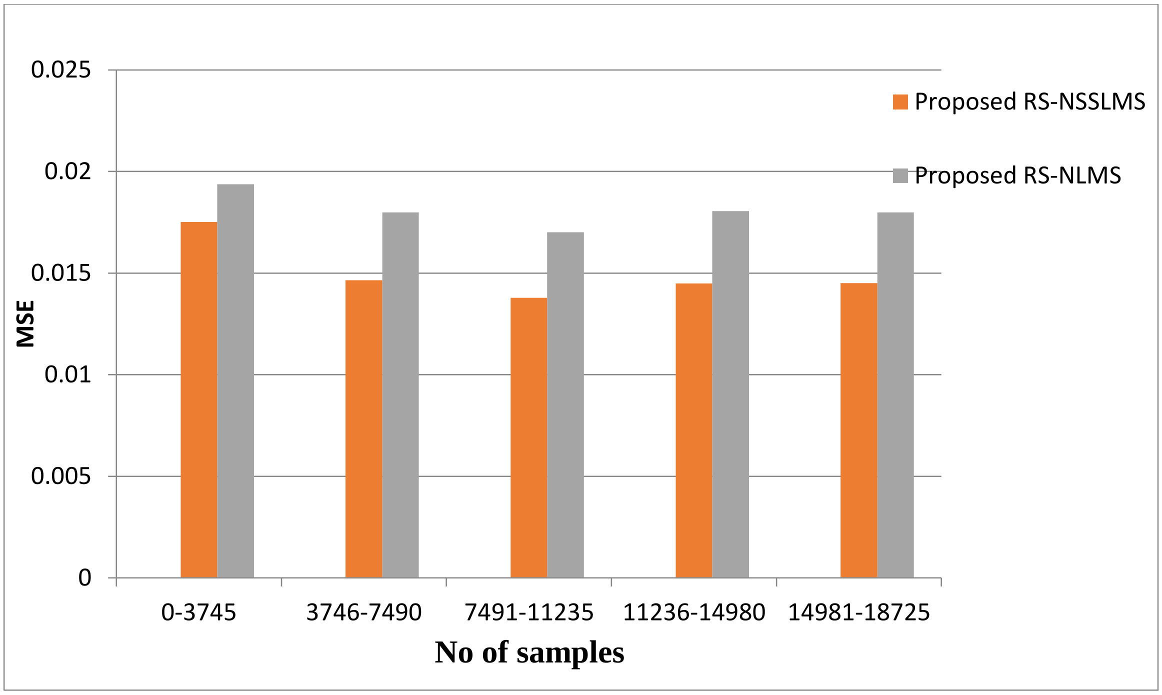


Figure 4.9: Comparison of MSE for proposed RS-NLMS and RS-NSSLMS algorithms

The mean square error simulation results also confirm that suggested RS-NSSLMS gives lowest MSE and fastest convergence as compared to the RS-NLMS as depicted in Fig. 4.9. The mean square value of RS-NSSLMS algorithm is below -8dB, whereas RS-NLMS algorithm has MSE value less than -12dB.

Another representation of the MSE of two variants of proposed hybrid technique is depicted in Table 4.5. The x-axis of the bar chart represent the 5 sets of 3745 data samples and on the y-axis the average MSE value of each 3745 samples block is illustrated. It is obvious that RS-NSSLMS hybrid scheme gives lowest MSE as compared to the proposed hybrid technique based on RS-NLMS.

Table 4.5: Bar Chart of Average Mean Square Error



The comparison of our proposed hybrid technique (RS-NSSLMS) with individual RS coding and NSSLMS filtering is performed in Fig. 4.10 for suppressing impulsive noise in AWGN channel. In these results, the NSSLMS filtering shows better performance when compared to RS coding alone. However, significant BER improvement is achieved in our proposed dual faceted technique by combining RS error correction codes with NSSLMS filter. This is because NSSLMS filter creates a more accurate estimate of the original OFDM signal after impulsive noise cancellation and the residual impulsive noise is managed by the RS decoder in the second stage of proposed technique. Moreover, the proposed technique outperforms another hybrid technique based on clipping and NLMS filter reported in literature [93] in Fig. 4.10 for mitigation of impulsive noise.

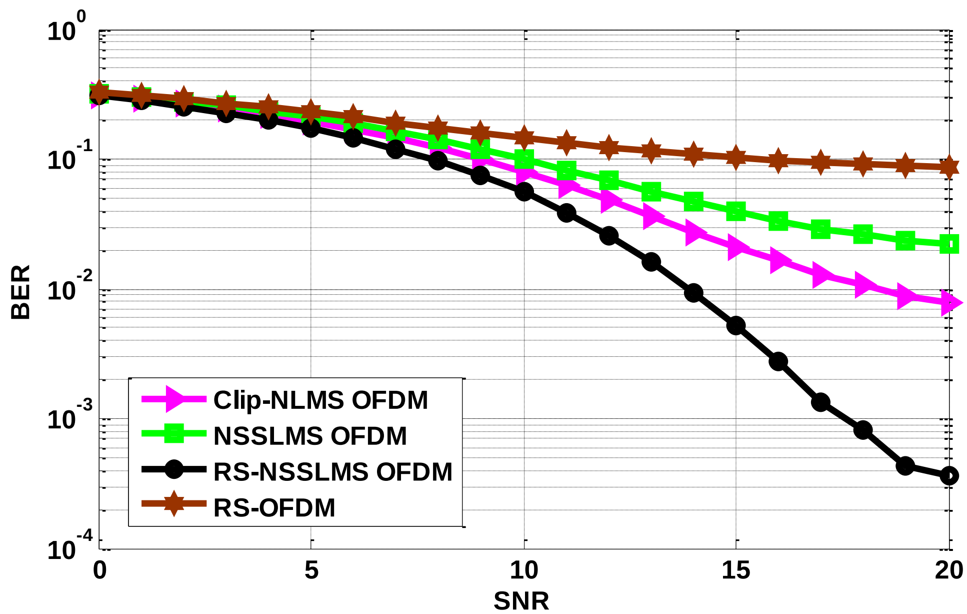


Figure 4.10: BER comparison of proposed hybrid technique with RS coding, NLMS filtering and Clip-NLMS based technique employed in OFDM system

The new proposed algorithms that are RS-NLMS and RS-NSSLMS are also compared in terms of SNR degradation in Table 4.6. It is evident from the table that RS-NLMS based technique produces an SNR degradation which is more than RS-NSSLMS. This again verifies our claim that RS-NSSLMS gives better performance for impulsive noise mitigation in OFDM systems than that of RS-NLMS. The SNR degradation is obtained by the difference of SNR of OFDM signal and filtered signal, where the maximum SNR of the OFDM signal is 4.512dB. The SNR is estimated as:

$$Filtered\ Signal\ SNR = 10\log_{10}\left(\frac{\sum(ofdm\ signal\ after\ filtering)^2}{\sum(Noise)^2}\right) \tag{4.16}$$

$$Max\ OFDM\ Signal\ SNR = 10\log_{10}\left(\frac{\sum(ofdm\ signal\ )^2}{\sum(Noise)^2}\right) \qquad (4.17)$$

Table 4.6: SNR comparison of Proposed Techniques

Algorithms	**Max Signal SNR**	**Filtered Signal SNR**	**SNR Degradation**
RS-NSSLMS	4.512	3.8069	0.7051dB
RS-NLMS	4.512	3.39	1.12dB

The performance gain of proposed technique is also investigated for Rician fading channel. The purpose of selecting Rician channel is to analyse the robustness of proposed technique against changes in the environment. Fig. 4.11 shows BER comparison of our proposed hybrid technique (RS-NSSLMS) with individual RS coding and NSSLMS filtering in Rician fading channel. The performance of our suggested composite technique also outperforms another hybrid technique reported in [93] for impulsive noise cancellation as depicted in Fig. 4.11.

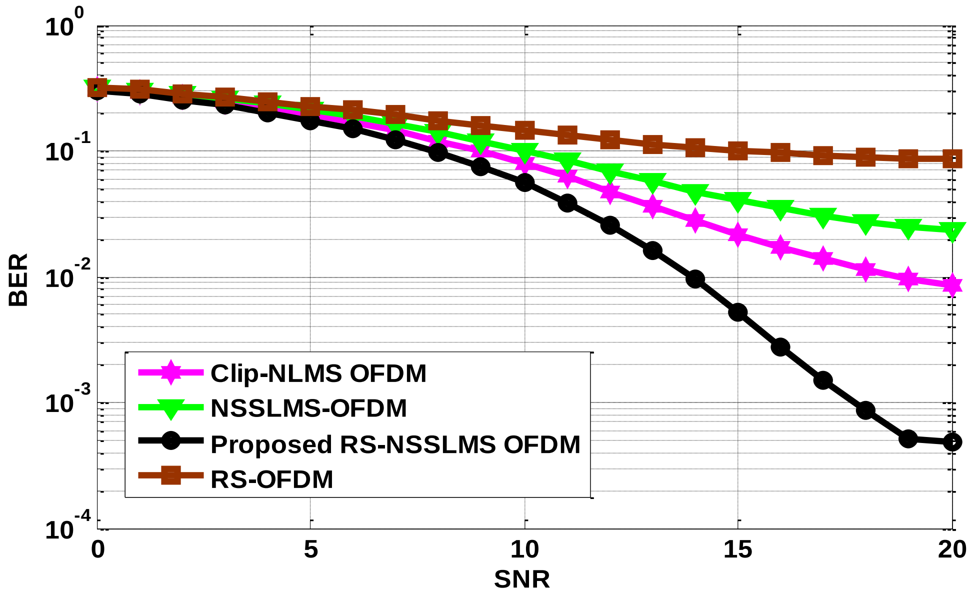


Figure 4.11: BER comparison of proposed hybrid technique employed in OFDM system for Rician Channel

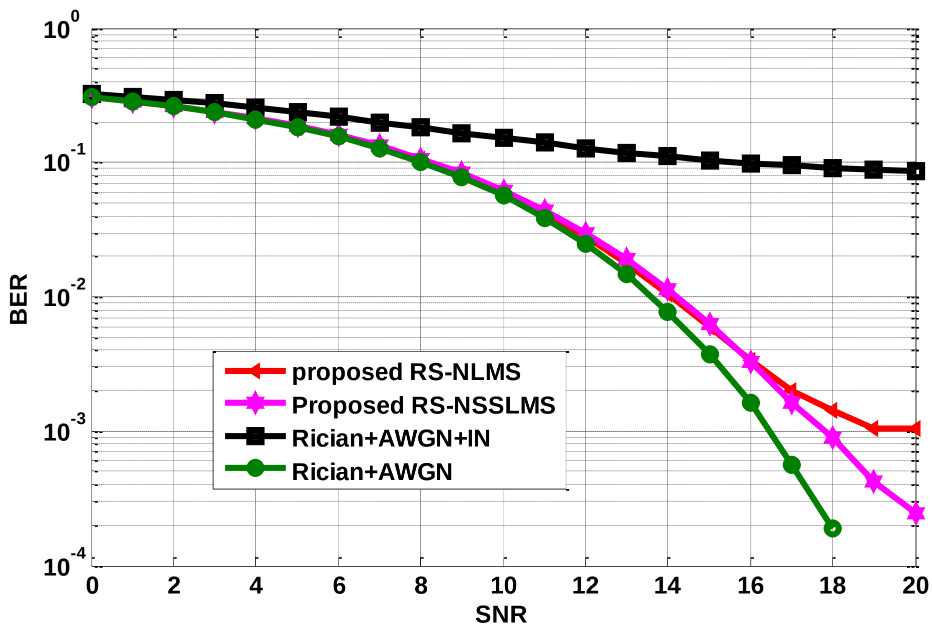
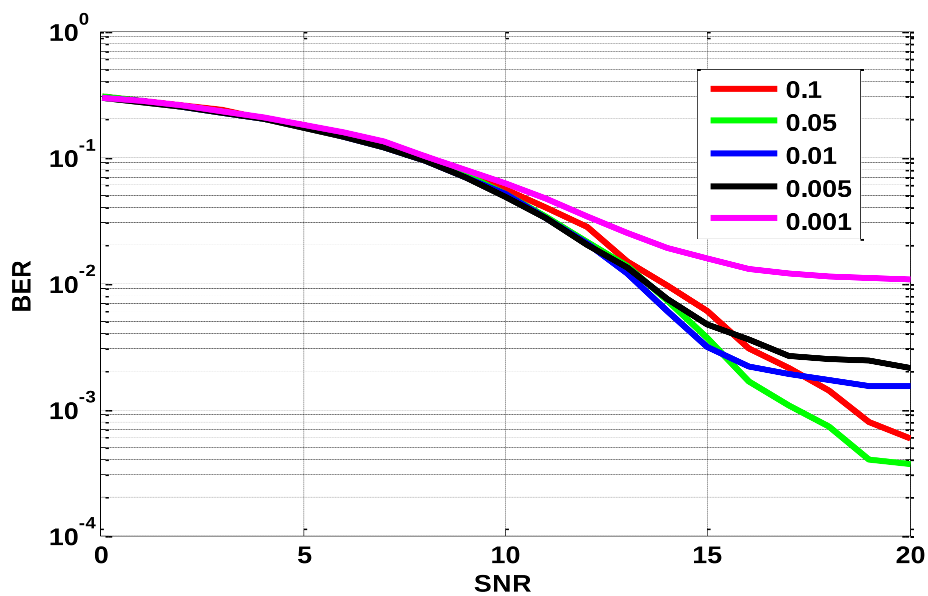


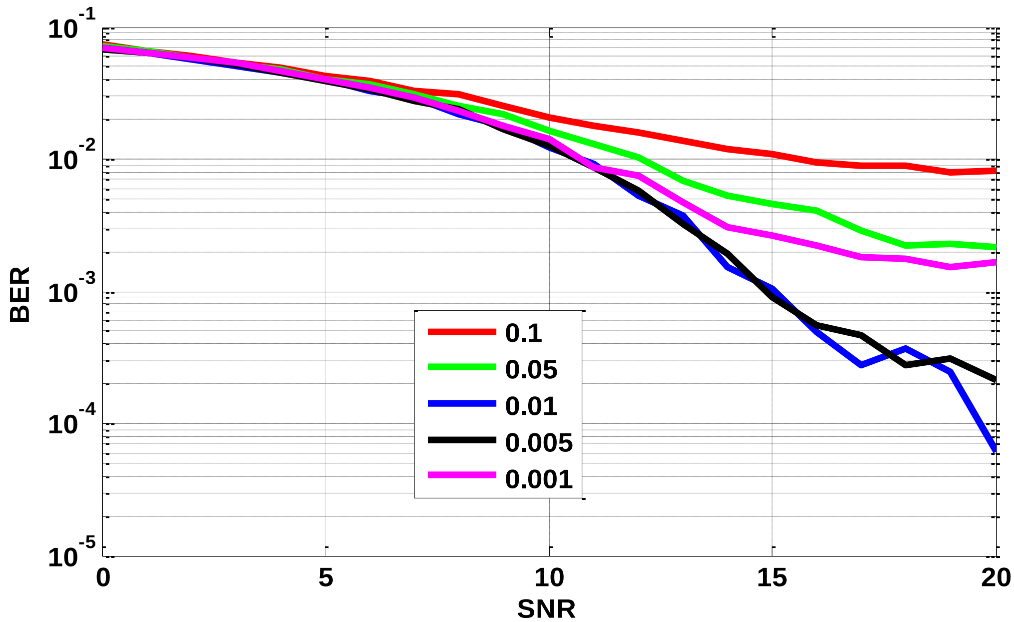
Figure 4.12: Comparison of BER for proposed RS-NLMS algorithm and RS-NSSLMS algorithm in Rician Channel

Fig. 4.12 shows BER comparison for the two proposed techniques under Rician fading channel with impulsive noise. It can be seen that BER curves for suggested RS-NLMS and RS-NSSLMS algorithms overlap for low SNR values however for high SNR, RS-NSSLMS algorithm gives better performance.

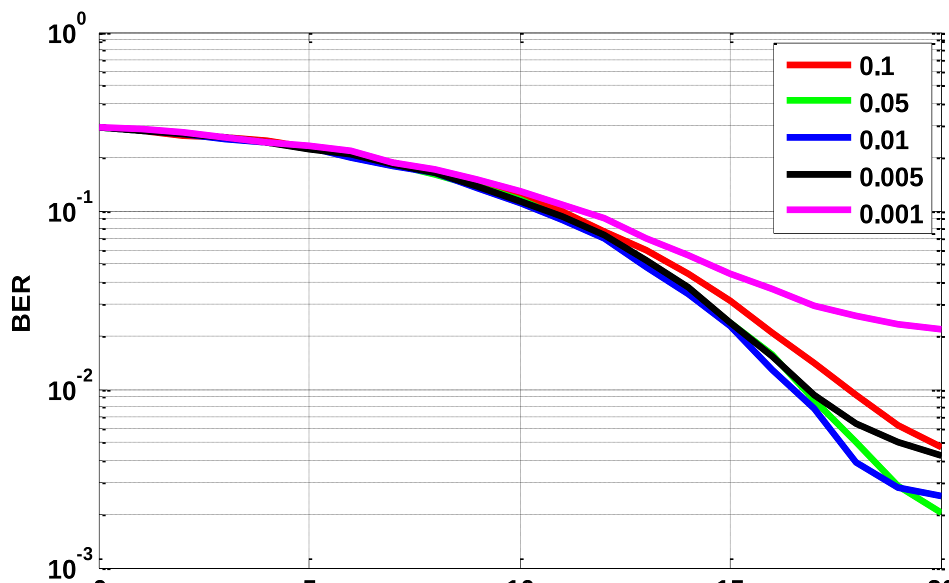
In order to further strengthen my point that adaptive filter can better mitigate impulsive noise, in the next part of chapter 4 simulation section, we have used two more adaptive filters RLS and Bhagyashri algorithm in suggested hybrid technique and their comparison is carried out with RS-NLMS technique. The performance of NLMS, Bhagyashri and RLS filters in combination with RS code are compared in terms of BER. Extensive simulations are carried out to study the effect of step size on NLMS and Bhagyashri filters by varying different modulation schemes. Fig. 4.13 and Fig. 4.14 shows the BER curves of RS-NLMS and RS-Bhagyashri algorithms in AWGN channel for various values of step sizes parameter for BPSK, QPSK and 16 QAM constellation



(a)

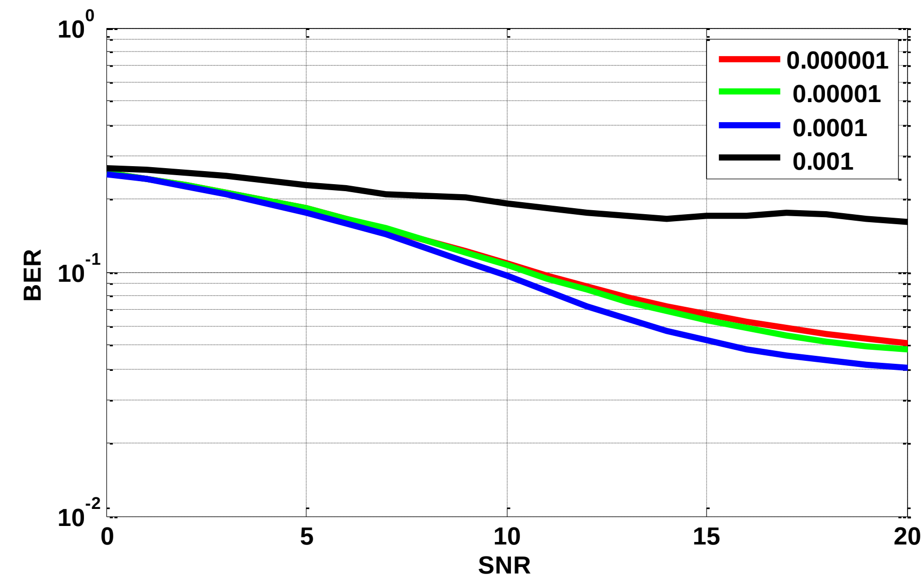


(b)

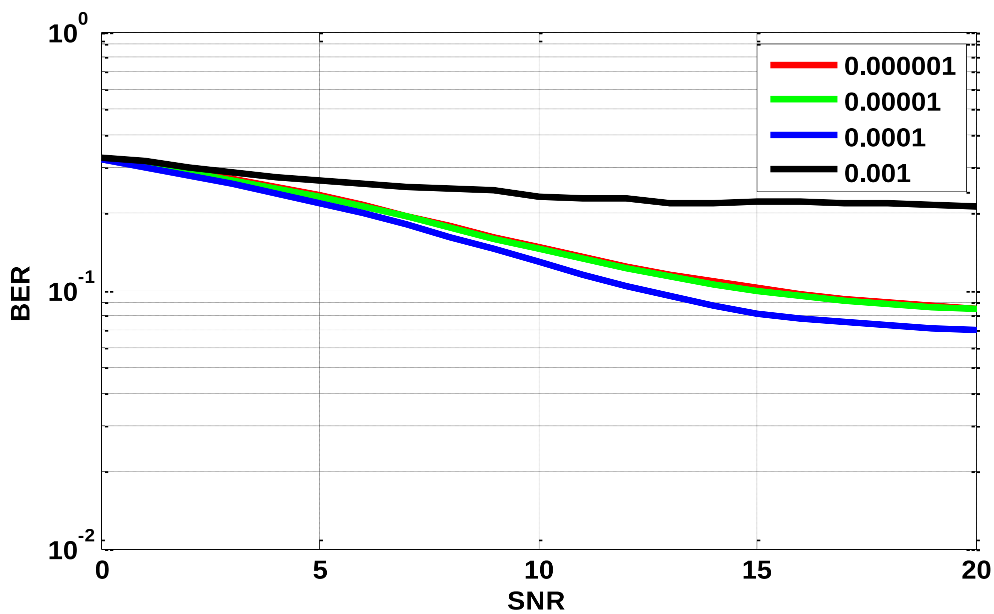


(c)

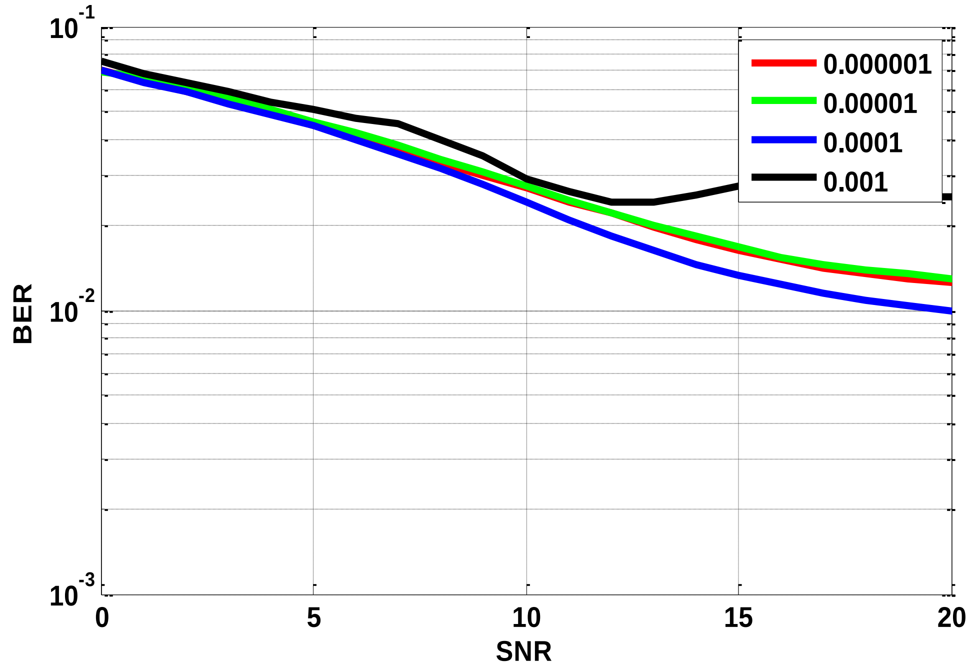
Figure 4.13: BER Curves of RS-NLMS Algorithm in AWGN Channel for Various values of step sizes for a) BPSK b) QPSK c) 16-QAM Constellation


10^0
10^-1
10^-2
BER
0
5
10
15
20
SNR
0.000001
0.00001
0.0001
0.001

a)


10^0
10^-1
10^-2
BER
0
5
10
15
20
SNR
0.000001
0.00001
0.0001
0.001

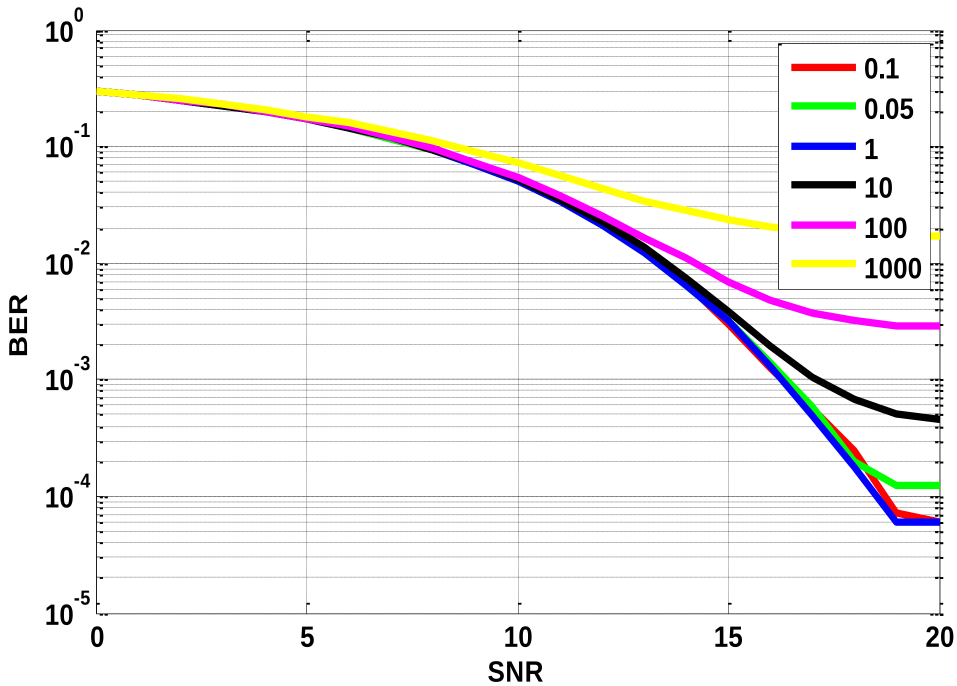
b)



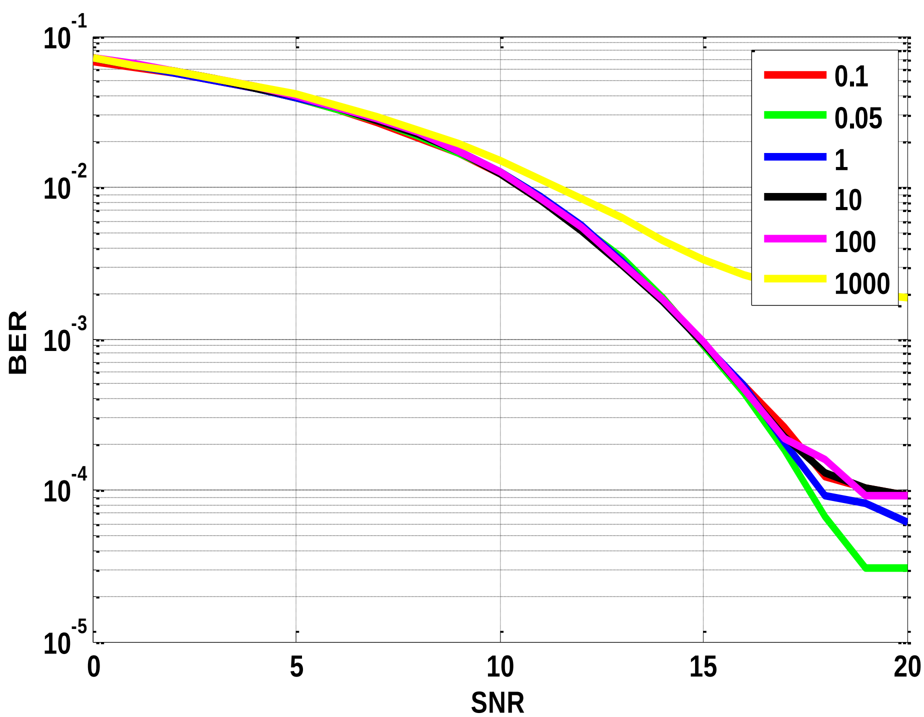
c)

Figure 4.14: BER Curves of RS-Bhagyashri Algorithm in AWGN Channel for Various values of step sizes for a) BPSK b) QPSK c) 16-QAM Constellation

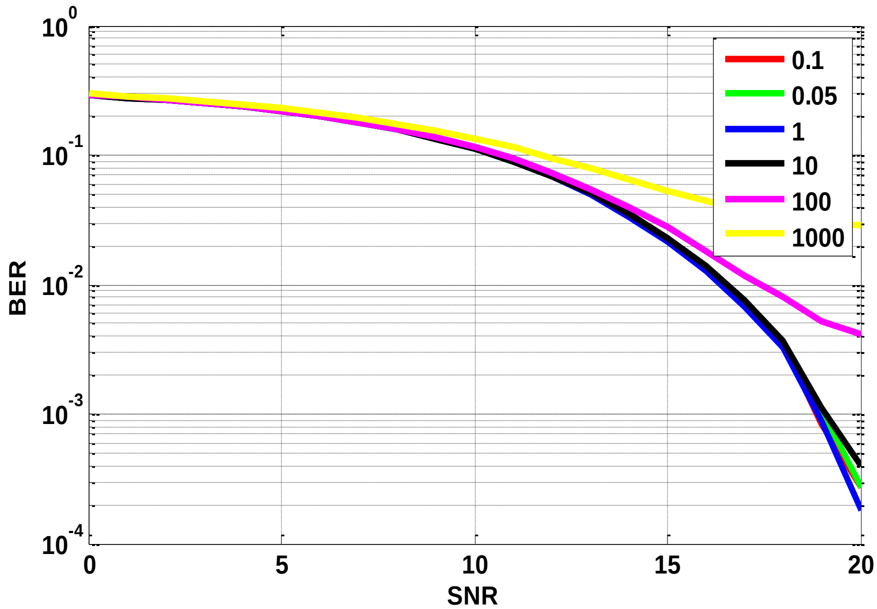
Initialization of the RLS algorithm is a critical point for convergence of the algorithm. The regularization parameter delta (δ) depends on SNR or in other words, variance of input signal *x'(n)* [69]. When the noise level in the tap inputs is low, the RLS algorithm exhibits high convergence rate, provided that δ is chosen small enough; whereas, if noise level is very high it is preferable to initialize the algorithm with large value of δ [69]. The effect of varying delta (δ), from very small value to quite large values for impulsive noise is shown in Fig. 4.15.



a)



b)



c)

Figure 4.15: BER Curves of RS-RLS Algorithm in AWGN Channel for Various values of Delta for a) BPSK b) QPSK c) 16-QAM Constellation

From these experiments, the optimum parameters selected for proposed hybrid technique are shown in Table 4.7.

Table 4.7: Best Selected Parameters for Variants of Proposed Hybrid Technique

Modulation	**RS-NLMS (step size values)**	**RS-Bhagyashri (step size values)**	**RS-RLS (delta values)**
BPSK	0.05	0.0001	1
QPSK	0.01	0.0001	1
16QAM	0.01	0.0001	0.05

Fig. 4.16 shows the performance comparison between RS-NLMS, RS-Bhagyashri and RS-RLS algorithms for AWGN channel uses the best parameters from Table 4.7.

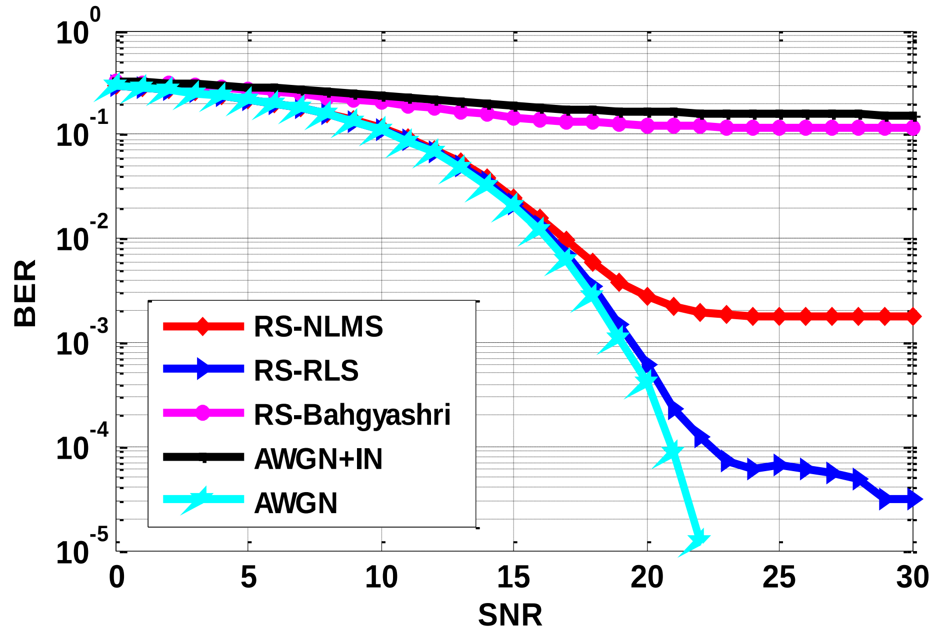
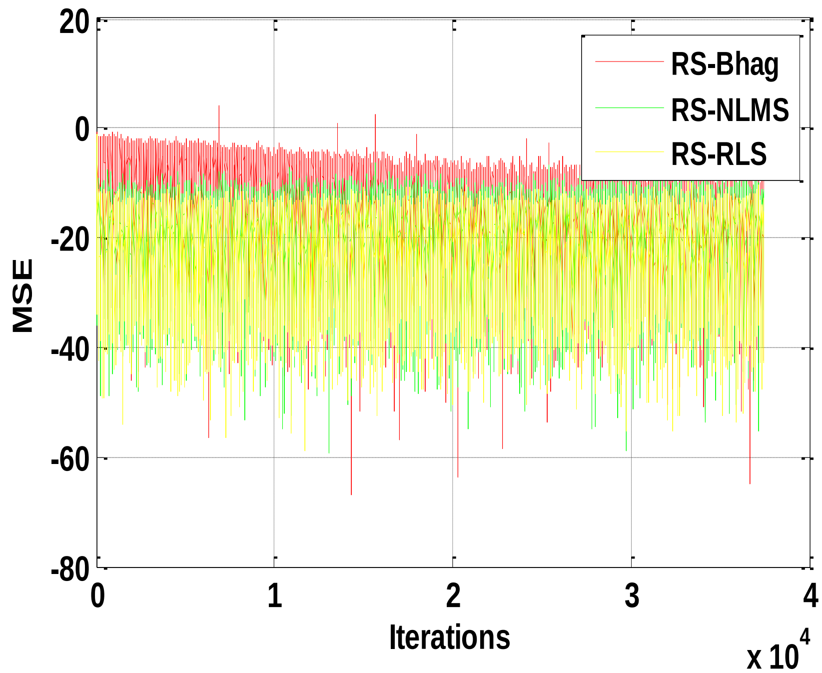


Figure 4.16: Comparison of BER Curves for RS-NLMS, RS-RLS and RS-Bhagyashri Algorithms

It is important to note that RLS filter gives better BER performance than NLMS and Bhagyashri filter when used in our proposed hybrid technique. The proposed RS-RLS algorithm BER curve is close to AWGN curve up to 20dB SNR as illustrated in Fig 4.16.

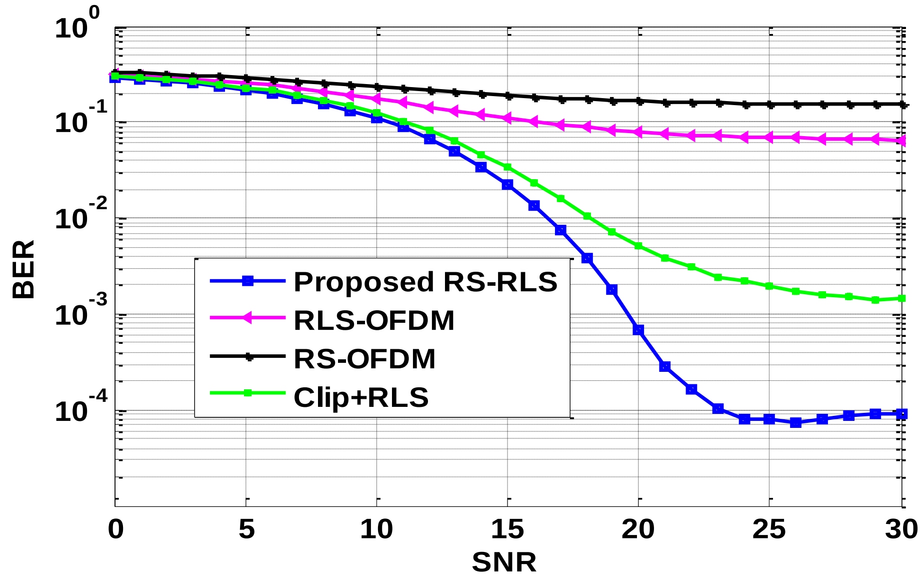
The Mean Square Error (MSE in dB) simulation result also confirms that RS-RLS gives lowest MSE and fastest convergence as compared to the RS-NLMS and RS-Bhagyashri algorithms as depicted in Fig. 4.17. The mean square value of RS-RLS algorithm is below -14dB, whereas RS-Bhagyashri algorithm has MSE value less than -2dB.



. Figure 4.17: Comparison of MSE for RS-NLMS, RS-Bhagyashri and RS-RLS Algorithms

The comparison of our proposed hybrid technique (RS-RLS) with individual RS coding and RLS filtering is performed in Fig. 4.18 for suppressing impulsive noise in AWGN channel. In these results,.the.RLS.filtering.shows.better.performance.when.compared.to.RS.coding.alone.

However, significant BER improvement is achieved in our proposed dual faceted technique by combining RS error correction codes with RLS filter. Actually, OFDM signal accurate estimate can be achieved by RLS filter after suppression of impulsive noise and RS decoder removes the enduring impulsive noise in second step of proposed dual faceted technique. Moreover, the proposed technique outperforms another hybrid technique based on clipping and RLS filter reported in literature [93] in Fig. 4.18 for mitigation of impulsive noise.



. Figure 4.18: BER Comparison of proposed hybrid technique with RS coding, RLS filter and Clip-RLS Algorithm employed in OFDM System

The new proposed algorithms that are RS-NLMS, RS-Bhagyashri and RS-RLS are also compared in terms of SNR degradation in Table 4.8. It is shown from the table that the RS-RLS proposed technique produces minimum SNR degradation. This again verifies our claim that RS-RLS give better performance for impulsive noise mitigation in OFDM systems than other variants. The SNR degradation is obtained by the difference of SNR of OFDM signal and filtered signal, where the maximum SNR of the OFDM signal is 4.512dB.

Table 4.8: SNR Comparison of Proposed Techniques

Algorithms	Max Signal SNR	Filtered Signal SNR	SNR Degradation
RS-NLMS	4.512	3.8069	0.7051dB
RS-Bhagyashri	4.512	0.27	4.242dB
RS-RLS	4.512	3.966	0.546dB

The performance gain of proposed technique is also investigated for Rician fading channel. Fig. 4.19 shows BER comparison of variants of our proposed hybrid technique in Rician fading channel. The `

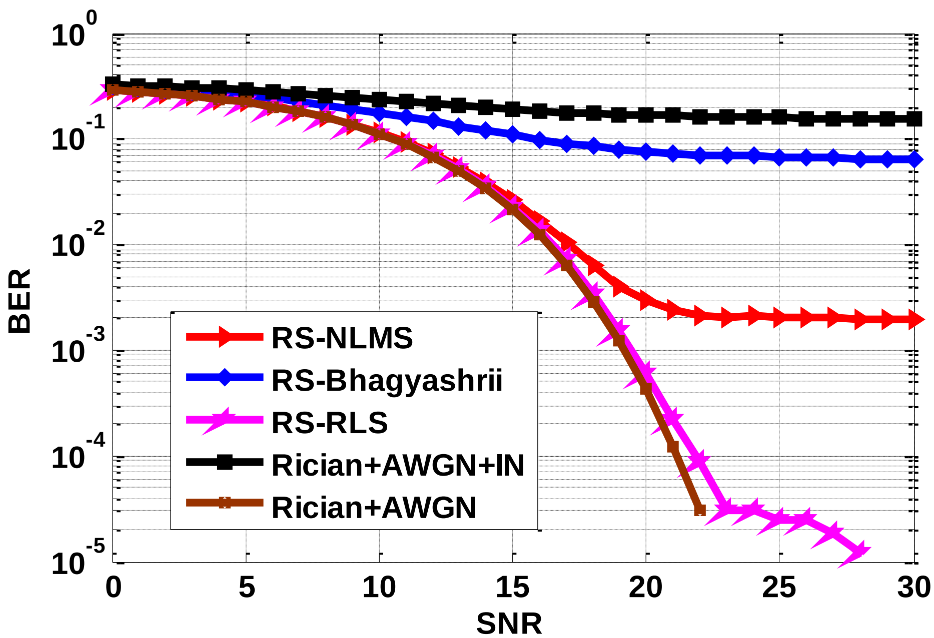


Figure 4.19: Comparison of BER for Proposed Dual Protection Technique with RS Coding, RLS filter and Clip-RLS Algorithm in Rician Fading Channel

4.4 Summary

New technique for impulsive noise cancellation based on combination of Reed Solomon and adaptive filter for OFDM systems is presented in this chapter. The four variants of adaptive family i.e. NLMS, NSSLMS, Bhagyashri and RLS algorithm are used for mitigating impulsive noise from received OFDM signal. Due to adaptive algorithm`s ability to track time variations of signal statistics in non-stationary environment, better reduction in impulsive noise is achieved and enhanced signal reception is attained by employing Reed Solomon error correction codes. The suggested scheme improves the quality of OFDM signal by exhibiting low MSE and BER, along with improved SNR, when compared with recently reported scheme. Moreover, the comparative analysis of proposed dual protection technique is tested in AWGN and Rician fading channel. It is verified from simulation results that proposed RS-RLS outperforms the other investigated variants in impulsive noise suppression.

Chapter 5

Robust Adaptive Algorithm for Active Control of Impulsive Noise

5.1 Introduction

The biggest challenges incurred in the ANC of impulsive noise are convergence and stability of the noise reducing algorithms. The simplest and less complex filtered-x least mean square (FxLMS) algorithm for ANC is designed to minimize the variance of error signal [4]. However, since the second order moment does not exist in case of impulsive noise [105], it cannot be used for impulsive noise reduction. Sun et al. [106] proposed a modification in FxLMS algorithm which ensures stability of the system. They applied fixed thresholds on the reference signal in order to eliminate the effect of large amplitudes of impulses. Instead of ignoring the samples as in [107], Akhtar et al. [55] improved the Sun's algorithm by replacing impulses with new threshold values of error and reference signals and achieved faster convergence along with enhanced stability. The algorithms [2], [55], [107] are bound to update their threshold parameters during online operation which increases computational complexity. To reduce the complexity, another normalized step size FxLMS (NSS-FxLMS) algorithm is reported in [108], which does not need modified reference or error signal. And in consequence to that, no selection of the threshold parameters are required. Qiu et al. in [109] suggested a new technique (FxlogLMS) based on fair M–estimator that minimizes the squared logarithmic transformations of error signal to achieve robustness. However, the algorithm has the drawback of reaching a dead zone in process of updating the filter coefficients. Bergamasco et al. [110] provided a solution based on online estimation of secondary path for ANC applications. A modified FxLMM algorithm established on two-part skewed triangular M–estimate, was presented to achieve stability in FxLMM when exposed to high-peaked impulses. Data reusing based normalized step size FxLMS (DR-NSSFxLMS) algorithm, recommended in [57] for ANC of impulsive noise improved the performance with increased computational complexity. Similarly, FxRLS algorithm [58] gives fast convergence along with high complexity during impulsive noise control. Gauss Siedal algorithm [111] and dichotomous coordinate descent algorithm (DCD) [112] are used for recursive least square adaptive filtering that gives reduced computational complexity. However, the main problem with RLS family algorithms is lack of robustness. To enhance the robustness of the RLS algorithm, a modification i.e. State Space RLS, is presented in [59], [113]. SSRLS exhibits excellent tracking performance due to its model dependent state space formulation but has not been tested in the ANC domain. Fig.5.1 demonstrates the schematic diagram of an ANC system for impulsive noise. Due to the presence of secondary path $s(z)$ in Fig. 5.1, SSRLS cannot be used in its existing form. Therefore, in this chapter, we have modified SSRLS algorithm to track the filtered reference noise, making it suitable for ANC applications. The SSRLS algorithm is used in combination with filtered reference input and hence named as Filtered-x SSRLS algorithm.

In section 5.2, proposed Filtered-x SSRLS (FxSSRLS) algorithm for ANC domain with its associated schematics is presented. The results of proposed FxSSRLS algorithm came out to be more effective in the elimination of high-peaked impulses than that of the recently reported algorithms for ANC applications. Moreover, the suggested solution exhibits better stability and faster convergence without jeopardizing the performance of proposed solution in terms of residual noise suppression in the presence of impulses. In sub-section 5.2.1, detailed computational analysis of presented algorithm along with that of recently reported algorithms is also done. The performance comparison of the proposed algorithm with other reported algorithms is shown in section 5.3. Finally, section 5.4 concludes the summary of chapter 5.

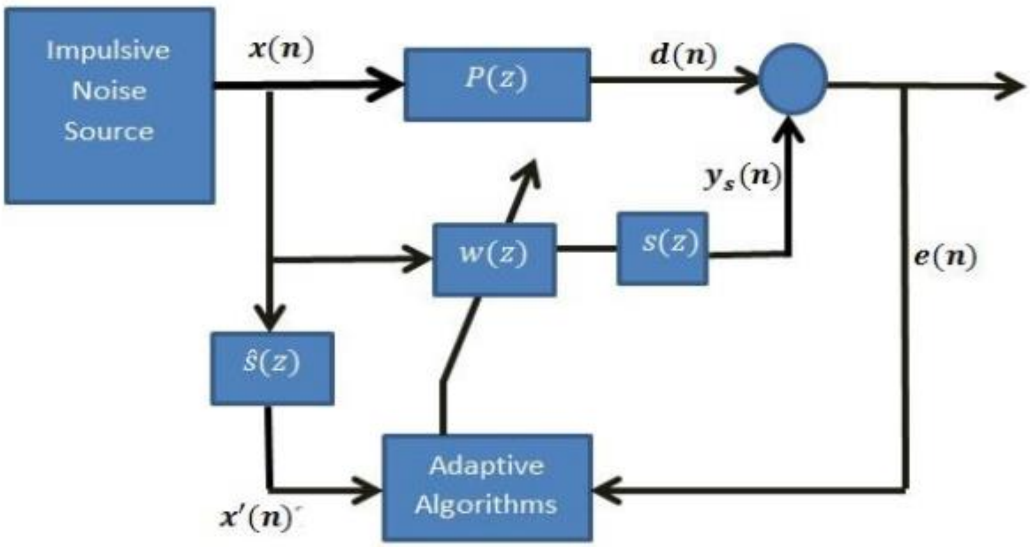


Figure 5.1 Block diagram of ANC system for impulsive noise

5.2. Proposed Algorithm

Consider the unforced discrete time system

$$r[n+1] = Ar[n] \tag{5.1}$$

$$y[n] = Cr[n] \tag{5.2}$$

Where *r* are the process states and *y* is the output, while *A* and *C* represent the system and the observation matrices respectively. We assume that the pair (*A*,*C*) is L-step observable and *A* is invertible. The state space formulation of SSRLS provides designer with the freedom to choose an appropriate model for the underlying environment. However, the reasons that SSRLS cannot be used in its existing form for active noise control are as under:

1) SSRLS is designed for unforced system i.e system without input.

2) ANC applications have a secondary path *s(z)* followed by adaptive filter $w(z)$ as shown in Fig. 5. 1.

3) Impulsive noise state space model is unknown.

According to the required modifications in SSRLS for ANC domain the schematic diagram of proposed algorithm is depicted in Fig. 5.2.

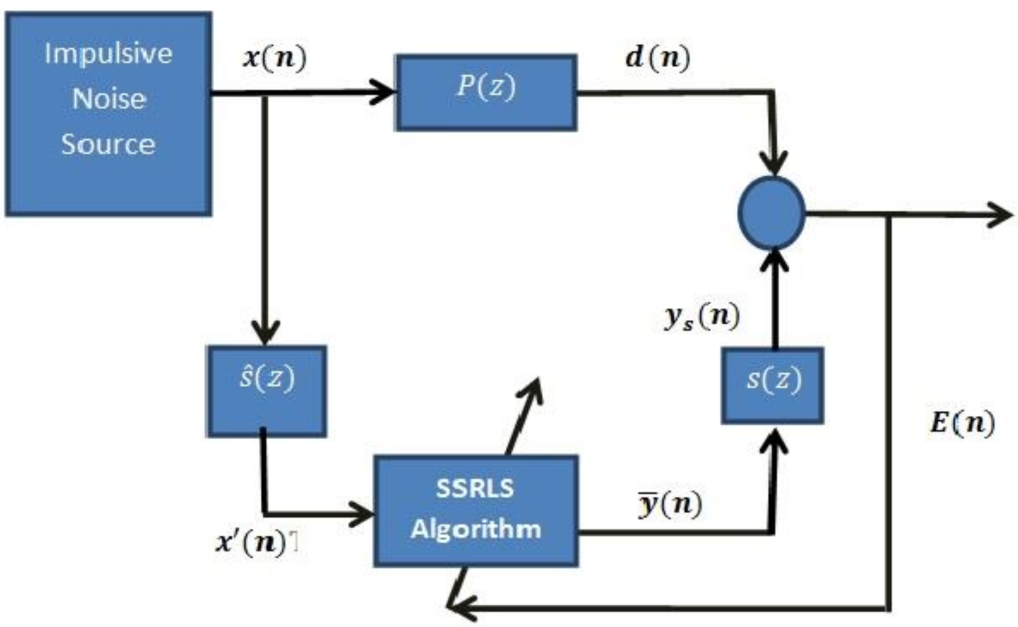


Figure 5.2: Block diagram of proposed algorithm for ANC system

In this figure, the reference noise signal vector is $x(n) = [x(n), x(n-1) \ldots \ldots . x(n-L+1)]'$, where L is the length of the reference noise. The desired signal *d(n)* is calculated as

$$d(n) = P(n) * x(n) \quad \text{where operator * represents the convolution} \tag{5.3}$$

The filtered reference noise $\boldsymbol{x}'(n) = [\boldsymbol{x}'(n), \boldsymbol{x}'(n-1) \ldots \ldots \boldsymbol{x}'(n-L+1)]'$ and the error signal $E(n)$ measured by the error microphone is:

$$\boldsymbol{x}'(n) = \hat{s}(n) * \boldsymbol{x}(n) \tag{5.4}$$

$$E(n) = d(n) - \boldsymbol{y_s}(n) \tag{5.5}$$

The $s(n)$ and $\hat{s}(n)$ are impulse responses of the secondary path and its estimate respectively. Due to the presence of secondary path following the adaptive filter, phase mismatch occurs between the desired signal and output of the filter as shown in Fig. 5.2, which consequently degrades the performance of ANC system. Thus, for incorporating the effect of secondary path, an identical filter is placed in the reference signal path leading to input of the filter. The modified output of adaptive filter followed by the secondary path is given by

$$\boldsymbol{y_s}(n) = s(n) * \bar{y}(n) \tag{5.6}$$

The filtered reference noise signal $\boldsymbol{x}'(n)$ is passed to the SSRLS adaptive filter block which computes $\overline{y}(n)$. Table 5.1 describes the parameters used for our modified Fx-SSRLS algorithm

Table 5.1 Detail of variables

Variables	**Description**
P(z)	Primary path transfer function
S(z)	Secondary path transfer function of
x(n)	Reference impulsive noise
S'(z)	Estimated transfer function of secondary path
d(n)	Desired signal
x'(n)	Filtered reference noise
$\hat{r}[n]$	Estimated states of adaptive filter
$\bar{r}[n]$	Predicted states of adaptive filter
$K[n]$	Gain of adaptive filter
$\varepsilon[n]$	Prediction error of adaptive algorithm
Δ	Regularization parameter
λ	Forgetting factor
$\overline{y}(n)$	Predicted output of adaptive filter
$y_s(n)$	Adaptive filter output followed by secondary path
N	Total samples

Since, the system given in eq (5.1) is for forced systems with $x'(n)$ being the input, the three special models of SSRLS in [59], [113] are modified in Table 5.2. 'T' represent the sampling time in the following Table 5.2.

Table 5.2 Modified state space models of SSRLS

Sinusoidal model	Velocity Model	Acceleration Model
$A = \begin{bmatrix} \cos(wT) & \sin(wT) \\ -\sin(wT) & \cos(wT) \end{bmatrix}$	$A = \begin{bmatrix} 1 & T \\ 0 & 1 \end{bmatrix}$	$A = \begin{bmatrix} 1 & T & \frac{T^2}{2} \\ 0 & 1 & T \\ 0 & 0 & 1 \end{bmatrix}$
$C = [x'(n) \;\; 0\,]$	$C = [x'(n) \;\; 0\,]$	$C = [x'(n) \;\; 0 \;\; 0]$

After modification of SSRLS models, the next objective is to select the appropriate model for impulsive noise. To get the best match of the underlying environment with the presumed model of SSRLS for achieving enhanced performance of SSRLS. The exact model for impulsive noise cannot be determined because of its random nature. As the higher order models can better approximate the abrupt changes in impulsive noise therefore, we have used acceleration model in our application. The choice has been validated through extensive simulations. The proposed algorithm is summarized below.

Proposed FxSSRLS Algorithm

Parameters:

Select A, C, N

Initialize δ, λ, T_s , $\bar{r}[0] = 0$, $\Phi[0]= \delta I+C^TC$,$K[0]=\Phi^{-1}(0)C^T$, $\varepsilon[0] = y[0] - \bar{y}[0]$

Computation:

While {x(n)} available

do

$$y(\mathrm{n}) = \mathrm{p}(\mathrm{n}) * \mathrm{x}(\mathrm{n})$$

$$\mathrm{x}'(\mathrm{n}) = \hat{s}(\mathrm{n}) * \mathrm{x}(\mathrm{n})$$

$$\hat{\mathrm{r}}[\mathrm{n}] = \bar{\mathrm{r}}[\mathrm{n}] + \mathrm{K}[\mathrm{n}]\varepsilon[\mathrm{n}]$$

$$\Phi[\mathrm{n}] = \lambda\left(\mathrm{A}^{-\mathrm{T}}\Phi[\mathrm{n}-1]\right)\mathrm{A}^{-1} + \mathrm{C}^{\mathrm{T}}\mathrm{C}$$

$$\mathrm{K}[\mathrm{n}] = \Phi^{-1}[\mathrm{n}]\mathrm{C}^{\mathrm{T}}$$

$$\bar{\mathrm{r}}[\mathrm{n}] = \mathrm{A}\hat{\mathrm{r}}[\mathrm{n}]$$

$$\bar{\mathrm{y}}[\mathrm{n}] = \mathrm{C}\bar{\mathrm{r}}[\mathrm{n}]$$

$$\mathrm{y}_s(\mathrm{n}) = \mathrm{s}(\mathrm{n}) * \bar{\mathrm{y}}(\mathrm{n})$$

$$\varepsilon[\mathrm{n}] = \mathrm{y}[\mathrm{n}] - \mathrm{y}_s[\mathrm{n}]$$

end while

5.2.1 Performance Analysis and Computational Complexity

For adaptive filters, when a new algorithm is developed, it is important to carry out its performance analysis. Although the FxLMS algorithm has been widely used for the implementation of ANC applications, its convergence analysis is still an active area of research [114-115]. The inclusion of secondary path in FxLMS makes its convergence analysis complex as compared to the standard LMS algorithm. Various attempts on derivation of theoretical convergence analysis for FxLMS algorithm have been made with different simplified assumptions on inputs being single or multitonal, stationary or purely white and secondary path being pure delay or moving average model etc [116 - 117]. The analysis of SSRLS algorithm for the standard adaptive filter has been presented in [59], [113], which may be extended to perform theoretical analysis of Fx-version of SSRLS algorithm for the ANC systems. This chapter of dissertation develops a modified SSRLS (FxSSRLS) algorithm for ANC of impulsive sources being modelled as SαS distributions. For stable distributions, the moments only exist for the order lesser than the characteristic exponent [105] i.e. for impulsive noise 2nd order moments do not exist. The lower order moments are more difficult to compute than the second order moment [119], which makes the theoretical analysis difficult, if not impossible. The non-Gaussian signal processing is in general much more complicated in terms of finding statistics than that of Gaussian signal processing. This may be the reason that recent work on ANC of impulsive sources (being modelled as stable process) do not include the theoretical analysis, and in fact the simulations have been used as a major tool to demonstrate the effectiveness of the proposal (see for example, [106 - 107], [110]). The interested reader may also look into the recent works on ANC [120 - 126]. Though simulations do not prove, yet do demonstrate the effectiveness. In this chapter, we have also used computer simulations as the evaluation tool and it is observed that proposed algorithm outperforms the existing algorithms. Moreover, computational complexity of an algorithm is usually of significant importance particularly in real-time applications. The complexity of individual equations of proposed FxSSRLS algorithm is given in Table. 5.3. Followed by the complexity analysis of other investigated algorithms in Tables 5.4 - 5.7.

Table 5.3 Complexity analysis of proposed algorithm

Eq\`s	**Operations**	*****	**+/-**	**÷**
1	$\mathrm{x}'(\mathrm{n})_{1x1} = \hat{s}(n)_{1xM} \quad * x(\mathrm{n})_{Mx1}$	M	M-1	-
2	$\hat{\mathrm{r}}[\mathrm{n}]_{Lx1} = \bar{\mathrm{r}}[\mathrm{n}]_{Lx1} + \mathrm{K}[\mathrm{n}]_{Lx1}\varepsilon[\mathrm{n}]_{1x1}$	L	L	-
3	$\Phi[\mathrm{n}]_{LxL} = \lambda(\mathrm{A}^{-\mathrm{T}}{}_{LxL}\Phi[\mathrm{n}-1]_{LxL})\mathrm{A}^{-1}{}_{LxL} + \mathrm{C}^{\mathrm{T}}{}_{Lx1}\mathrm{C}_{1xL}$	$2L^3+2L^2$	$2L^3-2L^2$	1
4	$\mathrm{K}[\mathrm{n}]_{Lx1} = \Phi^{-1}(\mathrm{n})_{LxL}\mathrm{C}^{\mathrm{T}}{}_{Lx1}$	L^2	L^2-L	-
5	$\bar{\mathrm{r}}[\mathrm{n}]_{Lx1} = A_{LxL}\hat{\mathrm{r}}[\mathrm{n}]_{Lx1}$	L^2	L^2-L	-
6	$\bar{\mathrm{y}}[\mathrm{n}]_{1x1} = \mathrm{C}_{1xL}\bar{\mathrm{r}}[\mathrm{n}]_{Lx1}$	L	L-1	-
7	$\mathrm{y_s}(\mathrm{n})_{Mx1} = s(n)_{Mx1} * \bar{\mathrm{y}}(\mathrm{n})_{1x1}$	M	-	-
8	$\varepsilon[\mathrm{n}]_{1x1} = \mathrm{y}[\mathrm{n}]_{1x1} - \mathrm{y_s}[\mathrm{n}]_{1x1}$	-	1	-
	Total:	**$2L^3+4L^2+2L+2M$**	**$2L^3+M$**	**1**

Table 5.4 Complexity analysis of FxLMS algorithm

Eq`s	Operations	*	+/-	÷
1	$\mathrm{x}'(\mathrm{n})_{1x1} = \hat{s}(n)_{1\mathrm{xM}} * x(\mathrm{n})_{Mx1}$	M	M-1	-
2	$\mathrm{y}(\mathrm{n})_{1x1} = \mathrm{w}^{\mathrm{T}}(\mathrm{n})_{1xL} * x(\mathrm{n})_{Lx1}$	L	L-1	-
3	$\mathrm{w}(\mathrm{n}+1)_{Lx1} = \mathrm{w}(\mathrm{n})_{Lx1} - \mu_{1\mathrm{x}1} * \mathrm{e}(\mathrm{n})_{1\mathrm{x}1} * \mathrm{x}'(\mathrm{n})_{1xL}$	L+1	L	-
4	$\mathrm{e}(\mathrm{n})_{1x1} = \mathrm{d}(\mathrm{n})_{1x1} - \mathrm{y_s}(\mathrm{n})_{1x1}$	-	1	-
5	$\mathrm{y_s}(\mathrm{n})_{1x1} = s(n)_{1xM} * \mathrm{y}(\mathrm{n})_{Mx1}$	M	M-1	-
	Total:	**2L+2M+1**	**2L+2M-2**	-

Table 5.5 Complexity analysis of NSS-FxLMS algorithm

Eq`s	Operations	*	+/-	÷
1	$\mathrm{x}'(\mathrm{n})_{1x1} = \hat{s}(n)_{1\mathrm{xM}} * x(\mathrm{n})_{Mx1}$	M	M-1	-
2	$\mathrm{y}(\mathrm{n})_{1x1} = \mathrm{w}^{\mathrm{T}}(\mathrm{n})_{1xL} * x(\mathrm{n})_{Lx1}$	L	L-1	-
3	$\mathrm{w}(\mathrm{n}+1)_{Lx1} = \mathrm{w}(\mathrm{n})_{Lx1} - \mu(\mathrm{n})_{1\mathrm{x}1} * \mathrm{e}(\mathrm{n})_{1\mathrm{x}1} * \mathrm{x}'(\mathrm{n})_{1xL}$	L+1	L	-
4	$\mu(\mathrm{n})_{1\mathrm{x}1} = \frac{\overline{\mu(\mathrm{n})_{1\mathrm{x}1}}}{\delta + \mathrm{x}^{\mathrm{T}}(\mathrm{n})_{1xL} * \mathrm{x}(\mathrm{n})_{Lx1} + \mathrm{E}(\mathrm{n})}$	L	L+1	1
5	$\mathrm{e}(\mathrm{n})_{1x1} = \mathrm{d}(\mathrm{n})_{1x1} - \mathrm{y_s}(\mathrm{n})_{1x1}$	-	1	-
6	$\mathrm{y_s}(\mathrm{n})_{1x1} = s(n)_{1xM} * \mathrm{y}(\mathrm{n})_{Mx1}$	M	M-1	-
7	$\mathrm{E}(\mathrm{n})_{1x1} = \lambda E(n-1)_{1x1} + (1-\lambda)\mathrm{E}^2(\mathrm{n})_{1x1}$	3	2	
	Total:	**3L+2M+4**	**3L+2M+1**	1

Table 5.6 Complexity analysis of FxRLS algorithm

Eq`s	Operations	*	+/-	÷
1	$x'(n)_{1x1} = \hat{s}(n)_{1xM} * x(n)_{Mx1}$	M	M-1	-
2	$y(n)_{1x1} = w^{T}(n)_{1xL} * x(n)_{Lx1}$	L	L-1	-
3	$w(n+1)_{Lx1} = w(n)_{Lx1} + K(n)_{LxL} * e(n)_{1x1}$	L	L	-
4	$K(n)_{Lx1} = \frac{\pi(n)_{Lx1}}{\lambda + x'(n)_{Lx1} * \pi(n)_{Lx1}}$	2L	L	1
5	$\pi(n)_{Lx1} = p(n-1)_{LxL} * x'(n)_{Lx1}$	L^2	L^2-L	
6	$p(n)_{LxL} = \lambda^{-1} * p(n-1)_{LxL} - \lambda^{-1} * K(n)_{Lx1} * x'(n)_{1xL} * p(n-1)_{LxL}$	$3L^2$	$2L^2 - L$	1
7	$e(n)_{1x1} = d(n)_{1x1} - y_s(n)_{1x1}$	-	1	-
8	$y_s(n)_{1x1} = s(n)_{1xM} * y(n)_{Mx1}$	M	M-1	-
	Total:	**$4L^2$+4L+2M**	**$3L^2$+L+2M-2**	2

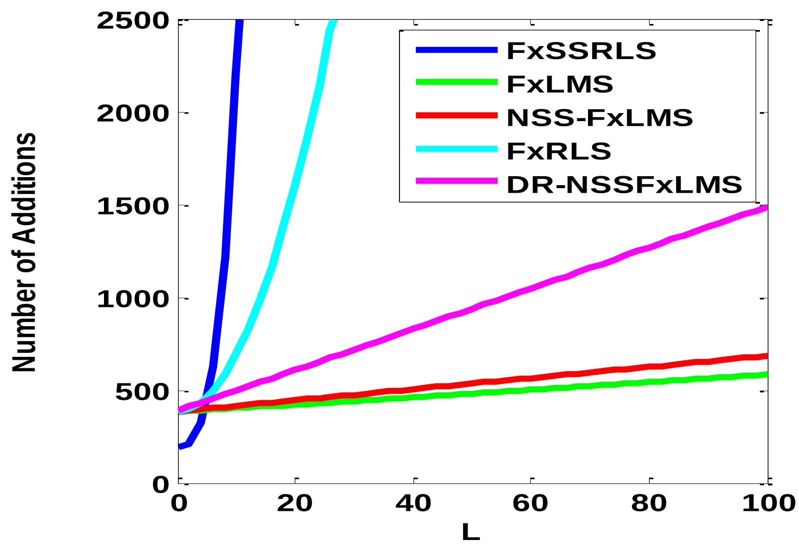
Table 5.7 Complexity analysis of DR-NSSFxLMS algorithm

Eq`s	Operations	*	+/-	÷
1	$x'(n)_{1x1} = \hat{s}(n)_{1xM} * x(n)_{Mx1}$	M	M-1	-
2	$y(n)_{1x1} = w^{T}(n)_{1xL} * x(n)_{Lx1}$	L	L-1	-
3	$d_1(n)_{1x1} = e(n)_{1x1} + s(n)_{1xm} * y(n)_{mx1}$	M	M	-
4	$e_1(n)_{1x1} = d_1(n)_{1x1} - w_1^{T}(n)_{1xL} * x'(n)_{Lx1}$	L	L	-
5	Compute $w_1(n+1)_{Lx1}$ using DR algorithm in Table 2 from [25]	N(3L+4)	N(3L+2)	-
	Total:	**2L+2M+N(3L+4)**	**2L+2M-2+N(3L+2)**	-

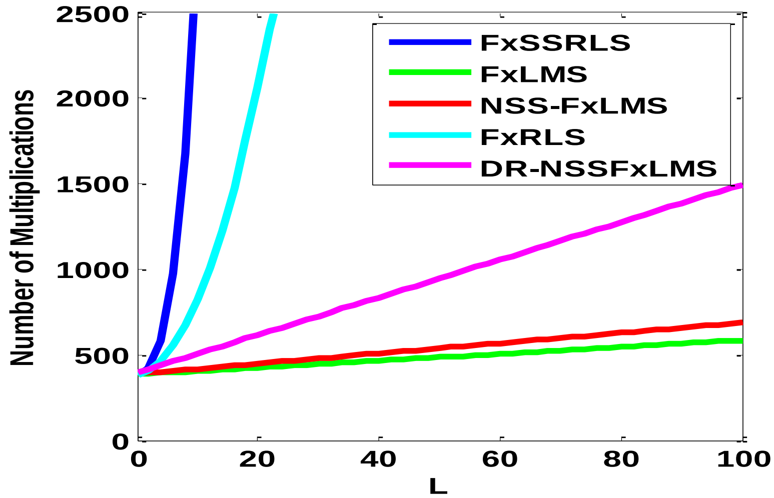
Here, L represents the total number of states in FxSSRLS algorithm while, in other investigated algorithms it represents the number of filter coefficients [55,57-58]. M represents the secondary path and N represents the data reuse order for DR-NSSFxLMS algorithm. The computational complexities along with the memory requirements of the investigated algorithms are summarized in Table 5.8. The memory of investigated algorithms is calculated using the method given in [52].

Table 5.8 Performance analysis of investigated algorithms

Algorithm	Complexity		Memory
	Additions	Multiplications	
FxLMS	2L+2M-2	2L+2M+1	2(L+M)
NSS-FxLMS	3L+2M+1	3L+2M+4	2(L+M)
DRNSS-FxLMS	2L+2M-2+N(3L+2)	2L+2M+N(3L+4)	(N+2)L+3M
FxRLS	$3L^2$+L+2M-2	$4L^2$+4L+2M	3L+2M
Proposed FxSSRLS	$2L^3$+M	$2L^3+4L^2$+2L+2M	4L+2M



a)



b)

Figure 5.3: Complexity analysis of investigated algorithms (a) Number of additions (b) Number of multiplications

Fig. 5.3 shows the plots for computational complexities of investigated algorithms. The proposed FxSSRLS algorithm has high computational complexity as compared to FxLMS and FxRLS algorithms family, which makes it costly for few applications. Nevertheless, in the practical applications where stability and fast convergence is a matter of concern, the implementation of FxSSRLS in ANC system can be easily handled by the latest DSP`s.

5.3 Comparison with Existing Techniques and Simulation Results

The ANC system for impulsive noise is implemented using the MATLAB platform. The performance of proposed algorithm is compared with that of already reported adaptive algorithms in literature [51], [55], [57 - 58], [106 - 107]. The parameters used in simulating the ANC system are tabularized below:-

Table 5.9 Parameter set for proposed technique simulation

ANC System			Impulsive Noise		
Parameters	**Symbols**	**Values**	**Parameters**	**Symbols**	**Value**
Primary path tap size	L	256	Total samples	N	10000
Secondary path tap size	M	128	Total realizations	Avg	5
Adaptive filter tap size	L_w	192	Characteristic exponent	α	1.85,1.65,1.45
DR-NSSFxLMS algorithm step size	$\bar{\mu}$	$5e^{-2}$	Scale parameter	γ	1
NSS-FxLMS algorithm step size	$\bar{\mu}$	$5e^{-2}$	Location parameter	C	0
RLS forgetting factor	λ	0.99	Skewedness parameter	δ	0
SSRLS forgetting factor	λ	0.01			

In our simulation setup, the SαS distributions model the statistical parameters of impulsive noise [105]. The closed form for PDF of stable distributions doesn't exist, so they are normally expressed by their characteristic equations which are actually Fourier transform of its PDF.

$$\varphi(t) = e^{-|t|^{\alpha}} \tag{5.7}$$

Some PDFs for SαS distributions are shown in Fig. 5.4. The SαS distributions have parameter α ($0 < \alpha < 2$), which controls the spread of the PDF, i.e., smaller value of α indicates that noise will be more impulsive with heavier tail. For the stable distributions α ranges between 0-2. It is characterized as normal distribution for α = 2, while the distribution is Cauchy for α = 1. In Fig. 5.5, impulsive noise generated by standard SαS process with α=1.65 is shown with the parameters used for simulating the impulsive noise in the simulations are mentioned in Table. 5.9.

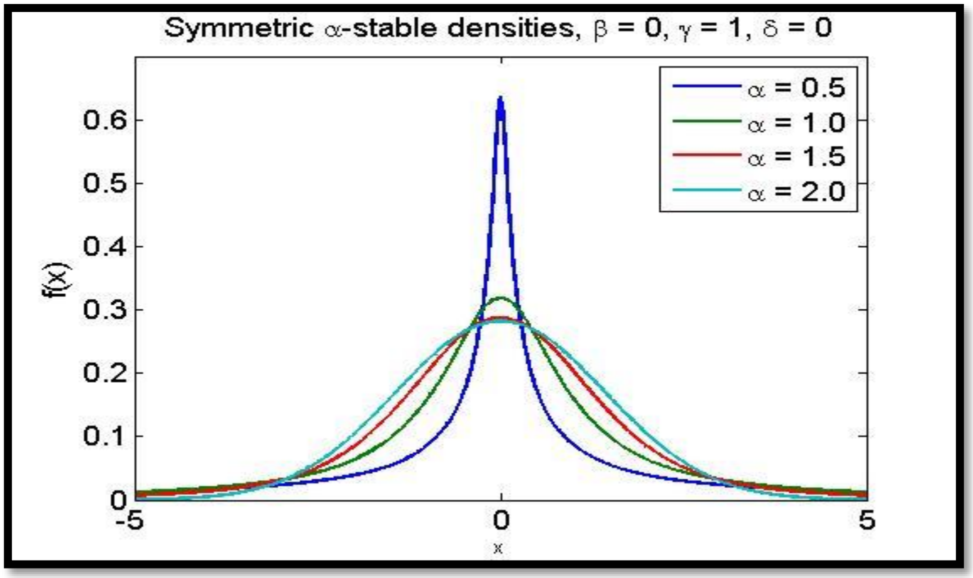


Figure 5.4: PDFs of standard SαS process with different values of α

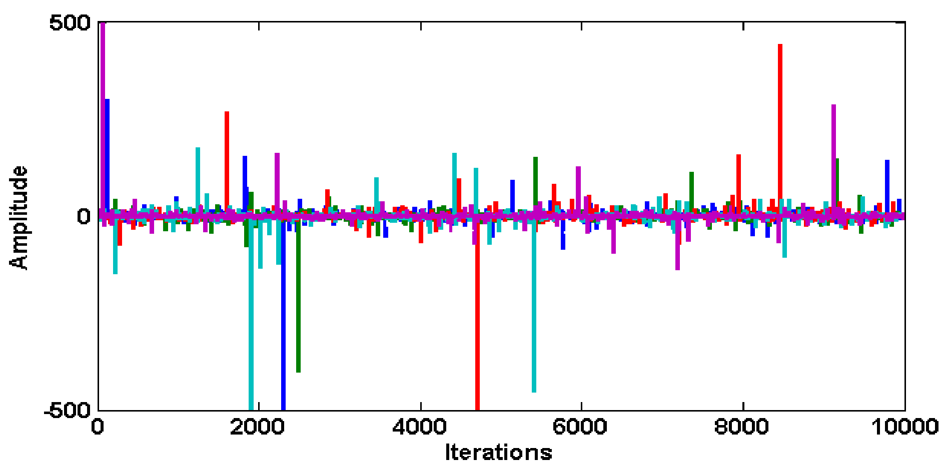


Figure 5.5: Impulsive noise generated by standard SαS process with α=1.65

The primary noise d(n) for α=1.65 picked by reference microphone is depicted in Fig. 5.6.

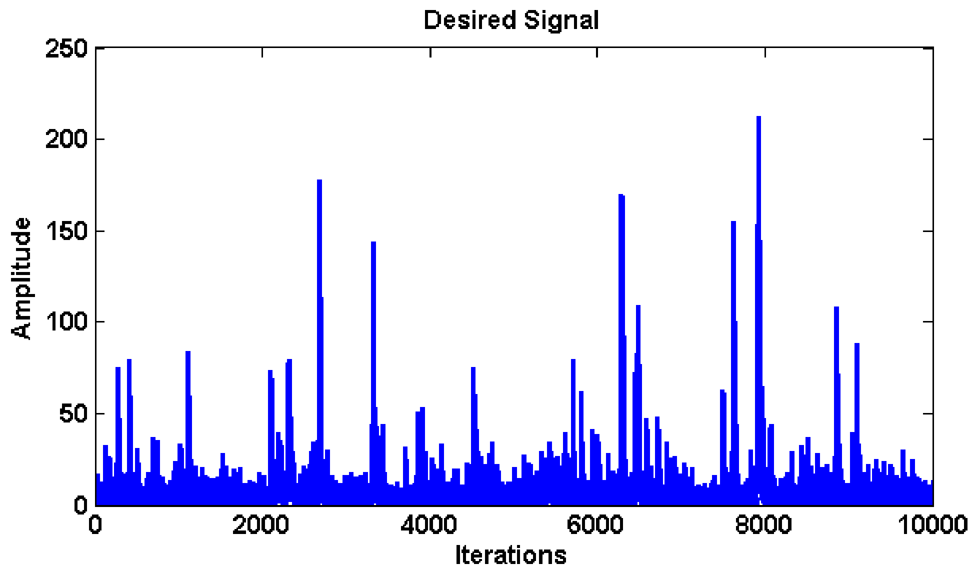


Figure 5.6: Primary noise signal

For the simplicity of our simulations, we have made an assumption that estimated secondary path model $\hat{s}(z)$ is same as $s(z)$ [55-58]. The numeric values of coefficients of primary $p(z)$ and secondary $s(z)$ acoustic paths are taken from data set given in [51]. Fig. 5.7 depicts the frequency response comprising of magnitude and phase of both path filters.

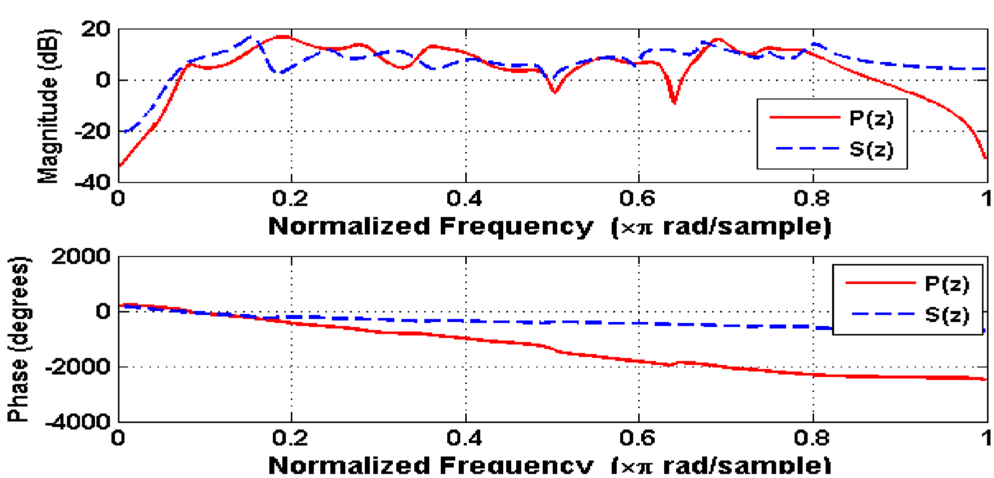


Figure 5.7: Frequency response of acoustic primary and secondary path

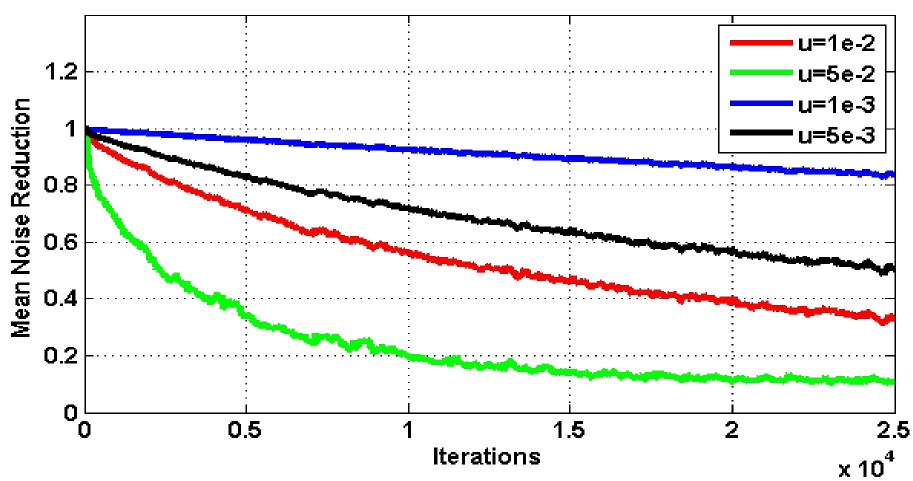
The performance metric used in this research for comparison of studied algorithms is mean noise reduction. It is calculated as

$$MNR(n) = E\left\{\frac{A_e(n)}{A_d(n)}\right\} \tag{5.8}$$

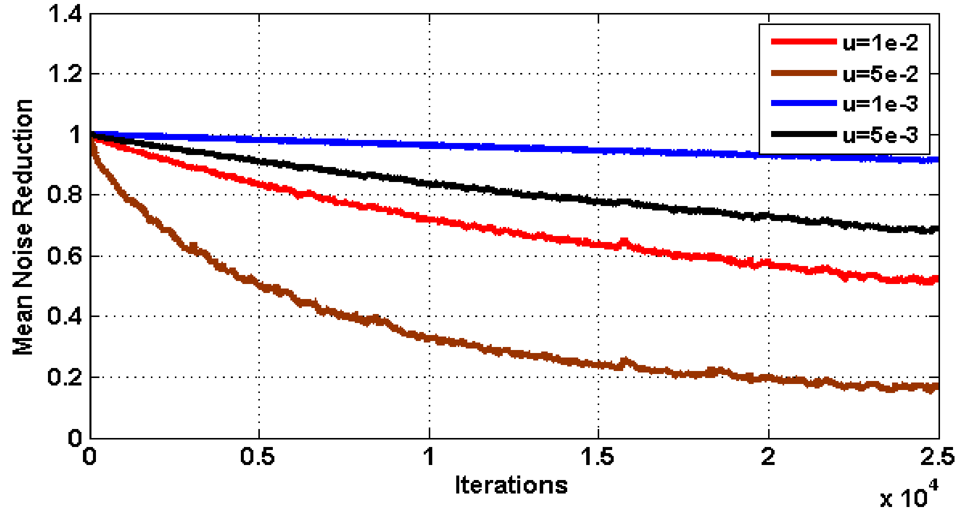
$$A_e(n) = \lambda A_e(n-1) + (1-\lambda)|e(n)| \tag{5.9}$$

$$A_d(n) = \lambda A_d(n-1) + (1-\lambda)|d(n)| \tag{5.10}$$

where $A_e(n)$ and $A_d(n)$ are estimated absolute values of residual error and disturbance signal. The impulses for the research are generated by the symmetric alpha stable model by considering α=1.85, α=1.65 and α=1.45 respectively, indicating small, mild and heavy impulsiveness. Extensive simulations are carried out to find the optimum values of controlling parameters of discussed algorithms. Fig. 5.8 shows the detailed simulation results for step size parameter of NSS-FxLMS and DR-NSSFxLMS algorithm for α=1.65. It can be observed from Fig. 5.8 (a & b), that optimum steps size value for both algorithms is 5e-2.



a)



b)

Figure 5.8: Effect of varying step sizes on the performance of a) NSS-FxLMS b) DR-NSSFxLMS for α=1.65

Similarly, the effect of regularization parameter delta (δ) of FxRLS algorithm is shown in Fig. 5.9 for α=1.65. The parameter δ depends on SNR [69], i.e. greater the value of SNR smaller value of delta is selected for better performance of algorithms and vice versa. The optimum value selected for further simulation is 100000 for α=1.65.

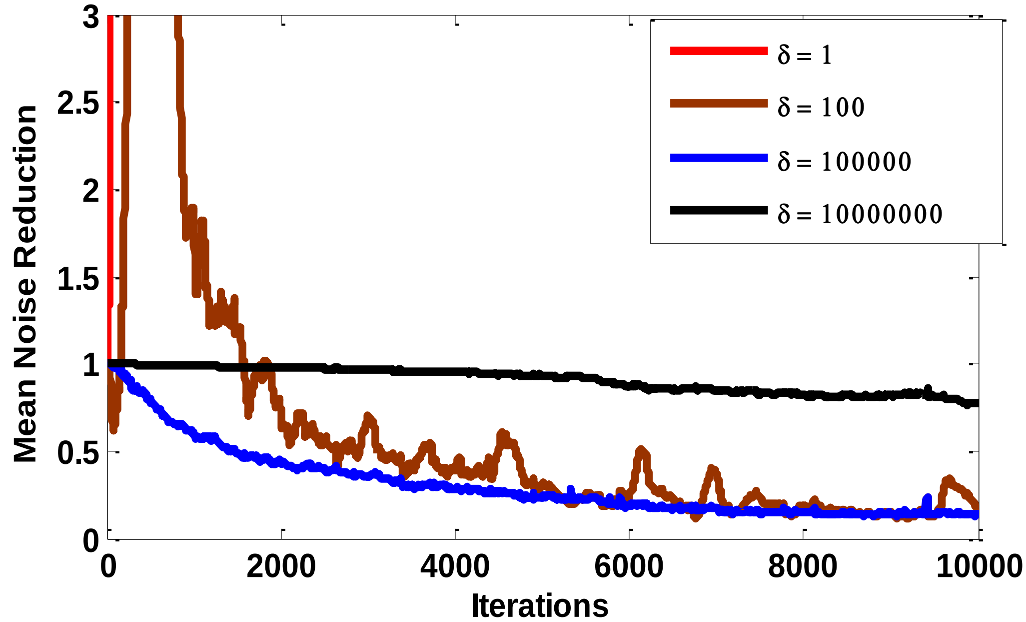


Figure 5.9: Performance comparison of FxRLS with varying delta for α=1.65

Fig. 5.10 depicts the convergence curves of most widely used adaptive algorithms in ANC domain for α=1.65. The optimum step sizes for the FxLMS, Sun`s, Modified Sun`s and Akhtar`s algorithm used in this simulation are 1e-3, 5e-6, 5e-5 and 5e-5 respectively. It can be seen that among the investigated algorithms of LMS family, the NSSFxLMS and DR-NSSFxLMS algorithms converge quickly after 1000 iterations and give good noise reduction by achieving the lowest MNR as compared to the other investigated algorithms. Similarly, the DR-NSSFxLMS algorithm is comparatively less affected by the occurrence of impulsive noise at different iterations and thus exhibits better stability. Therefore, we have selected the NSS-FxLMS and DR-NSSFxLMS algorithms for further comparison with our proposed FxSSRLS algorithm which can be visualized in Fig. 5.11.

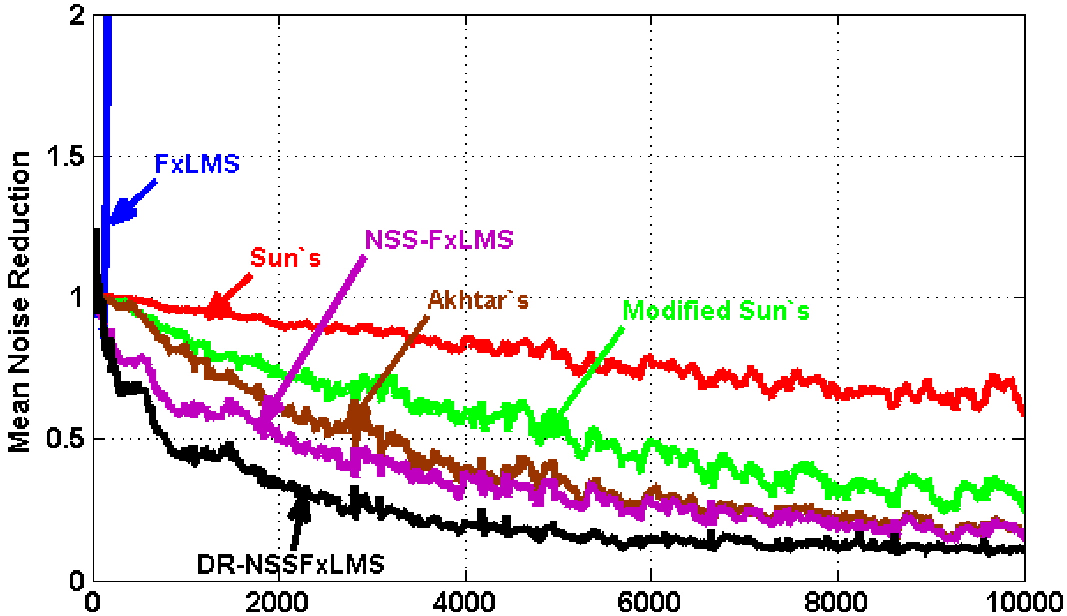


Figure 5.10: Convergence curves comparison of various algorithms with α=1.65

It can be noticed from Fig. 5.11, that NSS-FxLMS and DR-NSSFxLMS algorithms give slow convergence as compared to FxRLS and FxSSRLS algorithms that achieve steady state value at about 2000 and 500 iterations, respectively. The convergence curves of FxSSRLS and FxRLS algorithm almost overlap after 3500 iterations. However, when an impulse is encountered at about 800th iteration, the FxRLS algorithm exhibits a sudden increase in MNR while the FxSSRLS algorithm is robust enough to remain unaffected.

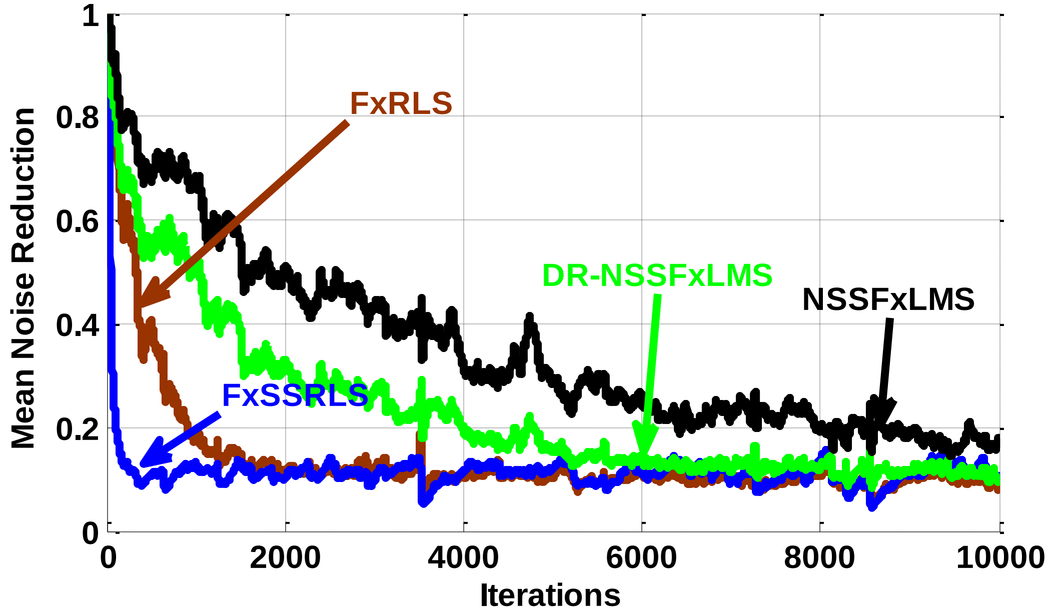


Figure 5.11: Comparison of MNR of FxSSRLS algorithm with various algorithms α=1.65

Similarly, other two simulation cases of alpha= 1.85 and 1.45 also proved the efficacy of proposed FxSSRLS algorithm over the investigated algorithms. Fig. 5.12 and Fig. 5.13 illustrates the steady state performance of FxRLS and proposed FxSSRLS is better than NSS-FxLMS and DR-NSSFxLMS algorithms. Also, the proposed FxSSRLS can yield improved convergence rate and robustness even in presence of large impulses than that of FxRLS, NSS-FxLMS and DRNSS-FxLMS algorithms. Thus, making our proposed solution an excellent choice for mitigating the influence of impulses in ANC applications.

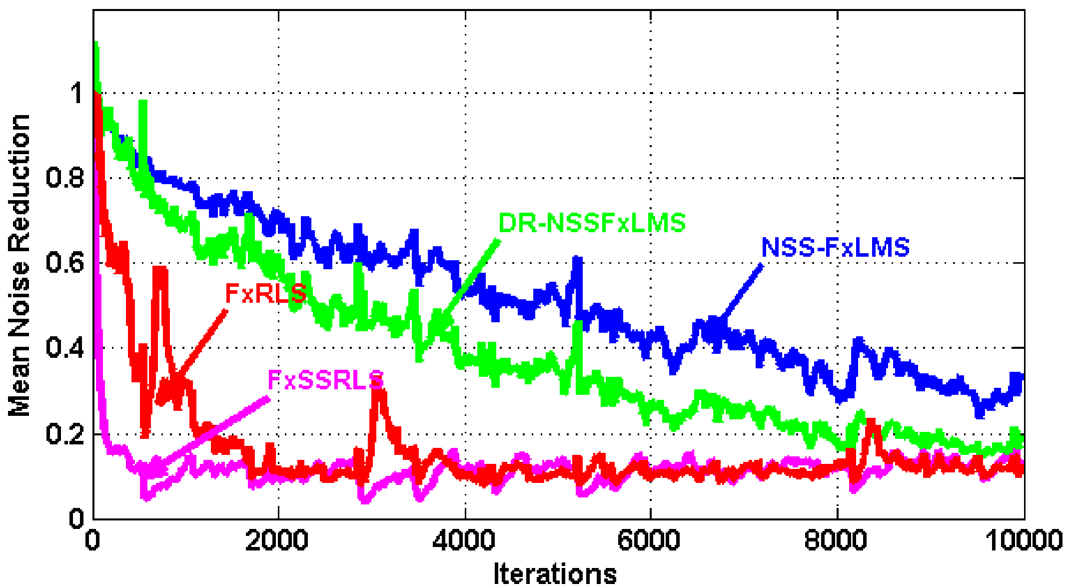


Figure 5.12: Comparison of MNR of FxSSRLS algorithms with various algorithms α=1.85

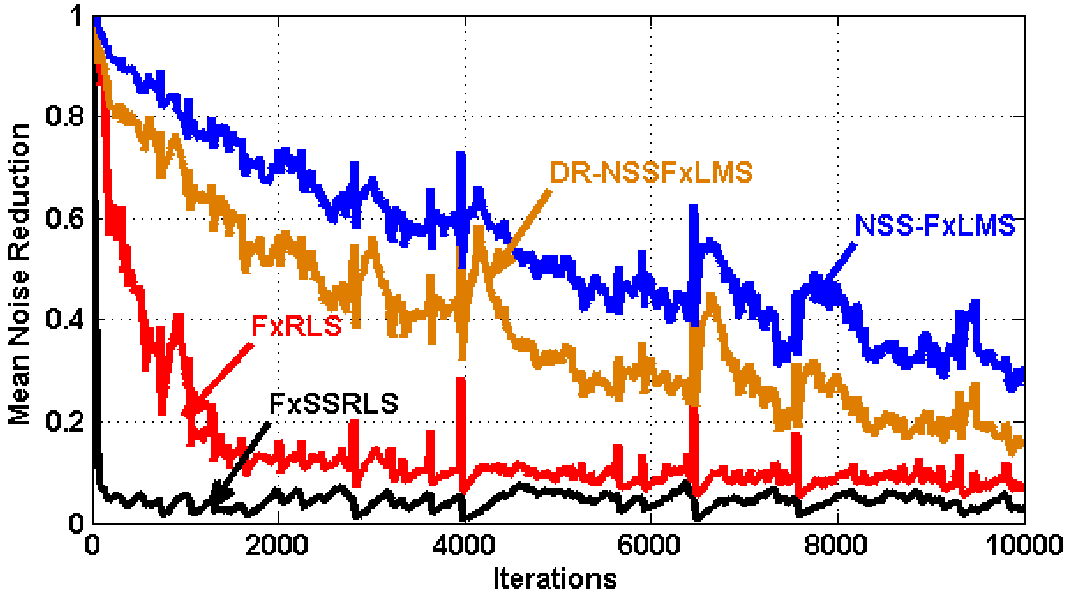


Figure 5.13: Comparison of MNR of FxSSRLS algorithm with various algorithms α=1.45

5.4. Summary

In this chapter, impulsive noise in the ANC domain is analysed. The adaptive algorithms employed in the ANC applications become unstable and lack robustness in the presence of impulsive noise. To overwhelm this limitation in ANC applications, a new algorithm FxSSRLS is developed and presented in this chapter. Due to the recursive parameters of the proposed adaptive algorithm, the reduction in impulsive noise is achieved, which is further enhanced by the state space formulation of SSRLS models. To validate the improved performance of the newly suggested solution, extensive simulations have been performed. The results clearly show that with use of the presented algorithm for ANC, the large amplitude impulses are significantly reduced. Moreover, the proposed FxSSRLS is a good contribution in ANC domain. The suggested algorithm for ANC applications outperforms the existing algorithms in terms of mean noise reduction, convergence and stability. However, this improved performance is achieved at the cost of slight increase in computational complexity. In applications where stability and fast convergence is a matter of concern, little price paid in terms of computational complexity can be ignored.

Chapter 6

LESS COMPLEX SOLUTIONS IN ANC

6.1 Introduction

The main limitation of LMS based algorithms is their lower rate of convergence and larger steady state mean square error as compared to RLS [69]. The performance of proposed FxSSRLS in previous chapter gives a robust solution for active control of impulsive noise but at cost of high computational complexity. Therefore, there was a need to further investigate less complex solutions for ANC of impulsive noise. In this chapter, we tested FxBhagyashri algorithm in the ANC domain and also suggested two modifications for enhancing the stability of this algorithm in presence of impulsive noise.

In section 6.2, the proposed FxBhagyashri algorithm with its two suggested modification is presented in detail. The simulation results along with their discussion is presented in section 6.3 and 6.4 concludes the chapter 6 of this dissertation.

6.2 FxBhagyashri algorithm based proposed solution for ANC of impulsive noise

The first solution for active control of impulsive noise is FxBhagyashri algorithm proposed in this chapter. From the literature survey, it was found that Bhagyashri Algorithm was never tested in the ANC domain. So, we have tested the performance of this Algorithm in ANC domain for impulsive noise suppression. The schematic diagram of proposed FxBhagyashri algorithm for impulsive noise control is depicted in Fig. 6.1.

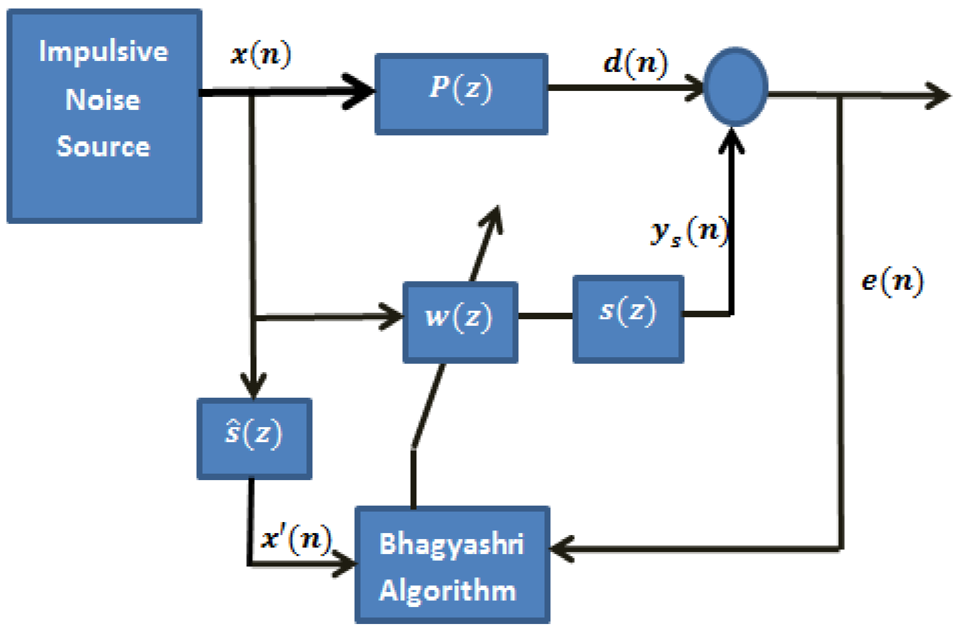


Figure 6.1: Schematic of proposed FxBhagyashri algorithm based ANC system

The overall principle of ANC system remains same except that instead of conventional adaptive filter, Bhagyashri algorithm is used. The weight update equation of proposed Fx-Bhagyashri algorithm is as follow:-

$$w(n+1) = w(n) + \mu.\tanh[\,\beta.e(n)].[x_f(n)] \tag{6.1}$$

$$\tanh[\,\beta.e(n)] = \begin{cases} sign(e(n)), & |e(n)| \geq 1/\beta \\ -e(n).|e(n)|.\beta^2 + 2.\beta.e(n) & otherwise \end{cases} \tag{6.2}$$

The selection of optimum value of step size in proposed FxBhagyashri algorithm is a very critical point as the convergence of algorithm depends on the step size μ. The optimum value of step size is determined by repeated simulations for best convergence of the proposed algorithm.

The point to be noted is that if large amplitude impulses are encountered in reference $x_f(n)$ or error signal $e(n)$ of eq (6.1), then the proposed FxBhagyashri algorithm will diverge and become unstable. Practically in case of large impulsive noise, FxBhagyashri algorithm becomes unstable. Thus, there is a need to suggest few solutions to make it stable. Therefore, in this chapter, we have suggested two modifications in FxBhagyashri algorithm to make it stable in presence of impulsive noise. They are:-

i) Clipped Filtered x Bhagyashri Algorithm (CFxBhagyashri Algorithm)

ii) Modified Step Size Filtered x Bhagyashri Algorithm (MFxBhagyashri Algorithm)

6.2.1 Clipped Filtered x Bhagyashri Algorithm

First modification in FxBhagyashri algorithm is based on thresholding technique. If the magnitude of samples of reference and error signals of FxBhagyashri algorithm is greater than the selected thresholds, the reference and error samples are cropped above their threshold set by signal statistics. Practically, offline estimation of signal statistics is performed. The schematics of proposed Clipped Fx Bhagyashri algorithm is shown in Fig. 6.2.

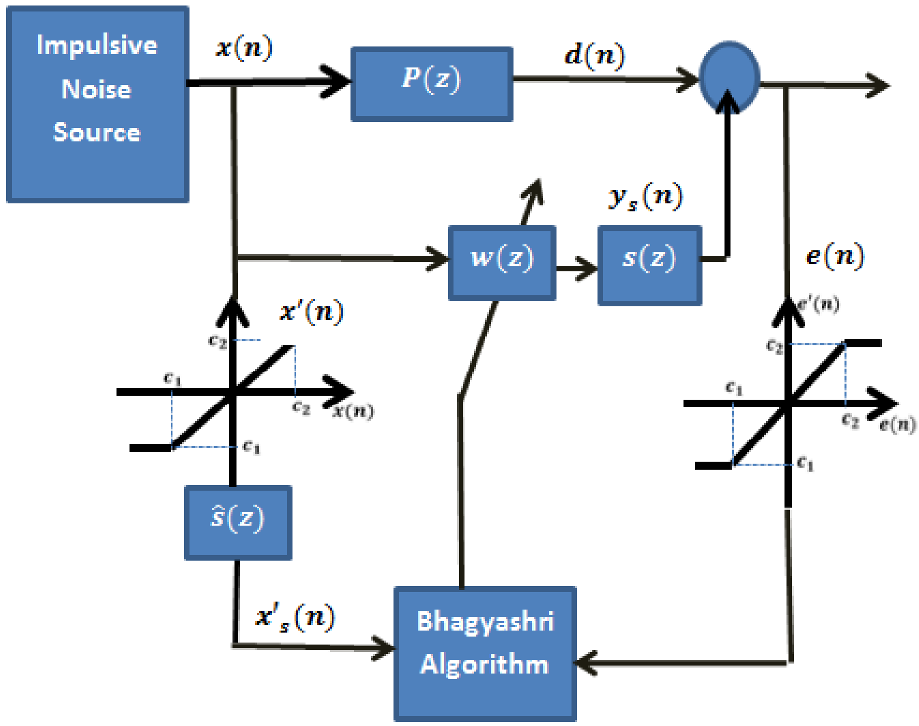


Figure 6.2: Schematic of proposed Clipped FxBhagyashri algorithm based ANC system

The weight update equation of proposed clipped FxBhagyashri algorithm with modified reference and error signal is given as:-

$$w(n+1) = w(n) + \mu \tanh[\beta . e'(n)][s(n) * x'(n)] \tag{6.3}$$

The reference and error signals of proposed clipped FxBhagyashri algorithm are modified as follow:-

$$x'(n) = \begin{cases} c_1\,, & if\ x(n) \leq c_1 \\ c_2\,, & if\ x(n) \geq c_2 \\ x(n), & otherwise \end{cases} \tag{6.4}$$

$$e'(n) = \begin{cases} c_1 , & if\ e(n) \leq c_1 \\ c_2 , & if\ e(n) \geq c_2 \\ e(n), & otherwise \end{cases} \tag{6.5}$$

Where c_1 and c_2 are the two thresholds and are calculated by the 1 and 99th percentile of reference and error signal already reported in literature [55]. The performance of proposed clipped FxBhagyashri algorithm totally depends on the thresholds. Therefore, their values must be very carefully selected; otherwise the performance of first proposed modification clipped FxBhagyashri algorithm will be degraded as compared to the standard FxBhagyashri algorithm in the active control of impulsive noise.

6.2.2 Modified Filtered x Bhagyashri (MFxBhagyashri) algorithm

In this sub-section, the second modification is presented for making FxBhagyashri stable in presence of impulsive noise. As discussed in previous subsection 6.2.1 that first modification proposed clipped FxBhagyashri algorithm is dependent on thresholds and in appropriate selection of thresholds will affect its performance. So another modification named as Modified FxBhagyashri Algorithm (MFxBhagyashri Algorithm) based on varying the step size of FxBhagyashri algorithm is presented. The step size of FxBhagyashri algorithm is made variable and is given as:-

$$\mu(n) = \frac{\hat{\mu}}{\left\| x_f(n) \right\|^2 + \delta + E_e(n)} \tag{6.6}$$

where $\hat{\mu}$ is the optimum step size of the FxBhagyashri algorithm, $\mu(n)$ is the time varying normalized step size, $x_f(n)$ is the excitation reference signal, $E_e(n)$ is the energy of the residual error signal $e(n)$ that is estimated online using a low pass estimator of the form

$$E_e(n) = \lambda E_e(n-1) + (1-\lambda)|e^2(n)| \tag{6.7}$$

where λ, called as forgetting factor, has value 0.9<λ<1. The FxBhagyashri algorithm is made stable by incorporating power of the excitation signal and error signal in the step size parameter. Furthermore, the step size parameter is inversely proportional to the power of the excitation and error signal. However, when the excitation signal is impulsive in nature, the error signal also has large variations that still cause gradient noise amplification in FxBhagyashri algorithm. In order to tackle the effect of large error signal variations, the power of the excitation signal $\|x_f(n)\|^2$ as well as error signal $E_e(n)$ is incorporated in the denominator of modified step size. By doing this modification, the reduced step size of FxBhagyashri algorithm will freeze the adaptation of the algorithm momentarily for large impulses; the FxBhagyashri algorithm will become stable and robust enough for catering impulsive noise. Any positive number delta δ is added in denominator of eq (6.6) to simplify calculations.

The update equation of proposed Modified FxBhagyashri algorithm is as follow:-

$$w(n+1) = w(n) + \mu(n).\tanh[\beta.e(n)].[x_f(n)] \tag{6.8}$$

The proposed modified FxBhagyashri (MFxBhagyashri) algorithm does not depend on threshold parameters $[c_1, c_2]$. Although the proposed MFxBhagyashri algorithm is based on an intuition based modification, the simulations suggest its improved robustness in comparison with other discussed algorithms.

The two proposed modifications i.e. CFxBhagyashri algorithm and MFxBhagyashri algorithm have better stability than that of FxBhagyashri algorithm. The MFxBhagyashri algorithm has high convergence speed than the best variant of FxLMS family (NSSFxLMS) with almost same computational complexity as of NSSFxLMS algorithm [55] for ANC of impulsive noise.

6.2.3 Complexity Analysis

Computational complexity of an algorithm is usually of significant importance particularly in real-time applications. The complexity analysis of individual equation of newly proposed FxBhagyashri and MFxBhagyashri algorithms is carried out and are tabulated below in Table 6.1-6.2.

Table 6.1 Complexity analysis of proposed FxBhagyashri algorithm

Eq`s	Operations	*	+/-	÷
1	$\mathrm{x}'(\mathrm{n})_{1x1} = \hat{s}(n)_{1\mathrm{xM}} * x(\mathrm{n})_{Mx1}$	M	M-1	-
2	$\mathrm{y}(\mathrm{n})_{1x1} = \mathrm{w}^{\mathrm{T}}(\mathrm{n})_{1xL} * x(\mathrm{n})_{Lx1}$		L-1	-
3	$\mathrm{w}(\mathrm{n}+1)_{Lx1} = \mathrm{w}(\mathrm{n})_{Lx1} + \mu_{1x1}\mathrm{sign}[\mathrm{e}(\mathrm{n})_{1x1]}\mathrm{x}'_f(\mathrm{n})_{Lx1}$ $\mathrm{w}(\mathrm{n})_{Lx1} + \mu_{1x1}[2\beta_{1x1} - \beta^2{}_{1x1}\lvert \mathrm{e}(\mathrm{n})_{1x1]}\rvert \mathrm{e}(\mathrm{n})_{1x1]}\mathrm{x}'_f\ (\mathrm{n})_{lx1}$	L+1 L+3	L L+1	- -
4	$\beta_{1x1} = \dfrac{3}{m_{1x1} + 3\sigma_{1x1}}$	1	1	1
5	$\mathrm{e}(\mathrm{n})_{1x1} = \mathrm{d}(\mathrm{n})_{1x1} - \mathrm{y_s}(\mathrm{n})_{1x1}$	-	1	-
6	$\mathrm{y_s}(\mathrm{n})_{1x1} = s(n)_{1xM} * \mathrm{y}(\mathrm{n})_{Mx1}$	M	M-1	-
	Total:	**2L+2M+2** **2L+2M+4**	**2L+2M-1** **2L+2M**	1 1

Table 6.2 Complexity analysis of proposed Modified FxBhagyashri algorithm

Eq`s	Operations	*	+/-	÷
1	$\mathrm{x}'(\mathrm{n})_{1x1} = \hat{s}(n)_{1\mathrm{xM}} * x(\mathrm{n})_{Mx1}$	M	M-1	-
2	$\mathrm{y}(\mathrm{n})_{1x1} = \mathrm{w}^{\mathrm{T}}(\mathrm{n})_{1xL} * x(\mathrm{n})_{Lx1}$	L	L-1	-
3	$\mathrm{w}(\mathrm{n}+1)_{Lx1} = \mathrm{w}(\mathrm{n})_{Lx1} + \mu(\mathrm{n})_{1x1}\mathrm{sign}[\mathrm{e}(\mathrm{n})_{1x1]}\mathrm{x}'(\mathrm{n})_{Lx1}$ $\mathrm{w}(\mathrm{n})_{Lx1} + \mu(\mathrm{n})_{1x1}[2\beta_{1x1} - \beta^2{}_{1x1}.\lvert \mathrm{e}(\mathrm{n})_{1x1]}\rvert \mathrm{e}(\mathrm{n})_{1x1]}\mathrm{x}'(\mathrm{n})_{lx1}$	L+1 L+3	L L+1	- -
4	$\beta_{1x1} = \dfrac{3}{m_{1x1} + 3\sigma_{1x1}}$	1	1	1
5	$\mu(\mathrm{n})_{1x1} = \dfrac{\mu_{1x1}}{\delta + x^T(\mathrm{n})_{1xL}\mathrm{x}(\mathrm{n})_{Lx1} + \mathrm{E}(\mathrm{n})}$	L	L+1	1
6	$\mathrm{E}(\mathrm{n})_{1x1} = \lambda E(n-1)_{1x1} + (1-\lambda)\mathrm{E}^2(\mathrm{n})_{1x1}$	3	2	
7	$\mathrm{e}(\mathrm{n})_{1x1} = \mathrm{d}(\mathrm{n})_{1x1} - \mathrm{y}_s(\mathrm{n})_{1x1}$	-	1	-
8	$\mathrm{y_s}(\mathrm{n})_{1x1} = s(n)_{1xM} * \mathrm{y}(\mathrm{n})_{Mx1}$	M	M-1	-
	Total:	**3L+2M+5**	**3L+2M+2**	2

		3L+2M+7	**3L+2M+3**	2

Here, L denotes filter coefficients length and M denotes secondary path. Table 6.3 represents the computational complexities of the newly proposed algorithms with the investigated algorithms [52], [55], [57].

Table 6.3 Performance analysis of Proposed Bhagyashri Algorithms and its variants

Algorithm	**Complexity**	
	Additions	**Multiplications**
FxLMS	2L+2M-2	2L+2M+1
NSS-FxLMS	3L+2M+1	3L+2M+4
Proposed FxBhagyashri	2M+2L-1 2M+2L	2M+2L+2 2M+2L+4
Proposed Clipped FxBhagyashri	2M+2L-1 2M+2L	2M+2L+2 2M+2L+4
Proposed Modified FxBhagyashri	2M+3L+2 2M+2L+3	2M+3L+5 2M+3L+7
DRNSS-FxLMS	2L+2M-2+N(3L+2)	2L+2M+N(3L+4)
FxRLS	$3L^2$+L+2M-2	$4L^2$+4L+2M
Proposed FxSSRLS	$2L^3$+M	$2L^3+4L^2$+2L+2M

6.3 Performance Comparison of Proposed Modifications in FxBhagyashri Algorithm

The ANC system for impulsive noise is implemented using the MATLAB platform. The performance of proposed algorithms in this chapter is compared with that of already reported adaptive algorithms in literature [52], [55], [57]. The parameters used in simulating the ANC system are tabularized below.

Table 6.4 Parameter set for proposed technique simulation

ANC System			**Impulsive Noise**		
Parameters	**Symbols**	**Values**	**Parameters**	**Symbols**	**Value**
Primary path tap size	L	256	Total samples	N	10000
Secondary path tap size	M	128	Total realizations	Avg	5
Adaptive filter tap size	L_w	192	Characteristic exponent	α	1.65, 1.45
NSS-FxLMS algorithm step size	$\bar{\mu}$	$5e^{-2}$	Scale parameter	γ	1
RLS forgetting factor	λ	0.99	Location parameter	C	0
FxBhagyashri algorithm step size	μ	5e-1	Skewness parameter	δ	0

Already discussed in chapter 5, the SαS distributions models impulsive noise [105]. Some PDFs for SαS distributions are shown in Fig.6.3. Fig 6.3- 6.6 are exactly same as Fig 5.4-5.7. for the better understanding of readers Fig 5.4- 5.7 are presenting in this chapter as Fig 6.3- 6.6 In Fig. 6.4, impulsive noise is generated using standard SαS process with α=1.65 is shown with the parameters used for simulating the impulsive noise in the simulations are mentioned in Table. 6.4.

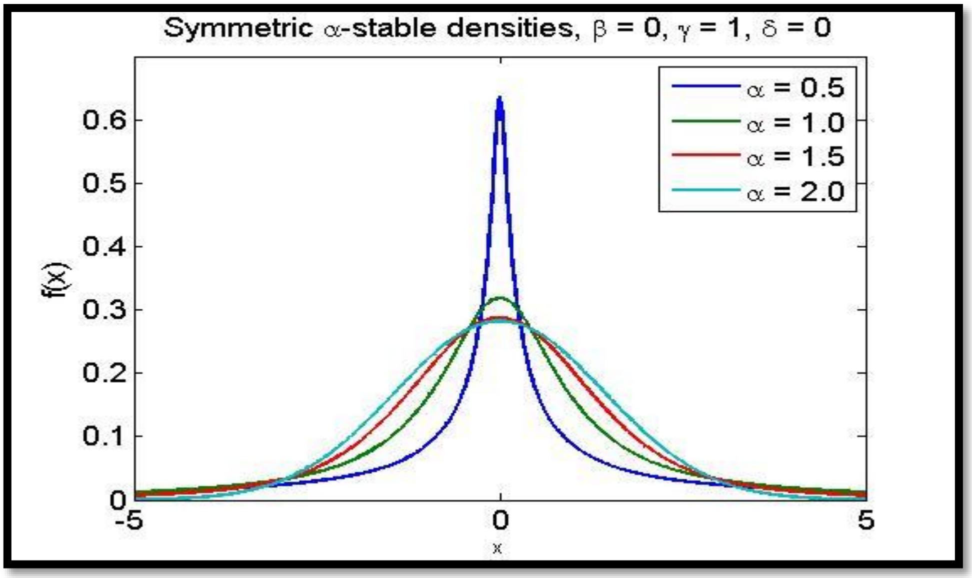


Figure 6.3: PDFs of standard SαS process with different values of α

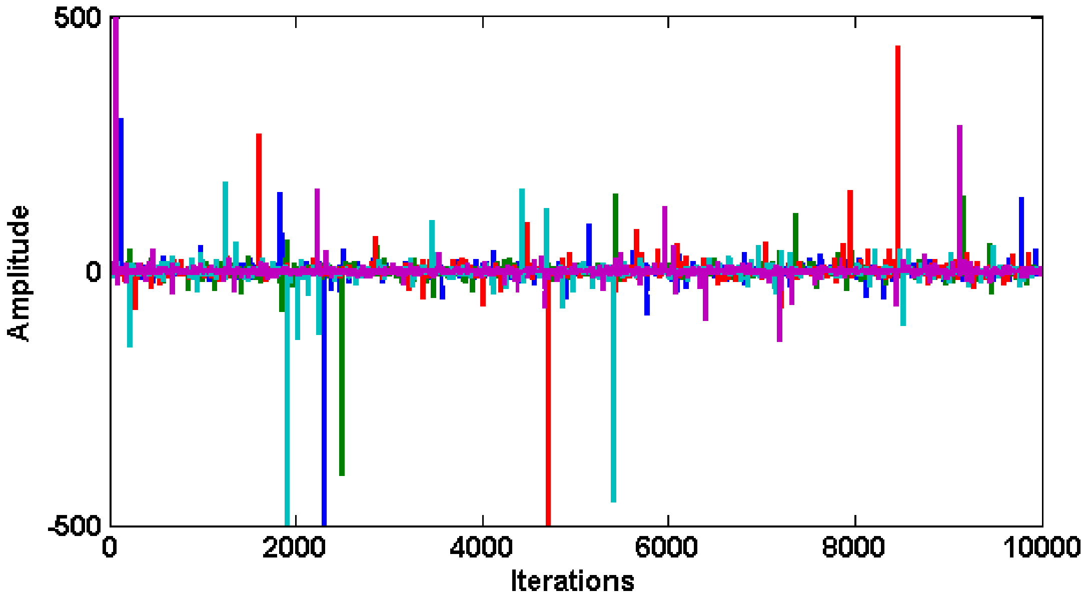


Figure 6.4: Impulsive noise modelled by SαS with α=1.65

The primary noise d(n) for α=1.65 picked by reference microphone is depicted in Fig. 6.5**.**

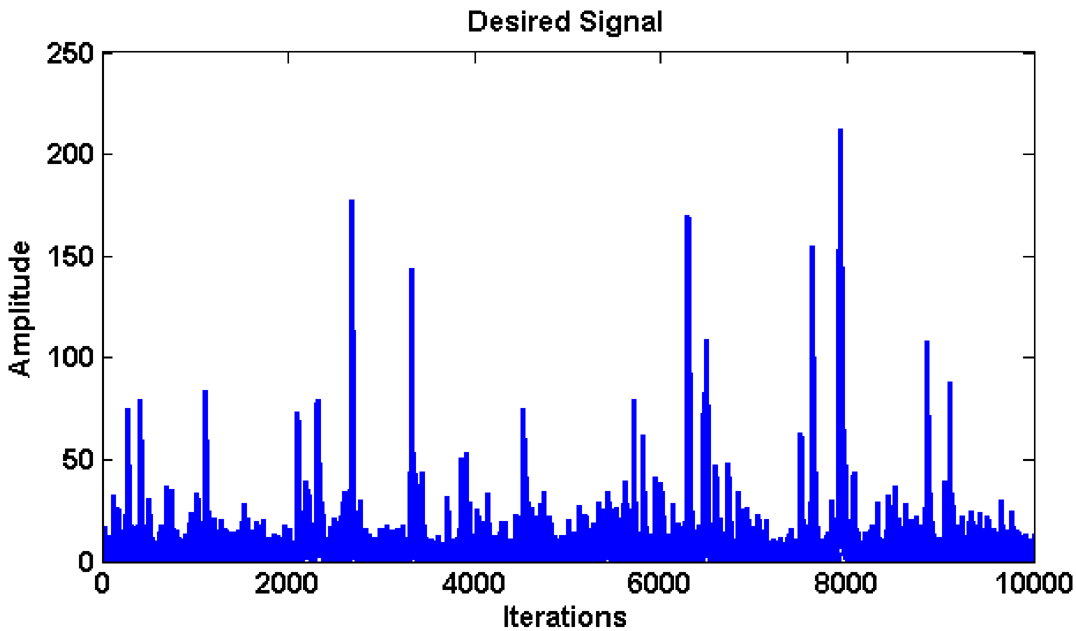


Figure 6.5: Primary noise signal

For the simplicity of our simulations, we have made an assumption that estimated secondary path model $\hat{s}(z)$ is same as $s(z)$ [55-58]. The numeric values of coefficients of primary and secondary acoustic paths are taken from data set given in [51]. The frequency response comprising of magnitude and phase of both path filters are depicted in Fig. 5.7 and for reader clarity it is provided again in the following Fig 6.6.

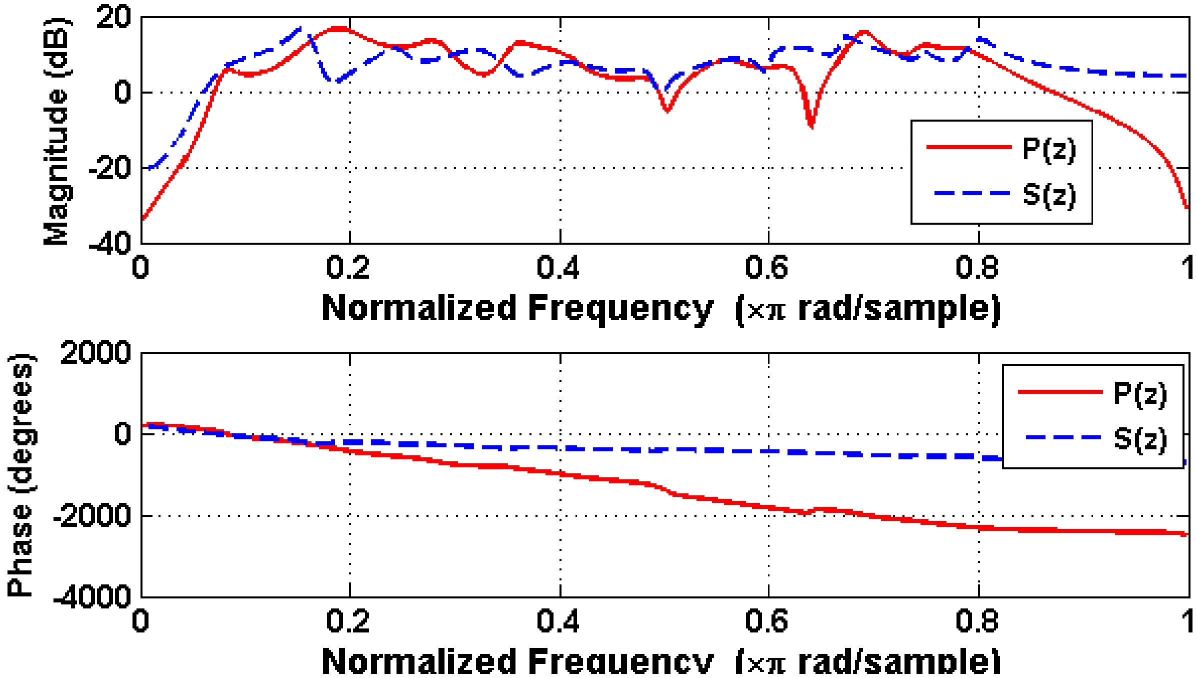


Figure 6.6: Frequency response of acoustic primary and secondary path

The performance metric used in this research for comparison of studied algorithms is mean noise reduction as discussed in section 5.3 of chapter 5.

Fig 6.7 presents the performance of FxBhagyashri algorithm with its two modifications (i.e CFxBhagyashri and MFxBhagyashri algorithms) for the impulsive noise shown in Fig 6.4. The MFxBhagyashri algorithm is more stable and has high convergence rate as compared to proposed FxBhagyashri and Clipped FxBhagyashri algorithms. Moreover, FxBhagyashri and CFxBhagyashri have same convergence rate but CFxBhagyashri is more stable than FxBhagyashri algorithm. However, the CFxBhagyashri algorithm is dependent on appropriate selection of threshold parameters. If these parameters are not selected appropriately then the performance of CFxBhagyashri algorithm is degraded.

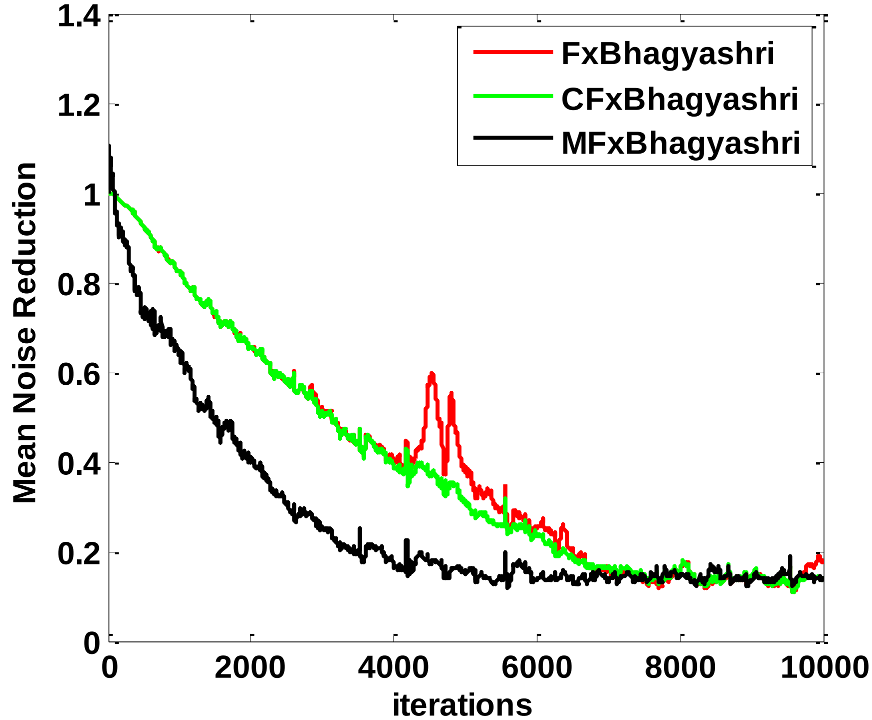


Figure 6.7: Comparison of MNR of proposed FxBhagyashri and its variants for α=1.65

Similarly, other simulation case with SαS impulsive noises of alpha=1.45 was performed to certify the efficacy of proposed MFxBhagyashri algorithm for higher value of alpha. It is noticed that proposed MFxBhagyashri algorithm demonstrates its improved performance among other selected values of impulsive noise over the other proposed FxBhagyashri and CFxBhagyashri algorithms. The convergence speed of CFxBhagyashri algorithm is more than MFxBhagyashri algorithm for more impulsive case i.e alpha=1.45, but we will still continue with the MFxBhagyashri algorithm as CFxBhagyashri algorithm is limited by its threshold value.

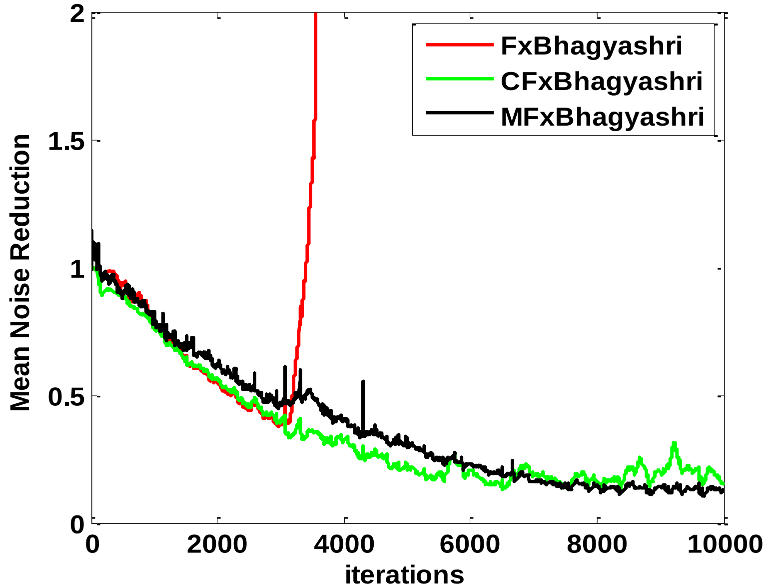


Figure 6.8: Comparison of MNR of proposed FxBhagyashri and its variants for α=1.65

Fig. 6.9 depicts the comparison of convergence curves of best variants of FxLMS and FxRLS family with the proposed MFxBhagyashri algorithm in ANC domain for α=1.65. It can be seen from Fig 5.10 of this dissertation that convergence speed of Normalized step size FxLMS (NSSFxLMS) algorithm is best among FxLMS family. And FxRLS algorithm is better than the FxLMS family with respect to fast convergence speed and low steady state error. Therefore, the performance of proposed MFxBhagyashri algorithm is compared with that of NSSFxLMS and FxRLS algorithm for α=1.65. Fig.6.9 shows that proposed MFxBhagyashri algorithm gives better convergence than NSSFxLMS algorithm and almost achieve the same steady state error that of FxRLS algorithm.

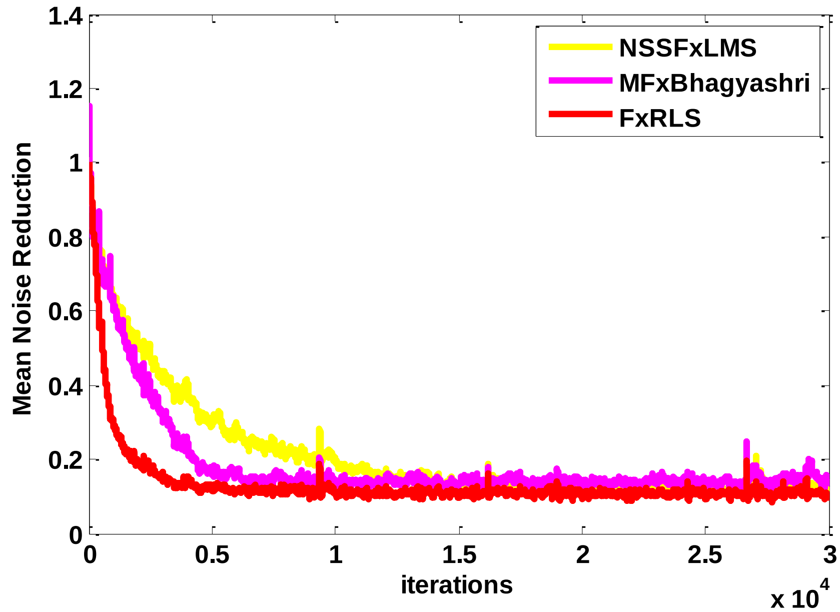


Figure 6.9: Comparison of MNR of Proposed MFxBhagyashri algorithm with various algorithms

α=1.65

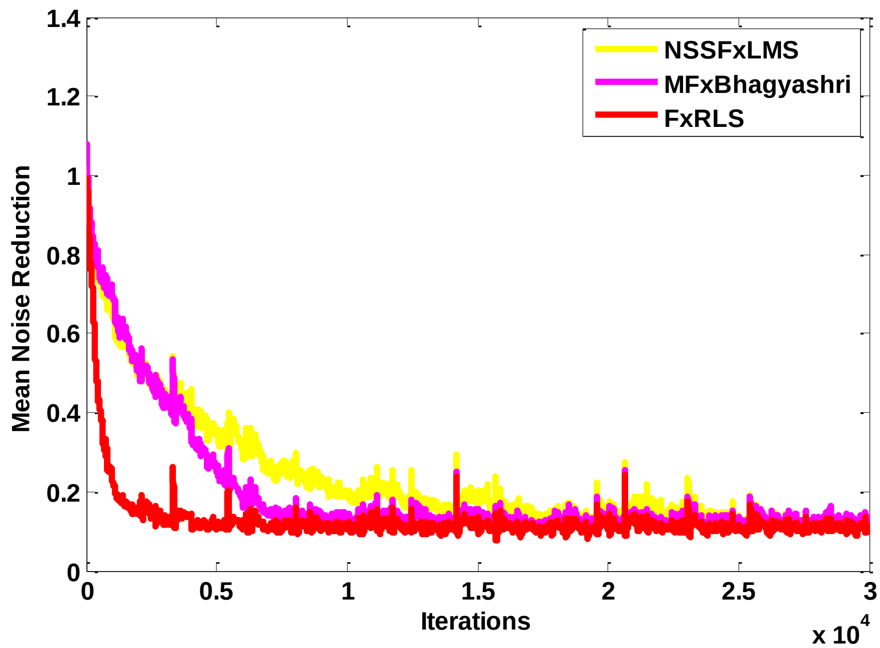


Figure 6.10: Comparison of MNR of Proposed MFxBhagyashri algorithm with various algorithms

α=1.45

It can be noticed from Fig. 6.10, that NSS-FxLMS and proposed MFxBhagyashri algorithms give slow convergence as compared to FxRLS algorithm that achieve steady state value at about 200 iterations. The convergence curves of proposed MFxBhagyashri algorithm and FxRLS algorithm almost overlap after 700 iterations. However, when an impulse is encountered, the FxRLS algorithm exhibits a sudden increase in MNR while the proposed MFxBhagyashri algorithm remains stable. The proposed MFxBhagyashri algorithm is a trade-off between FxLMS and FxRLS family. It has fast convergence speed than FxLMS family algorithms and can approach steady state error of FxRLS family with computational complexity of almost FxLMS family.

6.4 Summary:

In this chapter, Bhagyashri algorithm is first time tested in the ANC domain for impulsive noise. The FxBhagyashri algorithm becomes unstable in presence of impulsive noise, therefore two modifications Clipped FxBhagyashri and Modified FxBhagyashri algorithms are proposed in this chapter. Both modifications gave better performance in terms of stability and robustness than that of standard FxBhagyashri algorithm. Moreover, the results proved that the proposed MFxBhagyashri algorithm is a trade-off between FxLMS and FxRLS family. It has fast convergence speed than FxLMS family algorithms and can approach steady state error of FxRLS family with computational complexity of almost FxLMS family.

CHAPTER 7

Steady State Analysis of Normalized Bhagyashri Algorithm

7.1 Introduction

It has been reported in literature that Bhagyashri algorithm is successfully implemented for impulsive noise suppression and was never tested in ANC domain. Therefore, we proposed FxBhagyashri algorithm for active control of impulsive noise in chapter 6 of this dissertation and simulation results proved its significant performance in impulsive noise suppression.

In this chapter, we have performed the steady state analysis of normalized Bhagyashri algorithm. The steady state analysis of Bhagyashri algorithm is already done in [127]. This analysis will serve as a starting point for the researchers who intend to work in this area.

In section 7.2, standard Bhagyashri algorithm cost function is explained with its pros and cons. The steady state analysis of normalised Bhagyashri algorithm is carried out on same lines as of Bhagyashri algorithm in section 7.3.1. Moreover, the assumptions for performing the steady state analysis of normalized Bhagyashri algorithm are kept same as of Bhagyashri algorithm [128] i.e. error produced is Gaussian. The steady state analysis of proposed FxBhagyashri algorithm has not been performed because of the presence of secondary path which makes its analysis difficult. The analysis of proposed FxBhagyashri and its modifications for enhancing stability of FxBhagyashri algorithms may be recommended in future.

7.2 Description of Bhagyashri Algorithm

The cost function of widely used adaptive filters is based on MSE minimization. This error is assumed to be Gaussian, used by the adaptive filters to adjust their weights. In real time applications, noise encountered is impulsive rather than following Gaussian distribution. Therefore, different cost functions are reported in literature. A well-known solution in context of impulsive noise, based on robust statistics, is use of convex combination of cost functions.

$$J(n) = \lambda(n)E\{e^2(n)\} + [1 - \lambda(n)]E|e(n)| \tag{7.1}$$

Where $\lambda(n) \in [0,1]$ is the mixing parameter. The cost function used for Independent Component Analysis ICA is as follow [127]

$$J(n) = \frac{\log[\cosh(\beta e(n))]}{\beta} \tag{7.2}$$

Where β is the concavity control about origin and sensitive to the large outliers in error signal $e(n)$ [127]. A L length FIR filter with coefficients $w(n) = w_1(n) + w_2(n) + \cdots w_L(n)$ and input vector $x(n) = [x(n), x(n-1) \ldots \ldots . x(n-L+1)]\_$ used for calculating the error signal is given by

$$e(n) = d(n) - w^T(n)x(n) \tag{7.3}$$

The filter coefficients are updated by the Delta rule, which is given by

$$w(n+1) = w(n) + \mu \tanh[\beta e(n)].x(n) \tag{7.5}$$

(i) The proposed cost function in Eq (7.5) is noise-robust because hyperbolic tangent saturates to ± 1 for extreme values i.e. the contribution of outliers in e(n) to the coefficient updates is limited and easily controlled with β.

(ii) Eq (7.5) can be easily implemented on hardware because of availability of efficient hardware of hyperbolic tangent based on fuzzy logic. [129].

Alternative expression using fuzzy logic approach is obtained in [129] and is as follow.

$$\tanh[\beta\, e(n)] = \begin{cases} sign\big(e(n)\big) & |e(n)| > \frac{1}{\beta} \\ 2\beta e(n) - \beta^2 |e(n)| e(n) & |e(n)| \le \frac{1}{\beta} \end{cases} \tag{7.6}$$

The value of β is iteratively modified by classical threshold of three standard deviations to consider a pattern as an outlier. Moreover, since tanh(|3|) = |0.96|, i.e., a value close to unity, the parameter β can be obtained, as follows [129]:

$$\beta = \frac{3}{(m+3\sigma)} \tag{7.7}$$

where m is the mean and σ is standard deviation of error signal.

7.3 Normalized Bhagyashri Algorithm:

NLMS algorithm was proposed to overcome the gradient noise amplification problem associated with LMS algorithm, by incorporating energy of input signal. Therefore, we have proposed modification in Bhagyashri algorithm that makes it stable and robust enough to cater impulsive noise i.e. energy of input signal is incorporated in step size parameter to remove the gradient noise amplification. The modified step size is given as:

$$\mu(n) = \frac{\hat{\mu}}{\|x(n)\|^2 + \delta} \tag{7.8}$$

The weight update of normalized Bhagyashri algorithm is given below:

$$w(n+1) = \begin{cases} w(n) + \mu(n)\big[sign\big(e(n)\big)\big]x(n) & |e(n)| > \frac{1}{\beta} \\ w(n) + \mu(n)[2\beta e(n) - \beta^2 |e(n)| e(n)\,]x(n) & |e(n)| \le \frac{1}{\beta} \end{cases} \tag{7.9}$$

7.3.1 Steady State Analysis of Normalized Bhagyashri Algorithm:

The analysis of normalized Bhagyashri algorithm is performed on the method of energy conservation of an adaptive system [69] following the gradient updating rule. The system identification problem of Fig.1.7 is assumed, where the unknown system with coefficients is $w(n) = w_1(n) + w_2(n) + \cdots w_L(n)$, the output of system is d(n) which is corrupted with Gaussian noise v(n). d(n) and v(n) are not correlated with input x(n) of the system. The x(n) and d(n) are wide sense stationary (W.S.S) and zero mean processes. The coefficients update equation of normalized Bhagyashri algorithm is given by

$$w(n+1) = w(n) + \mu(n) g[e(n)][x(n)] \tag{7.10}$$

$$\mu(n) = \frac{\hat{\mu}}{\|x(n)\|^2 + \delta} \tag{7.11}$$

Where g[e(n)] is the gradient of error function and $\mu(n)$ is the modified step size.

For any adaptive filter in the steady state (n->∞) following relation must be satisfied.

$$E\{\mu(n)\|x(n)\|^2 [g(e(n))]^2\} = 2E\{ee_b(n) g[e(n)]\} \tag{7.12}$$

where $ee_b(n)$ is the noiseless error produced by the adaptive system without the effect of $v(n)$, i.e.:

$$ee_b(n) = e(n) - v(n) \tag{7.13}$$

Since $v(n)$ is not correlated to any of these errors, thereforewe can derive

$$\lim_{n\to\infty} |e(n)|^2 = \sigma_v^2 + \lim_{n\to\infty} |ee_b(n)|^2 = \sigma_v^2 + U \tag{7.14}$$

where σ_v^2 is the standard deviation of $v(n)$. Here in after,$U = \lim_{n\to\infty} |ee_b(n)|^2$, which is the performance metric of an adaptive algorithm. The input of adaptive filter and gradient of error are assumed independent [69], the gradient term in left side of eq (7.12) can be described as

$$[g(e(n))]^2 = 2\beta e(n) - \beta^2 |e(n)| e(n) \qquad e(n) \le \frac{1}{\beta} \tag{7.15}$$

Therefore,

$$E\{\mu(n)\|x(n)\|^2\left[g(e(n))\right]^2\} = E\left\{\frac{\hat{\mu}}{\{\|x(n)\|^2 + \delta\}}\right\} E\{\|x(n)\|^2\} E[2\beta e(n) - \beta^2|e(n)|e(n)]^{\,2}$$

$$= \left\{\frac{E\{\hat{\mu}\}}{E\{\|x(n)\|^2\}+E\{\delta\}} + Cov(\hat{\mu},\{\|x(n)\|^2 + \delta)\right\}\{Tr(R)\}\{E\left[4\beta^2 e^2(n) + \beta^4 e^4(n) - 4\beta^3|e(n)|e(n)\right]\} \tag{7.16}$$

Where $Tr(R) = E\{\|x(n)\|^2\}$ is the trace of autocorrelation matrix of input signal and C=E($Cov(\hat{\mu},\{\|x(n)\|^2 + \delta)$) is the covariance and the $E\{\hat{\mu}\} = \hat{\mu}\ and\ E\{\delta\} = \delta''$. The product $\beta.e(n)$ follows the Gaussian distribution (0,1). The expected values in eq (7.16) can be simplified by different moments of normal distribution.

$$\mu(n)E\{\|x(n)\|^2\left[g(e(n))\right]^2\} = \left(\frac{\hat{\mu}+C}{\mathrm{Tr(R)}+\delta''\}}\right) Tr(R)(7 - \frac{16}{\sqrt{2\pi}}) \tag{7.17}$$

The right side of (7.12) consist of product of two correlated terms, therefore, the expression of β obtained for steady state eq (7.7) is considered i.e; m=0 and $\beta = {}^{1}/_{\sigma_e}$.

Error e(n) is assumed to be Gaussian [69], the probability of occurrence of upper part of eq (7.9) is less i.e 0.32, and the probability of occurring lower part of eq (7.9) is considered high i.e. 0.68. Therefore,

$$E\{ee_b(n)g[e(n)]\} = p_1 E\{ee_b(n)[2\beta e(n) - \beta^2|e(n)|e(n)]\} + p_1 E\{ee_b(n)sign(e(n))\} \tag{7.18}$$

Price`s Theorem is used to simplify first and second term of right side of eq (7.18) and consider $\beta.e(n)$ follow Gaussian distribution.

$$E\{ag(b)\} = E\{ab\}E\left\{a\frac{dg(b)}{db}\right\} \tag{7.19}$$

Therefore,

$$p_1\left\{2 - \frac{4}{\sqrt{2\pi}}\right\} E\{ee_b(n)\beta e(n)\} \tag{7.20}$$

$$p_2\sqrt{\frac{2}{\pi}}E\{ee_b(n)\beta e(n)\} \tag{7.21}$$

In steady state, β is a constant and it value is close to $1/_{\sigma_e}$, and accordingly eq (7.20) and eq (7.21) becomes

$$p_1\left\{2-\frac{4}{\sqrt{2\pi}}\right\}\frac{E\{ee_b(n)e(n)\}}{\sigma_e} \tag{7.22}$$

and

$$p_2\sqrt{\frac{2}{\pi}}\frac{E\{ee_b(n)e(n)\}}{\sigma_e} \tag{7.23}$$

Above eq`s (7.14), (7.16),(7.22) and (7.23) are used to estimate U.

$$\left(\frac{\hat{\mu}+C}{\mathrm{Tr(R)}+\delta''}\right)Tr(R)\left(7-\frac{16}{\sqrt{2\pi}}\right)=\left[p_1\left(2-\frac{4}{\sqrt{2\pi}}\right)+\ p_2\sqrt{\frac{2}{\pi}}\right]\frac{U}{\sqrt{U+\sigma_v^2}} \tag{7.24}$$

where L denotes all the constants in eq (7.24)

$$L=\frac{\left(\left(\frac{\hat{\mu}+C}{\mathrm{Tr(R)}+\delta''}\right)Tr(R)\right)\ \left(7-\frac{16}{\sqrt{2\pi}}\right)}{p_1\left(2-\frac{4}{\sqrt{2\pi}}\right)+\ p_2\sqrt{\frac{2}{\pi}}}$$

The following closed form expression for U is given as

$$U=\frac{\mu L}{2}\left[\ \mu L+\ \sqrt{(\mu L)^2-4(1)(\sigma_v^2)}\ \right] \tag{7.25}$$

And eq 7.25 is derived below.

$$\mu L=\frac{U}{\sqrt{U+\sigma_v^2}}$$

$$U=\mu L\sqrt{U+\sigma_v^2}$$

$$U^2=\mu^2L^2(U+\sigma_v^2)$$

$$U^2=\mu^2L^2U+\mu^2L^2\sigma_v^2)$$

$$U^2 - \mu^2 L^2 U - \mu^2 L^2 \sigma_v^2 = 0$$

Apply quadratic equation

$$U = \frac{(\mu^2 L^2) \pm \sqrt{(\mu^2 L^2)^2 - 4(1)(-\mu^2 L^2 \sigma_v^2)}}{2}$$

The following expression is obtained for U:-

$$U = \frac{\mu L}{2}[\, \mu L + \ \sqrt{(\mu L)^2 - 4(1)(\sigma_v^2)}\,]$$

This closed form expression depicts the proposed algorithm robustness as error depends on noise standard deviation for low SNR. This expression is analogous to the relation obtained in [127] for the Bhagyashri Algorithm, except for L. The misadjustment in steady state of normalized Bhagyashri algorithm will be low than adaptation constant of Bhagyashri Algorithm due to presence of Tr(R) and Covariance C in the first term of adaptation constant L.

7.4 Summary

The steady state analysis of normalized Bhagyashri algorithm is carried out on same lines as of Bhagyashri algorithm in this chapter. This algorithm is robust to impulsive noise. This analysis will serve as a starting point for the researchers who intend to work in this area. The steady state analysis of modified step size Bhagyashri algorithm can be performed in future.

Chapter 8

Conclusions & Future Suggestions

In modern era of high speed communication and efficient bandwidth applications, impulsive noise severely affects the high data rate communication systems like Digital subscriber line (DSL), power line communication and cellular communication standards like LTE/LTE-A and WIMAX etc. A large amount of bandwidth is wasted with transmission impairments caused by impulsive noise. In this dissertation, efficient algorithms for impulsive noise reduction are proposed and implemented for OFDM and ANC applications. Adaptive filters can mitigate impulsive noise. The detailed description of proposed efficient algorithms is provided in chapter 2 to chapter 7. In this chapter, we demarcate our contributions, present the existing problems and suggest future recommendations.

We have proposed an adaptive impulsive noise canceller for supressing impulsive noise from sinusoidal and Electrocardiogram (ECG) signals. The proposed noise cancellation technique is based on state space recursive least square (SSRLS) algorithm, which show excellent tracking performance and low MSE as compared to Normalized Least Mean Square (NLMS), Recursive Least Square (RLS) and Bhagyashri Algorithms.

We then proposed an adaptive noise canceller for OFDM system based on SSRLS algorithm in chapter 3 of this dissertation. The presented adaptive noise canceller based on SSRLS gave low

MSE and BER than the adaptive canceller based on NLMS, RLS and Bhagyashri adaptive algorithms.

We also proposed hybrid technique based on combination of error correction codes i.e Reed Solomon and adaptive filter in chapter 4 of this thesis. Due to adaptive .algorithm`s ability .to .track time variations of signal statistics in non-stationary environment, better reduction in impulsive noise is achieved and enhanced signal reception is attained by employing Reed Solomon error correction codes. The suggested scheme improves the quality of OFDM signal in terms of MSE, improved SNR and BER, when compared with recently reported scheme used. Moreover, the comparative analysis of proposed dual protection technique is tested in AWGN and Rician fading channel. It is verified from simulation results that proposed RS-RLS outperforms the other investigated variants in impulsive noise suppression. The presented hybrid technique on combination of Reed Solomon and adaptive filter for OFDM systems is presented. The three variants of adaptive family i.e. NLMS, Bhagyashri and RLS algorithm are used for mitigating impulsive noise from received OFDM signal.

Furthermore, in chapter 5 of this dissertation, we proposed a new algorithm for Active noise control (ANC) applications. The impulsive noise makes adaptive algorithms in ANC applications unstable and less robust. Therefore, Filtered-x SSRLS (FxSSRLS), an SSRLS based practical and adaptive algorithm for Active noise control (ANC) applications is presented. The simulation results showed that large impulses are significantly reduced by the proposed FxSSRLS algorithm. Moreover, the suggested algorithm for ANC applications outperformed the existing algorithms in terms of mean noise reduction, convergence and stability.

Moreover, chapter 6 presents another proposed efficient Fx-Bhagyashri algorithm with its two modifications Clipped FxBhagyashri and Modified Fx-Bhagyashri algorithms in the ANC of impulsive noise. The both modifications gave better results in impulsive noise reduction as compared to standard Fx-Bhagyashri algorithm. It was also found that the proposed MFxBhagyashri algorithm can approach FxRLS algorithm in term of low steady state error with almost same computational complexity of FxLMS family algorithms.

The steady state analysis of Normalized Bhagyashri algorithm is performed on same lines as of Bhagyashri algorithm in chapter 7 of this dissertation. This analysis will serve as a starting point for the researchers who intend to work in this area.

The simulation results and their discussion is presented at the end of each chapter and new proposed algorithms are compared with existing techniques reported in literature through simulation results presented in terms of MSE, BER and SNR improvement. The results validate the effectiveness of the newly proposed algorithms based on adaptive filters for impulsive noise reduction.

8.1 Future Recommendations

Impulsive noise affects the information completely making difficult for the receiver to extract the actual information. This thesis focuses on the development of efficient algorithms for impulsive noise reduction in OFDM and ANC applications.

- In this thesis the proposed algorithms are simulated for OFDM system. The same algorithms are suggested to be implemented in MIMO-OFDM systems as well which may reveal several impediments in implementation and evolve new research areas.
- The proposed hybrid technique for impulsive noise suppression in OFDM system is a combination of Reed Solomon and Adaptive Filters. It can be recommended that variants of this hybrid technique be developed by using other error correction codes for different

applications. Moreover, the impulsive noise suppression can also be tried with Wavelet transform approach in future.

- The newly proposed algorithm for ANC application is based on modification in State Space RLS algorithm. The possible future work related to ANC application is to develop new algorithm based on State Space LMS algorithm and perform a comparison analysis with proposed algorithm for ANC.
- This thesis defends the proposed algorithms for impulsive noise cancellation through simulation results. The effectiveness of these proposed algorithms may be tested through hardware implementation. These experiments may result in the evolution of some new research issues.
- The convergence analysis of most commonly used FxLMS algorithm in ANC domain is still an active area of research. The convergence analysis of proposed FxSSRLS and already existing algorithms for impulsive noise reduction in ANC application can give new direction to the researchers.
- There is a need of developing new methodologies for removing impulsive noise of images. It is suggested that State Space RLS filter can be used in supressing impulsive noise from images.

References

[1] Vaseghi, S. V. (2006). *Advanced Digital Signal Processing and Noise Reduction.* 3rd edn, John Wiley & Sons, England.

[2] Haykin, S. S. (2001). *Adaptive Filter Theory.* 4th edn., Prentice-Hall, Englewood Cliffs, NJ.

[3] Nee, R. V., & Prasad, P. (2000). *OFDM for Wireless Multimedia Communications.* Artech House, London.

[4] Hansen, C. N. (2002). *Understanding Active Noise Cancellation.* CRC Press.

[5] Rappaport, T. S., & Bostian, C. W. (1993). Measurements and models of radio frequency impulsive noise for indoor wireless communications. *IEEE Journal on Selected Areas in Communications*, *11*(7), 991-1001.

[6] Skomal, E. N. (1970). The range and frequency dependence of VHF&# 8212; UHF man-made radio noise in and above metropolitan areas. *IEEE Transactions on Vehicular Technology*, *19*(2), 213-221.

[7] Kuran, M. S., & Tugcu, T. (2007). A survey on emerging broadband wireless access technologies. *Computer Networks*, *51*(11), 3013-3046.

[8] Saaifan, K.A. *Signal Detection in Non-Gaussian Interference for Wireless MIMO Systems.* PhD Proposal.

[9] Zimmermann, M., & Dostert, K. (2002). Analysis and modeling of impulsive noise in broad-band powerline communications. *IEEE transactions on Electromagnetic compatibility*, *44*(1), 249-258.

[10] Gotz, M., Rapp, M., & Dostert, K. (2004). Power line channel characteristics and their effect on communication system design. *IEEE Communications Magazine*, *42*(4), 78-86.

[11] Amirshahi, P., Navidpour, S. M., & Kavehrad, M. (2006). Performance analysis of uncoded and coded OFDM broadband transmission over low voltage power-line channels with impulsive noise. *IEEE Transactions on power delivery*, *21*(4), 1927-1934.

[12] Middleton, D. (1999). Non-Gaussian noise models in signal processing for telecommunications: new methods an results for class A and class B noise models. *IEEE Transactions on Information Theory*, *45*(4), 1129-1149.

[13] D. Middleton, D. (1960). *An Introduction to Statistical Communication Theory*. Vol (960), McGraw-Hill New York.

[14] Middleton, D. (1977). Statistical-physical models of electromagnetic interference. *IEEE Transactions on Electromagnetic Compatibility*, (3), 106-127.

[15] Middleton, D. (1979). Procedures for determining the parameters of the first-order canonical models of Class A and Class B electromagnetic interference [10]. *IEEE Transactions on Electromagnetic Compatibility*, (3), 190-208.

[16] Middleton, D. (1983). Canonical and quasi-canonical probability models of class A interference. *IEEE Transactions on Electromagnetic Compatibility*, (2), 76-106.

[17] Ghosh, M. (1996). Analysis of the effect of impulse noise on multicarrier and single carrier QAM systems. *IEEE Transactions on Communications*, *44*(2), 145-147.

[18] Ma, Y. H., So, P. L., & Gunawan, E. (2005). Performance analysis of OFDM systems for broadband power line communications under impulsive noise and multipath effects. *IEEE Transactions on Power Delivery*, *20*(2), 674-682.

[19] Hooijen, O. G. (1998). On the channel capacity of the residential power circuit used as a digital communications medium. *IEEE Communications Letters*, *2*(10), 267-268.

[20] Zhidkov, S. V. (2008). Analysis and comparison of several simple impulsive noise mitigation schemes for OFDM receivers. *IEEE Transactions on Communications*, *56*(1), 5-9.

[21] Zhidkov, S. V. (2006). Performance analysis and optimization of OFDM receiver with blanking nonlinearity in impulsive noise environment. *IEEE Transactions on Vehicular Technology*, *55*(1), 234-242.

[22] Rabiner, L. R., & Gold, B. (1975*). Theory and application of digital signal processing*. Vol (777), 1,Englewood Cliffs, NJ, Prentice-Hall, Inc.,.

[23] Abdelkefi, F., Duhamel, P., & Alberge, F. (2005). Impulsive noise cancellation in multicarrier transmission. *IEEE Transactions on Communications.* 53(1), 94-106.

[24] Oh, H. M., Park, Y. J., Choi, S., Lee, J. J., & Whang, K. C. (2006, March). Mitigation of performance degradation by impulsive noise in LDPC coded OFDM system. *IEEE International Symposium on Power Line Communications and Its Applications*, pp. 331-336, 2006.

[25] Hiking, J., & Vinck, A. H.(Apr 2001). Coding for Impulsive Noise Channels. *IEEE International Symposium on Power Line Communications and Its Applications*, pp. 103-108, 2001.

[26] Nguyen, H. H., & Bui, T. Q. (2007). Bit-interleaved coded modulation with iterative decoding in impulsive noise. *IEEE Transactions on Power Delivery*, *22*(1), 151-160.

[27] Nguyen, H. H., & Bui, T. Q. (2008). Bit-interleaved coded OFDM with iterative decoding in impulsive noise. *IEEE Transactions on Power Delivery*, *23*(2), 640-649.

[28] Nakagawa, H., Umehara, D., Denno, S., & Morihiro, Y. (2005, April). A decoding for low density parity check codes over impulsive noise channels. *IEEE International Symposium on Power Line Communications and Its Applications*, pp. 85-89, 2005.

[29] Carcelle, X. (2009). *Power Line Communications in Practice*. Artech House, London.

[30] Andreadou, N., & Pavlidou, F. N. (2010). Mitigation of impulsive noise effect on the PLC channel with QC–LDPC codes as the outer coding scheme. .*IEEE Transactions on Power Delivery*, *25*(3), 1440-1449.

[31] Fertonani, D., & Colavolpe, G. (2009). On reliable communications over channels impaired by bursty impulse noise. *IEEE Transactions on Communications*, *57*(7), 2024-2030.

[32] Zhidkov, S. V. (2003). Impulsive noise suppression in OFDM-based communication systems. *IEEE Transactions on Consumer Electronics*,*49*(4), 944-948.

[33] Al-Mawali, K., Sadik, A. Z., & Hussain, Z. M. (2008, December). Joint time-domain/frequency-domain impulsive noise reduction in OFDM-based power line communications. *IEEE Telecommunication Networks and Applications Conference (ATNAC 2008)*, pp. 138-142, 2008.

[34] Sliskovic, M. (2001). Impulse noise detection algorithms for multicarrier communication systems-performance analysis. *Proceedings of the 2nd International Symposium on Image and Signal Processing and Analysis,(ISPA 2001)*, pp. 496-501, 2001.

[35] Armstrong, J., & Suraweera, H. A. (2004, August). Impulse noise mitigation for OFDM using decision directed noise estimation. *IEEE 8th International Symposium on Spread Spectrum Techniques and Applications*, pp. 174-178, 2004.

[36] Haring, J., & Vinck, H. (2000, April). OFDM transmission corrupted by impulsive noise. *4th International Symposium on Power-Line Communications and its Applications (ISPLC2000)*.

[37] Sargrad, D. H., & Modestino, J. W. (1990). Errors-and-erasures coding to combat impulse noise on digital subscriber loops. *IEEE Transactions on Communications*, *38*(8), 1145-1155.

[38] Li, T., Mow, W. H., & Siu, M. (2008). Joint erasure marking and Viterbi decoding algorithm for unknown impulsive noise channels. *IEEE Transactions on Wireless Communications*, *7*(9), 3407-3416.

[39] Rappaport, T. S. (1996). *Wireless Communications: Principles and Practice.* (Vol. 2). New Jersey: Prentice Hall PTR.

[40] Faber, T., Scholand, T., & Jung, P. (2003). Turbo decoding in impulsive noise environments. *Electronics letters*, *39*(14), 1.

[41] Burnic, A., Hessamian-Alinejad, A., Scholand, T., Faber, T. E., Bruck, G. H., & Jung, P. (2006, September). Error correction in impulsive noise environments by applying Turbo codes. *IEEE 17th International Symposium on Personal, Indoor and Mobile Radio Communications* pp. 1-5, 2006.

[42] Nakagawa, H., Umehara, D., Denno, S., & Morihiro, Y. (2005, April). A decoding for low density parity check codes over impulsive noise channels. *International Symposium on Power Line Communications and Its Applications*, pp. 85-89, 2005.

[43] Wolf, J. (1983). Redundancy, the discrete Fourier transform, and impulse noise cancellation. *IEEE Transactions on Communications*, *31*(3), 458-461.

[44] Abdelkefi, F., Duhamel, P., & Alberge, F. (2005). Impulsive noise cancellation in multicarrier transmission. *IEEE Transactions on Communications*, *53*(1), 94-106.

[45] Haring, J., & Vinck, A. H. (2003). Iterative decoding of codes over complex numbers for impulsive noise channels. *IEEE Transactions on Information Theory*, *49*(5), 1251-1260.

[46] Paulo, S. D. (2008). Adaptive filtering: algorithms and practical implementation. *The international series in Engineering and Computer Science*.

[47] Snyder, S. D. (2012). *Active Noise Control Primer*. Springer Science & Business Media.

[48] Elliott, S. (2000). *Signal Processing for Active Control*. London, U.K, Academic Press.

[49] Elliott, S. J., & Nelson, P. A. (1993). Active noise control. *IEEE Signal Processing Magazine*, *10*(4), 12-35.

[50] https://en.wikipedia.org/wiki/Active_noise_control

[51] Kuo, S. M., & Morgan, D. R. (1996). *Active Noise Control Systems-Algorithms and DSP Implementation.* Wiley, New York.

[52] Kuo,S.M., & Chen, C. (1990). *Implementation of adaptive filters with the TMS320C25 or the TMS320C30, Digital Signal Processing Applications with the TMS320 Family*. Vol (3), pp. 191-271,edited by P. Papamichalis, Prentice-Hall, Englewood Cliffs, NJ.

[53] Olson, H. F., & May, E. G. (1953). Electronic sound absorber. *The Journal of the Acoustical Society of America*, *25*(6), 1130-1136.

[54] Olson, H. F. (1956). Electronic control of noise, vibration, and reverberation.*The Journal of the Acoustical Society of America*, *28*(5), 966-972.

[55] Akhtar, M. T., & Mitsuhashi, W. (2010, August). A modified normalized FxLMS algorithm for active control of impulsive noise. *Proceedings of the IEEE 20th European Signal Processing Conference*, pp. 1-5, 2010.

[56] Paleologu, C., & Benesty, J. (2012, August). A practical data-reuse adaptive algorithm for acoustic echo cancellation. *Proceedings of the IEEE 20th European Signal Processing Conference* ,pp. 2010-2014, 2012.

[57] BAkhtar, M. T., & Nishihara, A. (2015). Data-reusing-based filtered-reference adaptive algorithms for active control of impulsive noise sources. *Applied Acoustics*, *92*, 18-26.

[58] Zeb, A., Mirza, A., & Sheikh, S. A. (2015, December). Filtered-x RLS algorithm based active noise control of impulsive noise. *IEEE 7th International Conference on Modelling, Identification and Control (ICMIC)*, pp. 1-5, 2015.

[59] Malik. M.B. (2004),State-space recursive least-squares: part I & II, *Signal Processing*, 84(9), 1709 – 1728.

[60] Jimaa, S. A., Al-Araji, S. R., Al-Kaabi, A., & Shimamura, T. (2012, October). Impulsive noise reduction using adaptive receiver structure technique. *IEEE 11th International Conference on Signal Processing, V*ol. 1, pp. 119-122, 2012.

[61] Al-Araji, S. R., Al-Qutayri, M. A., & Al-Tenaiji, M. S. (2011, February). Impulsive noise reduction using Auto-Gating technique. IEEE *GCC Conference and Exhibition (GCC),* (pp. 104-107), 2011.

[62] Rehman, S. A., & Kumar, R. R. (2012). Performance comparison of adaptive filter algorithms for ECG signal Enhancement. *International Journal of Advanced Research in Computer and Communication Engineering*, *1*(2), 2278-1021.

[63] Chandrakar, C., & Kowar, M. K. (2012). Denoising ECG signals using adaptive filter algorithm. *International Journal of Soft Computing and Engineering (IJSCE)*, *2*(1), 120-123.

[64] Razzaq, N., Butt, M., Salman, M., Ali, R., Sadiq, I., Munawar, K., & Zaidi, T. (2013, August). Self tuned SSRLS filter for online tracking and removal of power Line Interference from Electrocardiogram. *Proceedings of International Conference on Modelling, Identification & Control (ICMIC),* (pp. 339-343), 2013.

[65] Gianfelici, F., Biagetti, G., Crippa, P., & Turchetti, C. (2007). Multicomponent AM–FM representations: an asymptotically exact approach. *IEEE Transactions on Audio, Speech, and Language Processing*, *15*(3), 823-837.

[66] Feldman, M. (2011). Hilbert transform in vibration analysis. *Mechanical systems and signal processing*, *25*(3), 735-802.

[67] Falcão, R. M. A. (2012). *Adaptive filtering Algorithms for Noise Cancellation.*Doctoral dissertation, Universidade do Porto.

[68] Singh, A. S.L (2001). *Adaptive Noise Cancellation.*

[69] Sayed, A. H. (2003). *Fundamentals of Aadaptive Filtering*. John Wiley & Sons.

[70] Chang, S. L., & Ogunfunmi, T. (1998, May). LMS/LMF and RLS Volterra system identification based on nonlinear Wiener model. *Proceedings of the 1998 IEEE International Symposium on Circuits and Systems, (ISCAS'98.),*Vol (5), pp. 206-209, 1998.

[71] Wahab, M. A., Uzzaman, M. A., Hai, M. S., Haque, M. A., & Hasan, M. K. (2008, December). Least-squares optimal variable step-size LMS for nonblind system identification with noise. *International Conference on Electrical and Computer Engineering, (ICECE),* pp. 428-433, 2008.

[72] Eweda, E. (1994). Comparison of RLS, LMS, and sign algorithms for tracking randomly time-varying channels. *IEEE Transactions on Signal Processing*, *42*(11), 2937-2944.

[73] Haykin, S., Sayed, A. H., Zeidler, J., Yee, P., & Wei, P. (1995, November). Tracking of linear time-variant systems. IEEE *Military Communications Conference (MILCOM'95),* Vol (2), pp. 602-606, 1995.

[74] Widrow, B., & Stearns, S. D. (1985). *Adaptive Signal Processing*. Vol (491), pp.1, Englewood Cliffs, NJ, Prentice-Hall, Inc.

[75] Eleftheriou, E., & Falconer, D. (1986). Tracking properties and steady-state performance of RLS adaptive filter algorithms. *IEEE Transactions on Acoustics, Speech, and Signal Processing*, *34*(5), 1097-1110.

[76] Bhagyashri B. S., & Deokar, S. (2014, April). Adaptive Filter for Removal of Impulsive Noise and Its Comparison with LMS Algorithm. International Conference on Industrial Automation and Computing, pp.12-14, 2014.

[77] Torío, P., Sánchez, M. G., & Cuiñas, Í. (2011, September). An algorithm to simulate impulsive noise. *IEEE 19th International Conference on Software, Telecommunications and Computer Networks (SoftCOM),* pp. 1-4, 2011.

[78] L. Goldberger et al., (2000) PhysioBank, PhysioToolkit and Physionet: Components of a new research resource for complex physiologic signals, Circulation. [Online] Available: Circulation Electronic:http://circ.ahajoumals.orglcgi/contentlfull/101I23/e215

[79] Suraweera, H. A., Chai, C., Shentu, J., & Armstrong, J. (2003, September). Analysis of impulse noise mitigation techniques for digital television systems. *8th International OFDM Workshop* (pp. 172-176), 2003.

[80] K. S. Al-Mawali and Z. M. Hussain (2009, October). Adaptive-threshold clipping for impulsive noise reduction in OFDM-based power line communications. *IEEE Conference i*n *Advanced Technologies for Communications,* pp. 43-48, 2009.

[81] Hirakawa, T., Fujii, M., Itami, M., & Itoh, K. (2006, January). Improving influence of impulse noise to OFDM signal by recovering time domain samples. *Digest of Technical Papers, IEEE International Conference on Consumer Electronics,* pp. 327-328, 2006.

[82] Umatani, T., Ohno, K., & Itami, M. (2010, January). A study on schemes of reducing influence of impulse noise in OFDM under multi-path channel. *Digest of Technical Papers, IEEE International Conference on Consumer Electronics (ICCE),* pp. 119-120, 2010.

[83] Kitamura, T., Ando, H., Ohno, K., & Itami, M. (2012, September). The impulsive noise reduction using it's replica signal under Class-A impulsive channel. IEEE *15th International Symposium on* In *Wireless Personal Multimedia Communications (WPMC),* pp. 463-467, 2012.

[84] Kitamura, T., Ohno, K., & Itami, M. (2011, January). Iterative impulsive noise reduction by generating its replica signal in OFDM reception. *IEEE International Conference on Consumer Electronics (ICCE),* pp. 389-390, 2011.

[85] Liu, R., Kung, T. L., & Parhi, K. K. (2014). Impulse noise correction in OFDM systems. *Journal of Signal Processing Systems*, *74*(2), 245-262.

[86] Mathew, S., & Murukan, P. (2014). Periodic impulsive noise reduction in OFDM based power line communication. *Internaional Journal of Research in Engineering and Technology*, *3,* 517-522.

[87] Ahmed, M. A., Jimaa, S. A., & Abualhaol, I. Y. (2012). Performance Enhancements of MIMO-OFDM System Using Various Adaptive Receiver Structures. *International Journal of Computer and Information Technology, 1(01), 2277–0764*.

[88] Hakam, A., Aly, N. A., Khalid, M., Jimaa, S., & Al-Araji, S. (2013, December). Impulsive noise reduction in MIMO-OFDM systems using adaptive receiver structures. *IEEE 20th International Conference on* In *Electronics, Circuits, and Systems (ICECS),* pp. 674-677, 2013 .

[89] Hakam, A., Aly, N. A., & Jimaa, S. (2014, March). Impulsive Noise Mitigation in a MIMO-OFDM Communication System. *IEEE 6th International Conference on New Technologies, Mobility and Security (NTMS),* pp. 1-5, 2014.

[90] Khedkar, A. R., & Murugan, M. M. (2015, January). Trained adaptive filter based approach to mitigate ICI in OFDM system. IEEE *International Conference on Pervasive Computing (ICPC),* pp. 1-4, 2015.

[91] Mirza, A., Kabir, S. M., & Ayub, S. (2015). Impulsive Noise Cancellation of ECG signal based on SSRLS. *Procedia Computer Science*, *62*, 196-202.

[92] Mirza, A., Kabir, S. M., Ayub, S., Arslan, M., & Sheikh, S. A. (2015, April). Enhanced impulsive noise cancellation based on SSRLS. IEEE International Conference on *Computer, Communications, and Control Technology (I4CT),* pp. 31-35, 2015.

[93] Kabir, S. M., Mirza, A., & Sheikh, S. A. (2015). Impulsive Noise Reduction Method Based on Clipping and Adaptive Filters in AWGN Channel. *International Journal of Future Computer and Communication*, *4*(5), 341.

[94] Al-Naffouri, T. Y., Quadeer, A. A., & Caire, G. (2011, July). Impulsive noise estimation and cancellation in DSL using orthogonal clustering. *IEEE International Symposium on* In*Information Theory Proceedings (ISIT)*, pp. 2841-2845, 2011.

[95] Ferreira, H. C., Lampe. L., Newbury. J., & Swart, T. G. (2010), *Power Line Communications: Theory and Applications for Narrowband and Broadband Communications over Power Lines,* John Wiley & Sons.

[96] Prasad, R. (2004). *OFDM for Wireless Communications Systems*. Artech House, London.

[97] Prasad, G., Latchman, H. A., Lee, Y., & Finamore, W. A. (2014, March). A comparative performance study of LDPC and Turbo codes for realistic PLC channels. *18th IEEE International Symposium on Power Line Communications and its Applications (ISPLC)*, pp. 202-207, 2014.

[98] Praveenkumar, P., Amirtharajan, R., Thenmozhi, K., & Rayappan, J. B. B. (2012). Regulated OFDM-role of ECC and ANN: A review. *Journal of Applied Sciences*, *12*(4), 301.

[99] Praveenkumar, P., Thenmozhi, K., Rayappan, J. B. B., & Amirtharajan, R. (2014). Reversible steganography on OFDM channel-a role of RS coding. *Information Technology Journal*, *13*(12), 2052.

[100] Hu, X., Chen, Z., & Yin, F. (2014). Impulsive noise cancellation for MIMO power line communications. *Journal of Communications*, *9*(3), 241-247.

[101] Jia, J., & Meng, J. (2014). A dual protection scheme for impulsive noise suppression in OFDM systems. *AEU-International Journal of Electronics and Communications*, *68*(1), 51-58.

[102] Jia, J., & Meng, J. (2014, September). A novel approach for impulsive noise mitigation in ZigBee communication system. *IEEE Global Information Infrastructure and Networking Symposium (GIIS),*pp. 1-3, 2014.

[103] Zhang, X., Viswanathan, V. R., & Unno, T. (2008). *U.S. Patent Application No. 12/167,026*.

[104] Sklar, B. (2001). *Digital Communications.* (Vol. 2). NJ: Prentice Hall.

[105] Nikias, C. L., & Shao, M. (1995). *Signal Processing with Alpha-Stable Distributions and Applications*. Wiley-Interscience.

[106] Sun, X., Kuo, S. M., & Meng, G. (2006). Adaptive Algorithm for Active Control of Impulsive Noise. *Journal of Sound and Vibration*, *291*(1), 516-522.

[107] Akhtar, M. T., & Mitsuhashi, W. (2009). Improving performance of FxLMS algorithm for active noise control of impulsive noise. *Journal of Sound and Vibration*, *327*(3), 647-656.

[108] Wu, L., He, H., & Qiu, X. (2011). An active impulsive noise control algorithm with logarithmic transformation. *IEEE Transactions on Audio, Speech, and Language Processing*, *19*(4), 1041-1044.

[109] Li, P., & Yu, X. (2013). Active noise cancellation algorithms for impulsive noise. *Mechanical Systems and Signal Processing*, *36*(2), 630-635.

[110] Bergamasco, M., Della Rossa, F., & Piroddi, L. (2012). Active noise control with on-line estimation of non-Gaussian noise characteristics. *Journal of Sound and Vibration*, *331*(1), 27-40.

[111] Albu, F. (2012). Leading element dichotomous coordinate descent exponential recursive least squares algorithm for multichannel active noise control. *Proc. of AAS Acoust*, 21-23.

[112] Albu, F., & Paleologu, C. (2008, August). A recursive least square algorithm for active noise control based on the Gauss-Seidel method. In *ICECS* , pp. 830-833.

[113] Malik, M. B. (2004). State-space recursive least squares: part II. *Signal processing*, *84*(9), 1719-1728.

[114] Ardekani, I. T., & Abdulla, W. H. (2013). Stochastic modelling and analysis of filtered-x least-mean-square adaptation algorithm. *IET Signal Processing*,*7*(6), 486-496.

[115] Sun, G., Feng, T., Li, M., & Lim, T. C. (2013). Convergence analysis of filtered-x least mean squares algorithm for active control of repetitive impact noise. *The Journal of the Acoustical Society of America*, *134*(5), 4190-4190.

[116] Sun, G., Feng, T., Li, M., & Lim, T. C. (2015). Convergence analysis of FxLMS-based active noise control for repetitive impulses. *Applied Acoustics*, *89*, 178-187.

[117] Ardekani, I. T., & Abdulla, W. H. (2012). Effects of imperfect secondary path modeling on adaptive active noise control systems. *IEEE Transactions on Control Systems Technology*, *20*(5), 1252-1262.

[118] Ardekani, I. T., & Abdulla, W. H. (2010). Theoretical convergence analysis of FxLMS algorithm. *Signal Processing*, *90*(12), 3046-3055.

[119] Shao, M., & Nikias, C. L. (1993). Signal processing with fractional lower order moments: stable processes and their applications. *Proceedings of the IEEE*, *81*(7), 986-1010.

[120] Akhtar, M. T. (2016). Binormalized data-reusing adaptive filtering algorithm for active control of impulsive sources, *Digital Signal Processing*, 49, 56-64.

[121] Bo, Z., Sun, C., Xu, Y., & Jiang, S. (2014). A variable momentum factor filtered-x weighted accumulated LMS algorithm for narrowband active noise control systems. *Measurement*, *48*, 282-291.

[122] Behera, S. B., Das, D. P., & Rout, N. K. (2014). Nonlinear feedback active noise control for broadband chaotic noise. *Applied Soft Computing*, *15*, 80-87.

[123] Wu, L., Qiu, X., Burnett, I. S., & Guo, Y. (2015). A recursive least square algorithm for active control of mixed noise. *Journal of Sound and Vibration*,*339*, 1-10.

[124] Wu, L., & Qiu, X. (2013). An M-estimator based algorithm for active impulse-like noise control. *Applied Acoustics*, *74*(3), 407-412.

[125] Zhou, Y., Zhang, Q., & Yin, Y. (2015). Active control of impulsive noise with symmetric α-stable distribution based on an improved step-size normalized adaptive algorithm. *Mechanical Systems and Signal Processing*, *56*, 320-339.

[126] Sun, G., Li, M., & Lim, T. C. (2015). A family of threshold based robust adaptive algorithms for active impulsive noise control. *Applied Acoustics*, *97*, 30-36.

[127] Soria, E., Martin, J., Calpe, J., Serrano, A., & Chambers, J. (2006). Robust adaptive algorithm with low computational cost. *Electronics Letters*, *42*(1), 2-60.

[128] Soria-Olivas, E., Martín-Guerrero, J. D., Serrano-López, A. J., Calpe-Maravilla, J., & Chambers, J. (2007). Steady-state and tracking analysis of a robust adaptive filter with low computational cost. *Signal Processing*, *87*(1), 210-215.

[129] Soria-Olivas, E., Martín-Guerrero, J. D., Camps-Valls, G., Serrano-López, A. J., Calpe-Maravilla, J., & Gómez-Chova, L. (2003). A low-complexity fuzzy activation function for artificial neural networks. *IEEE Transactions on Neural Networks*, *14*(6), 1576-1579.

List of Publications

Journal Papers:

a. Mirza, A., Zeb, A., & Sheikh, S. A. (2016). Robust Adaptive Algorithm for Active Control of Impulsive Noise. *EURASIP Journal on Advances in Signal Processing*, 2016(1), 1-13.

b. Mirza, A., Zeb, A., & Sheikh, S. A. (2016). Dual ProtectionTechnique for Impulsive Noise Suppression in OFDM Systems. accepted in *Mehran University Research Journal of Engineering & Technology*.

c. Mirza, A., Zeb, A., & Sheikh, S. A. (2016). A Composite Approach for Minimization of Impulsive Noise in OFDM Systems. submitted in *KSII Transactions on Internet and Information Systems.*

Conference Papers

d. Mirza, A., Kabir, S. M., Ayub, S. & Sheikh, S. A. (2015). Impulsive Noise Cancellation of ECG signal based on SSRLS. *Procedia Computer Science,* 62, 196-202.

e. Mirza, A., Kabir, S. M., & Sheikh, S. A. (2015). Enhanced impulsive noise cancellation based on SSRLS. *IEEE International Conference on Computer, Communications, and Control Technology* (I4CT), 2015.

f. Mirza, A., Kabir, S. M., & Sheikh, S. A. (2015). Reduction of Impulsive Noise in OFDM System Using Adaptive Algorithm. *World Academy of Science, Engineering and Technology, International Journal of Computer, Electrical, Automation, Control and Information Engineering*, 9(6), 1279-1283.

g. Mirza, A., Kabir, S. M., & Sheikh, S. A. (2015). SSRLS based Enhanced Impulsive Noise OFDM Suppressor in AWGN Channel. The 6th International Conference on Computational Methods (ICCM2015), 2015.

h. Mirza, A., Kabir, S. M., & Sheikh, S. A. (2015). Reduction of Impulsive noise in OFDM Systems using a hybrid method. The 6th International Conference on Signal and Information Processing (ICSIP 2015), 4(3), pp. 226-230, 2015.