ADDIS ABABA UNIVERSITY

SCHOOL OF GRADUATE STUDIES

INSTITUTE OF TECHNOLOGY

ELECTRICAL AND COMPUTER ENGINEERING DEPARTMENT

Performance Evaluation of Adaptive Arrays for MIMO Smart Antenna Systems

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Declaration

I, the undersigned, declare that this thesis is my original work, has not been presented for a degree in this or any other university, and all sources of materials used for the thesis have been fully acknowledged.

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Place: Addis Ababa

Date of Submission: ________________

This thesis has been submitted for examination with my approval as a university advisor.

Dr.-Ing Hailu Ayele _______________
Advisor's Name Signature

Dedicated to

MY Family and Tsadikan Wonde

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TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF ACRONYMS

AAA	Adaptive Array Antenna
AOA	Angle of Arrival
AWGN	Additive White Gaussian Noise
BER	Bit Error Rate
BPSK	Binary phase shift keying
BLAST	Bell Lab Layered Space Time
CMA	Constant Modulus Algorithm
DBLAST	Diagonal BLAST
EGC	Equal Gain Combining
FDD	Frequency Division duplex
IEEE	Institute of Electrical and Electronics Engineers
GSM	Global System for Mobile communication
LMS	Least Mean Square
LST	Layered Space Time
MIMO	Multiple Input Multiple Output
MISO	Multiple Input Single Output
ML	Maximum Likelihood
MMSE	Minimum Mean Square Error
MRC	Maximum Ratio Combing
MCMA	Modified Constant modulus algorithm
QAM	Quadrature Amplitude Modulation
RLS	Recursive Least Square Algorithm
SC	Selection Combining
SCMA	Simplified constant modulus algorithm
SD	Spatial Diversity
SIC	Successive Interference Cancellation
SIMO	Single Input Multiple Output

SINR	Signal interference noise ratio
SISO	Single input Single output
SGD	Stochastic Gradient Descent
SM	Spatial Multiplexing
SMI	Sample Matrix Inversion
SNR	Signal to Noise Ratio
STBC	Space Time Block Code
SVD	Singular Value Decomposition
TDD	Time division duplex
VBLAST	Vertical BLAST
ZF	Zero Forcing

ABSTRACT

The demand for wireless systems has been growing rapidly over the recent years due to improved reliability, high data rates, seamless connectivity and low deployment costs. MIMO systems are the most efficient leading innovation of wireless systems for maximum capacity and improved quality and coverage. This theory has been around for a long while but the complexity involved and the signal processing required has been a major drawback to its wide-spread use. However, recent improvements in Digital Signal Processing (DSP) technology has made it possible to now construct such transmission systems.

In this thesis we study different adaptive blind and nonblind algorithms for MIMO systems such as LMS, CMA, SMI, and combined algorithms, LMS-CMA, and SMI-CMA. Moreover, we compare these adaptive array algorithms with other known class of MIMO linear receiver (channel estimation) techniques like Zeroforcing (ZF) and minimum mean square error (MMSE) methods. In addition to this, we have discussed Capacity of MIMO systems and different MIMO transmission techniques such as spatial diversity (SD), Spatial multiplexing(SM).

The results of performance evaluation for Adaptive array MIMO receivers revealed that LMS has better BER performance than SMI, SMI-CMA, and ZF and the same performance with MMSE with no need of CSI. LMS algorithm has slow convergence but low complexity compared to MMSE algorithm that has fast convergence with very high complexity. Moreover, the number of training signals can minimized by 62.5% at the cost of 2-4dB SNR using nonblind algorithm(LMS) combined with blind algorithm(CMA).

Keywords: Adaptive arrays, MIMO systems, MIMO receivers, blind algorithms, nonblind algorithms, LMS

CHAPTER 1

INTRODUCTION

1.1 Background

New generations of wireless mobile radio systems aim to provide higher data rates and a wide variety of applications (like video, data, etc.) to mobile users while serving as many users as possible. However, this goal must be achieved under spectrum and power constraints. Given the high price of spectrum and its scarcity, the systems must provide higher system capacity and performance through better use of the available resources [15].

Wireless MIMO channels have been recently attracting a great interest since they provide significant improvements in terms of spectral efficiency and reliability with respect to single-input single-output (SISO) channels. The gains obtained by the deployment of multiple antennas at both sides of the link are the array gain, the diversity gain, and the multiplexing gain [41]. The array gain is the improvement in signal-to-noise ratio (SNR) obtained by coherently combining the signals on multiple-transmit or multiple-receive dimensions while the diversity gain is the improvement in link reliability obtained by receiving replicas of the information signal through independently fading dimensions. These gains are not exclusive to MIMO channels and also exist in single-input multiple output (SIMO) and multiple-input single-output (MISO) channels. In contrast, the multiplexing gain, which refers to the increase of rate at no additional power consumption, is a unique characteristic of MIMO channels [43]. The cost of this increased rate is the added cost of deploying multiple antennas, the space requirements of these extra antennas (spatially on small handheld units), and the added complexity required for multi-dimensional signal processing [15, 41, 43].

The maximization of SINR, achieved through focusing energy into the desired directions and minimizing energy towards all other directions, is commonly known as Beamforming. This allows spatial access to the radio channel by means of different approaches, e.g., based on directional parameters or by exploiting the second order spatial statistics of the radio channel. Thus, space-time processing reduces interference and enhances the intended signal. Moreover, adaptive antennas can exploit long-term and/or short-term properties of the mobile radio channel to achieve improved channel estimation accuracy and reduced computational complexity [25].

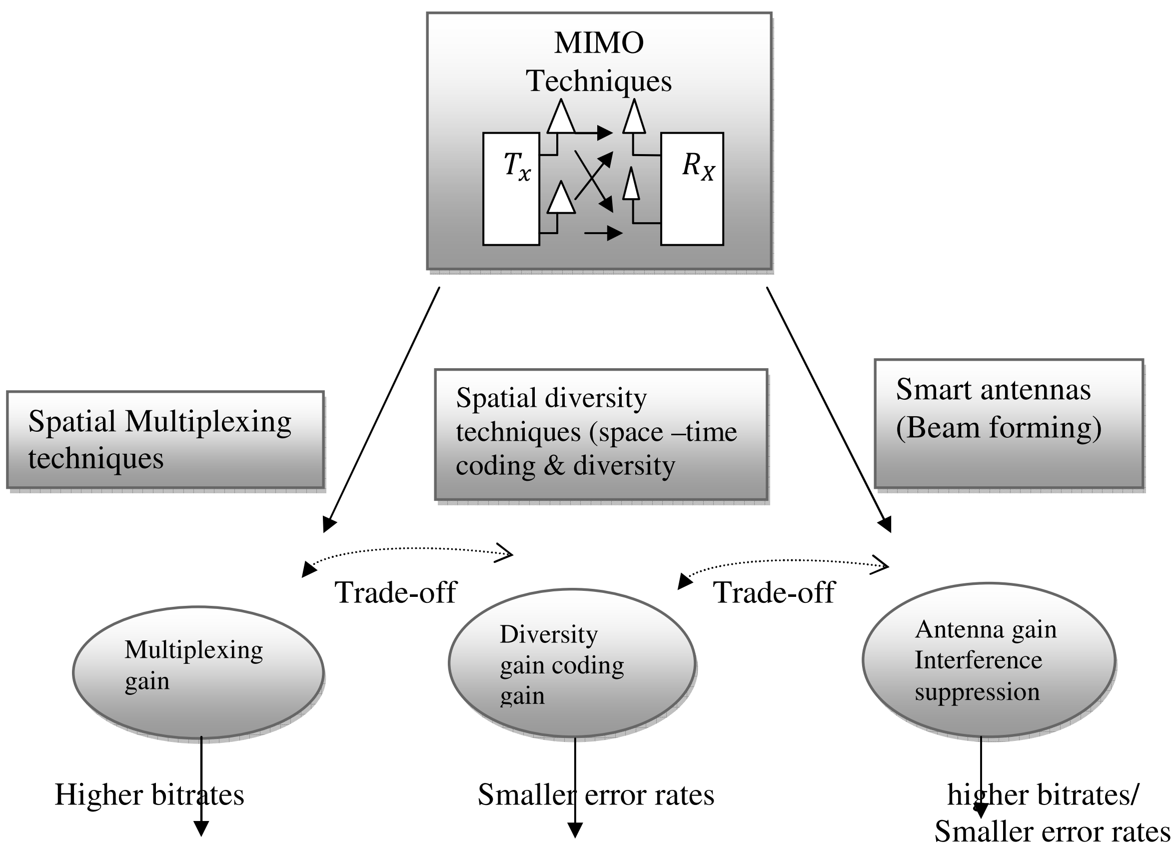


Fig.1.1 Benefits of multiple antenna techniques for wireless communication [30]

Smart antenna also known as adaptive array antennas ,multiple antennas and recently MIMO are antenna arrays with smart signal processing algorithms used to identify spatial signal signature such as the direction of arrival (DOA) of the signal, and use it to calculate beamforming vectors, to track and locate the antenna beam on the mobile /target. The antenna could optionally be any sensor. This can dramatically increase the performance characteristics (such as capacity) of wireless System [2].

These transmission strategies require efficient techniques to separate the signals of multiple sources sharing the spectrum resources at the receiver and to cancel interference, under various interference scenarios [28, 20]. Some of them use pilot signals known by both the transmitter and receiver (non blind techniques),Singular value decomposition (SVD), whereas other only employ a priori knowledge of the received signals (blind / semi-blind techniques) known as adaptive receivers. Another class of techniques assumes that the transmission channel is known at the transmitter, ZF and MMSE, this knowledge being obtained either by feedback or by time division duplexing (TDD) channel reciprocity assumption [20].

In this thesis work we study the detail, of blind and non blind adaptive array algorithms for MIMO detection methods and compare with other known class of signal separation (channel estimation) techniques such as Zeroforcing (ZF) and minimum mean square error (MMSE) methods. In addition to this we have analyzed other MIMO transmission techniques such as SM and STBC.

1.2 Thesis motivation and contribution

MIMO antenna systems are very important to increase capacity and bit error rate of wireless communication depending on the mode of transmission method such as spatial diversity and spatial multiplexing respectively. In addition to higher bit rates and smaller error rates, MIMO techniques can also be utilized to improve the signal to noise ratio (SNR) at the receiver and to suppress co-channel interference in a multiuser scenario. This is achieved by means of adaptive arrays [35], also called smart antennas. Using beam forming techniques the beam pattern of transmit and receive antennas can be steered in certain desired directions, whereas the undesired directions (e.g., directions of significant interference) can be suppressed.

The receiver must demultiplexes the spatial channels in order to detect the transmitted symbols. Various techniques have been used for this purpose, such as Zero-Forcing, which uses simple matrix inversion but results in poor results when the channel matrix is ill conditioned; MMSE, which is more robust in that sense but provides limited enhancement if knowledge of the noise or interference is not used; and Maximum Likelihood, which is optimal in the sense that it compares all possible combinations of symbols but can be too complex, especially for high-order modulation.

Instead of assuming known channel matrix H, which usually requires channel probing before each transmission and then calculating the estimated channel (W) in a burst manner, adaptive algorithms estimate W directly through iteration via the use of a known training sequence at the beginning of each transmission [34].

However at receiver side ZF, MMSE methods require Channel State information, adaptive receivers such as LMS need pilot /training signal which have a cost in bandwidth and blind algorithms such as CMA algorithms doesn't require pilot signal but has a problem in convergence.

Therefore, there is a demand of performance evaluation of adaptive array MIMO receivers, comparison of adaptive array receivers with other linear receivers such as ZF and MMSE and propose an algorithm that doesn't require CSI, minimized the number of training signals by using combination of blind and non blind algorithms. Thus contribution of this thesis includes:

- Evaluation of combined algorithm (blind and non blind) for MIMO system such as LMS-CMA
- Comparison of LMS and LMS-CMA ,SMI and SMI-CMA
- Comparison of selected Adaptive Arrays with ZF and MMSE (MIMO linear receivers)

1.3 Objective

1.3.1General objectives

The main objective of this research is to evaluate performance of Adaptive arrays for MIMO smart antenna systems.

1.3.2 Specific objectives

The detailed and specific objectives of this thesis work are outlined as follows:

- To understand different MIMO techniques
- To understand Adaptive arrays for MIMO wireless communication
- To analyze performance of different MIMO receiver systems
- Compare different adaptive algorithms for MIMO wireless communication
- To evaluate and analyze BER performance of adaptive arrays for MIMO systems
- To evaluate and analyze BER performance of combined (blind and nonblind) adaptive arrays for MIMO systems
- Compare selected adaptive array receivers with other linear MIMO detection techniques such as ZF and MMSE

1.4 Review of literatures

The performance of adaptive arrays and MIMO systems has been studied for decades from different perspectives. This subtopic aims to cover some of the literatures closely related to MIMO techniques and adaptive array systems.

A. Ikhlef and D. Le Guennec[3] investigated the problem of blind recovery of QAM and PSK signals for multiple-input multiple-output (MIMO) communication systems. They proposed a simplified version of the well-known constant modulus algorithm (CMA), namely simplified CMA (SCMA). It is shown that the proposed algorithm presents a lower computational complexity compared to the constant modulus algorithm (CMA) without loss in performances.

A.G. Constantinides et al. [12] propose novel blind separation techniques for MIMO systems based on least-squares constant modulus algorithm (LSCMA). The proposed algorithms exhibit better performance in terms of both bit error rate (BER) and convergence speed than multi-target LSCMA (MT-LSCMA) and LS multi-user CMA (LS-MU-CMA).

Zelalem F.[28] compared the performance of Spatial Multiplexing and Spatial Diversity in Rate Adaptive Wireless MIMO systems. He states that spatial multiplexing system has a higher throughput at high SNR values as compared to the spatial diversity system and at low SNR values spatial diversity system results in high throughput.

R.W.Heath Jr and A. Paulraj [35] investigated Switching between multiplexing and diversity based on constellation distance and proposed a practical algorithm that can switching between multiplexing and diversity based on constellation distance. They found a Demmel condition number of the channel matrix that provides a sufficient condition to test if multiplexing will outperform diversity for a given choice of constellation rate.

Sidi Bahri1 et al. [36] proposed a downlink multiple-input multiple-output multi-carrier code division multiple accesses (LMS-MCCDMA) system with adaptive beam forming algorithm for smart antennas. The algorithm used in this paper is based on the least mean square, with pilot channel estimation and the zero forcing equalizer in the receiver, requiring reference signal and no knowledge of the channel. They got better BER performance of LMS than STBC- multi-carrier code division multiple accesses with RMSE algorithm in the presence of large interference.

H. Dam et al [40] studied performance of adaptive antenna base stations in commercial GSM network. Their work presents system description of the first GSM prototype with adaptive antenna and a capacity increase of 120% has been achieved.

A.Bouacha et al.[46] proposed Simple Adaptive Beamforming algorithm with interference suppression that use combined algorithm (SMI-NCMA) and he has got better performance in terms of BER and Interference suppression for a SISO system.

From the above literatures we can clearly see that authors in [28] and [35] evaluated MIMO systems using only linear receivers. They didn't cover performance of adaptive array receivers. Authors in [40] and [46] evaluated performance of adaptive array for single transmitter antenna, but they didn't consider MIMO systems while authors in [3],[12] and [36] evaluate performance of MIMO system adaptive array for blind and non blind but their evaluation is only for a single algorithm and they didn't compare with other adaptive and non adaptive algorithms.

Based on these and other literature backgrounds that are referenced and used in the subsequent Chapters [2, 4, 5, 6, 7, 10, 11, 15, 20, 41, 48], the main goal of this thesis is to evaluate the performance of selected adaptive arrays algorithms for MIMO wireless communication and compare them with other MIMO system techniques such as ZF and MMSE.

1.5 Methodology

The methodology used in doing this thesis comprises **five** major phases. The first phase encompasses the reviews and study of various literatures on adaptive array and MIMO systems which help to understand the necessary theoretical background for the thesis work.

The other four phases clarify how such major tasks as Modeling, simulating, and performance analysis and evaluation are carried out. The major phases and the activities performed in each one of them are pictorially represented and elucidated below in figure 1.2, and they were performed in the order they appear in the figure.

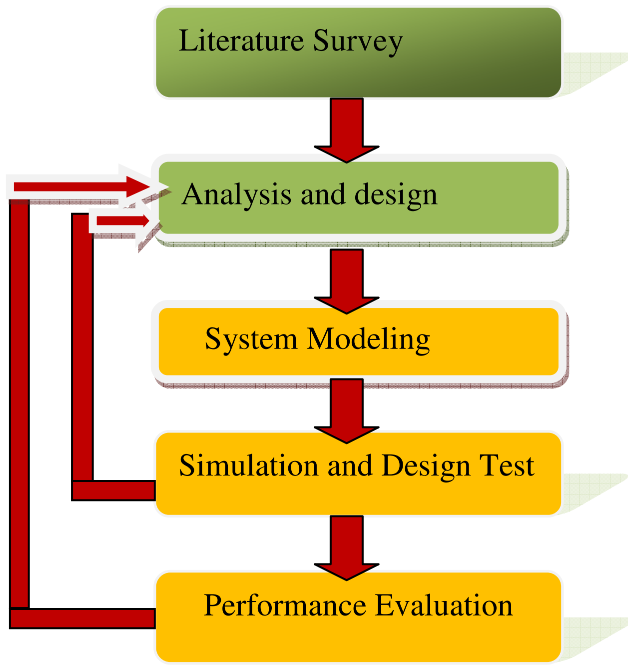


Figure.1.2 Summary of methodology

Literature Survey

This very first phase focuses on gaining all the necessary background information required to understand the broader picture of MIMO systems and the Adaptive arrays. This is accomplished by reviewing the literatures including books, articles, research publications, lecture notes, AAU previous thesis papers and other information from different related journals.

Analysis and design

This phase involves the study of various adaptive arrays and MIMO systems design and their performance , Advantages ,disadvantages and some solutions for the identified problem are also studied and finally designing the appropriate system.

System modeling

After an in-depth analysis of models and adaptive array processes, we select the appropriate adaptive process method or algorithm and develop appropriate Model of adaptive array MIMO systems.

Simulation and design test

The design is tested based on the standards. That is the Adaptive arrays are first tested for the basic parameters and then these algorithms in MIMO systems are tested through simulation for the system to check their validity and reliability.

Performance evaluation

Finally, the performance of the designed system is evaluated and analyzed for various adaptive algorithms and other linear receivers in terms of some standard measures including BER and convergence. Then the results are analyzed and conclusions on overall adaptive array MIMO smart antenna systems performance are drawn.

1.6 Organization of the thesis

The rest of the thesis is organized as follows. In chapter two, all the necessary background Information needed to become familiar with the basic and core concepts of various MIMO systems for wireless communication are presented .In chapter three, we present a detailed study of the most common blind and non blind adaptive algorithms and describe how the Adaptive Arrays work. Analytic performance analysis of different adaptive arrays for MIMO systems are presented in Chapter Four. In Chapter five Performances of the design and corresponding results are presented. Then eventually, conclusion and recommendation of the thesis works are presented in chapter six.

CHAPTER 2 MIMO SYSTEMS FOR WIRELESS COMMUNICATION

MIMO systems are defined as point-to-point communication links with multiple antennas at both the transmitter and receiver. The use of multiple antennas at both transmitter and receiver clearly provide enhanced performance over diversity systems where either the transmitter or receiver, but not both, have multiple antennas. In particular, recent research has shown that MIMO systems can significantly increase the data rates of wireless systems without increasing transmits power or bandwidth. The cost of this increased rate is the added cost of deploying multiple antennas, the space requirements of these extra antennas, and the added complexity required for multi-dimensional signal processing [15].

There are many ways to achieve the goals stated above (different MIMO techniques); each depends on the way the antennas are used and the channel model, some multiple antenna systems exist such as Single-Input Multiple-Output (SIMO), Multiple-Input Single–Output (MISO), and Space Time Coding but these are not MIMO systems.[19] Recent work in MIMO systems includes capacity of these systems under different assumptions about channel knowledge, optimal coding and decoding for these systems, and transmission strategies for uncoded systems [14].

In this chapter, we provide some background on MIMO transmission systems. We explain a general MIMO model and MIMO channel in section 2.1 and 2.2 respectively. In the next section, some introduction on MIMO capacity in comparison to SISO system is discussed. Then in section 2.3 Spatial Diversity techniques are introduced. In this subsection we consider 2X2 Alamouti STBC as an example. Spatial Multiplexing techniques such as VBLAST and DBLAST are studied in section 2.4. Finally, in section 2.5 different MIMO receiver techniques such as ZF, MMSE, ML and Adaptive receivers are discussed.

2.1 MIMO system model

In MIMO systems, the transmit and receive antennas can both be used for diversity gain. Multiplexing exploits the structure of the channel gain matrix to obtain independent signaling paths that can be used to send independent data [15]. A narrowband point-to-point communication system of N_t transmit and N_r receive antennas is shown in Figure 2.1. The transmitted matrix is a $N_t \times 1$ column matrix X, where X_i is the i^{th} component transmitted from the antenna i.

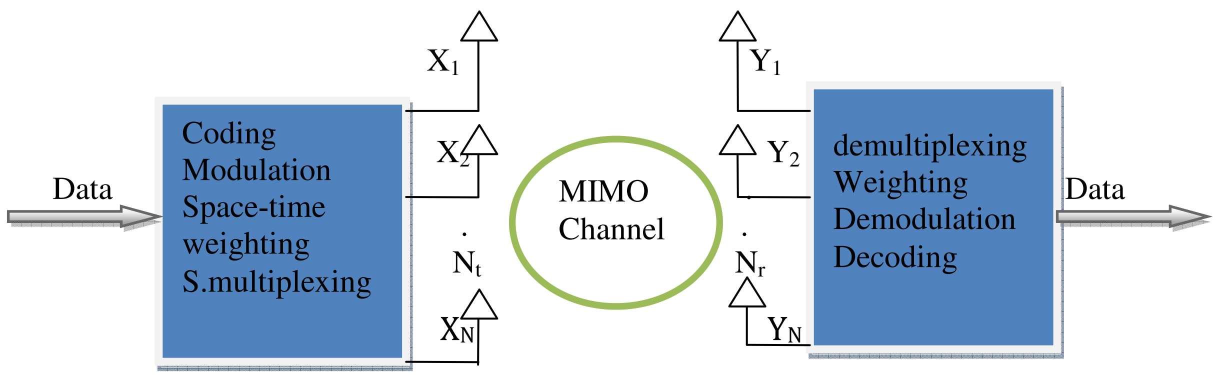


Fig 2.1 MIMO Model

2.2 MIMO channel

Since each of the receive antennas detects all of the transmitted signals, there are N x N independent propagation paths, where there are transmit and receive antennas. This allows the channel to be represented as N x N matrix. Again using a 2 x 2 System as an example, the matrix below is obtained as [8, 14, 5 and 45].

$$H = \begin{bmatrix} h_{11} & h_{12} \\ h_{21} & h_{22} \end{bmatrix} \tag{2.1}$$

Each of the elements in the channel matrix is define an independent propagation path. The transmitted signal can be represented as a vector, as can the received signal. Hence, the system can be represented as the following equation.

$$\mathbf{Y = HX + n} \tag{2.2}$$

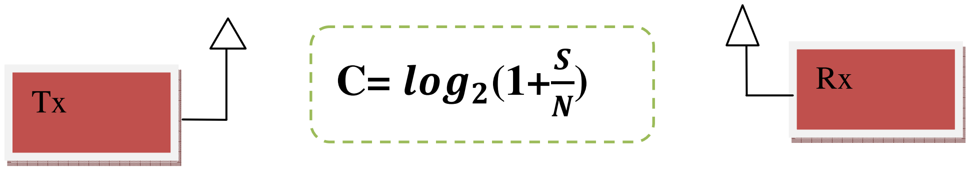
Where Y is the received signal vector, H is the channel Matrix, X is the transmitted signal vector, n is the noise. The transmitted signals in the vector Y are complex signals, as the channel matrix values and the received signals in vector X. The complex form in each of the elements in the vectors represents the power of the signal and its phase delay. The complex form of the elements of the channel matrix 'H' represent the attenuation and phase delay associated with that propagation path [45].

2.3 MIMO systems capacity

The MIMO systems provide tremendous capacity gains, which has incited significant activity to develop transmitter and receiver techniques that realize these capacity benefits and exploit diversity. This sub topic describes the Shannon capacity limits of single user MIMO system. The limits of single user MIMO systems show the maximum data rates that can be transmitted over the MIMO channel [27, 42].

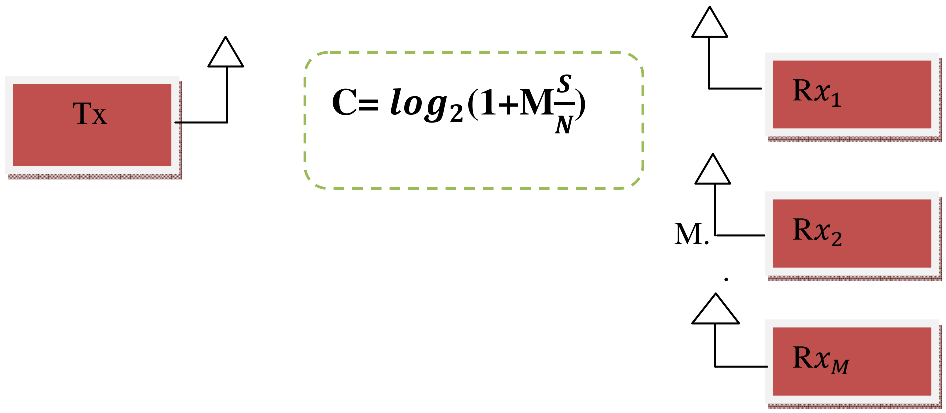
2.3.1 Channel unknown to the transmitter

The channels are assumed to have small error probability and we assume no constraints on the delay, we further assume the channel knowledge is unavailable at the transmitter and known only at the receiver.



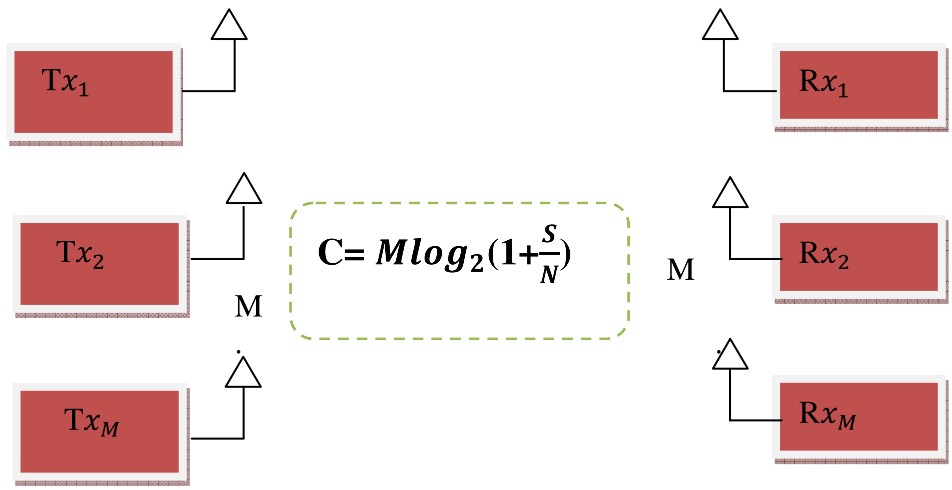
$$C = log_2(1+\frac{S}{N}) \tag{2.3}$$

Figure 2.2 Single Input Single Output (SISO) Capacity



(2.4)

Figure 2.3: Single Input Multiple Output (SIMO) Capacity



(2.5)

Fig 2.4: Multiple Input Multiple Output (MIMO) Capacity

From the above figures we can easily see that the normalized capacity of multiple antenna increases with the number of antennas. For SIMO system provides logarithmic growth of the bandwidth efficiency limit while MIMO system provides linear growth of bandwidth efficiency [27].

2.3.2 Channel known to the transmitter

It is possible by various means, which will be discussed in Chapter 4, to learn the channel state information (CSI) at the transmitter. In such an event the capacity can be increased by resorting to the so-called ‘‘water filling principle’’ [54], by assigning various levels of transmitted power to various transmitting antennas. This power is assigned on the basis that the better the channel gets, the more power it gets and vice versa. This is an optimal energy allocation algorithm [42].

Consider a MIMO channel where the channel parameters are known at the transmitter. The water-filling principle can be derived by maximizing the MIMO channel capacity under the rule that more power is allocated to the channel that is in good condition and less or none at all to the bad channels.

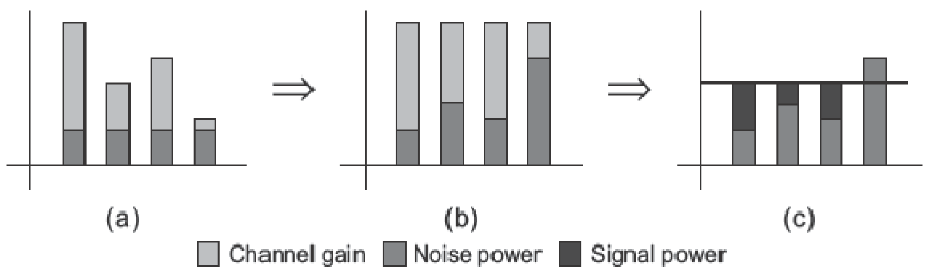


Fig2.5 Principles water-filling: (a) Channel gains and noise power on channel;(b) Channel gains and noise power after equalization;(c)determining signal power[54]

Figure 2.5- illustrates this principle, showing how the optimal transmitted power is determined. If different subchannels have different gains (a), the received signal is first equalized (b), so that all subchannels have the same gain but different noise power. The principle of water-filling is that the signal power is then added(c), such that as far as possible the total signal (equalized) noise is the same in all subchannels. We observe that less power or none at all is transmitted in subchannels with smaller gain (corresponding to smaller eigen values). Since this concentrates power where it will be most effective, it increases capacity as [37, 54].

$$C_{MIMO-WF} = W \sum_{i=1}^{n} \log_2\left(1 + \frac{S_i \lambda_i}{N}\right) \quad \textbf{(2.6)}$$

Where S_i is the signal power transmitted in the i^{th} subchannel, with $\sum_{i=1}^{n_m} S_i = S$, λ_i is the eigen value of i^{th} sub-channel. The effect is greatest on channels with reduced rank or very unbalanced, eigen-values, which typically occurs in relatively poor multipath environments, and can be equivalent to an increase in SNR of a factor up to the number of transmit antennas. This approach can be described as adaptive because the transmission in adapted to the channel [37, 54].

2.4 Spatial diversity

When a channel is rich in multipath signal components, it is possible to simulate independent virtual paths which can then be used to transmit signal copies for redundancy. The ability to transmit redundant data through independently faded channel is called Diversity. Diversity techniques like space, time and frequency are well known techniques used to improve reliability of wireless communication systems. Among them, spatial diversity technique is the most promising one, because it does not require any additional bandwidth and does not introduce additional delays in signal transmission [19].

Space–Time Block Codes (STBCs) are the simplest types of spatial temporal codes that exploit the diversity offered in systems with several transmit antennas. It was designed to achieve maximum diversity order for the given number of transmit and receive antennas subject to the constraint of having a simple decoding algorithm. In addition, space-time block coding provides full diversity advantage [19, 20].

Alamouti designed a simple transmission diversity technique for systems having two transmit antennas [14]. This method provides full diversity and requires simple linear operations at both transmission and reception side. The encoding and decoding processes are performed with blocks of transmission symbols. Detail analysis of 2X2 Alamouti space time coding is given below.

2.4.1 Alamouti space-time coding scheme (2×2)

The Alamouti space-time coding scheme for the system with two transmission antennas and two reception antennas in a memoryless channel, as proposed in [14], is shown in Figure 2.4. The transmission scheme is the same as with the 2×1 system [23].

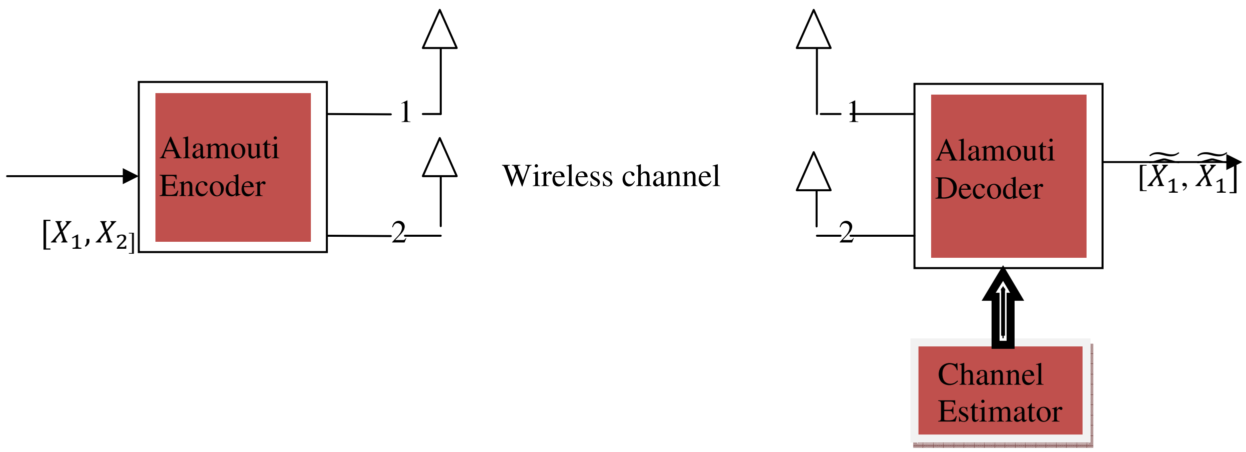


Fig.2.6. Alamouti 2×2 scheme flat slow fading channel [23]

Received signals at receive antenna 1 are [23]:

$$R_o(\mathrm{t}) = h_{11}(\mathrm{t})\, X_1(\mathrm{t}) + h_{21}(\mathrm{t})\, X_2(\mathrm{t}) + n_0(t) \tag{2.6}$$

And

$$R_1(\mathrm{t}) = -h_{11}(\mathrm{t}) X_2^*(\mathrm{t}) + h_{21}(\mathrm{n}) X_1^*(\mathrm{t}) + n_0(t+T) \tag{2.7}$$

Where n_0 represents noise at receive antenna 1.

At receive antenna 2 the received signals are:

$$R_2(\mathrm{t}) = h_{12}(\mathrm{t}) X_1(\mathrm{t}) + h_{22}(\mathrm{t}) X_2(\mathrm{t}) + n_1(t) \tag{2.8}$$

And

$$R_3(\mathrm{t}) = -h_{12}(\mathrm{t}) X_2^*(\mathrm{t}) + h_{22}(\mathrm{t}) X_1^*(\mathrm{t})(\mathrm{t}) + n_1(t+T) \tag{2.9}$$

At time instances t and t+T, respectively, where n_1 represents noise at receive antenna 2.

Again, the estimates of the signals in the decoder/combiner are given as [14, 23]

$$\widehat{X_1} = h^*{}_{11}(\mathrm{t}) R_0(\mathrm{t}) + h_{21}(\mathrm{t}) R^*{}_1(\mathrm{t}) + h^*{}_{12}(\mathrm{t}) R_2(\mathrm{t}) + h_{22}(\mathrm{t}) R_3(\mathrm{t}) \tag{2.10}$$

$$\widehat{X_2} = h^*{}_{11}(\mathrm{t}) R_0(\mathrm{t}) - h_{21}(\mathrm{t}) R^*{}_1(\mathrm{t}) + h^*{}_{12}(\mathrm{t}) R_2(\mathrm{t}) - h_{22}(\mathrm{t}) R_3(\mathrm{t}) \tag{2.11}$$

Decoded symbol blocks are obtained using a maximum likelihood (ML) detector. A maximum likihood detector maps the estimated symbols $\widehat{X_1}$ and $\widehat{X_2}$ to the most probable reference symbols from the phase shift keying modulation (PSK) or quadrature amplitude modulation (QAM) constellation being used. The measure used for mapping is the two dimensional distance between the estimated and the reference symbol on the constellation grid.

2.5 Spatial multiplexing

Spatial multiplexing scheme exploits the rich scattering wireless channel allowing the receiver antennas to detect the different signals simultaneously transmitted by the transmit antennas. That is, spatial multiplexing method uses multiple antennas at the transmitter and the receiver in conjunction with rich scattering environment within the same frequency band to provide a linearly increasing capacity gain in the number of antennas. Hence, the concept of spatial multiplexing is different from that of space-time coding method, which permits to efficiently introduce a space-time correlation among transmitted signals to improve information protection and increase diversity gain [16, 28].

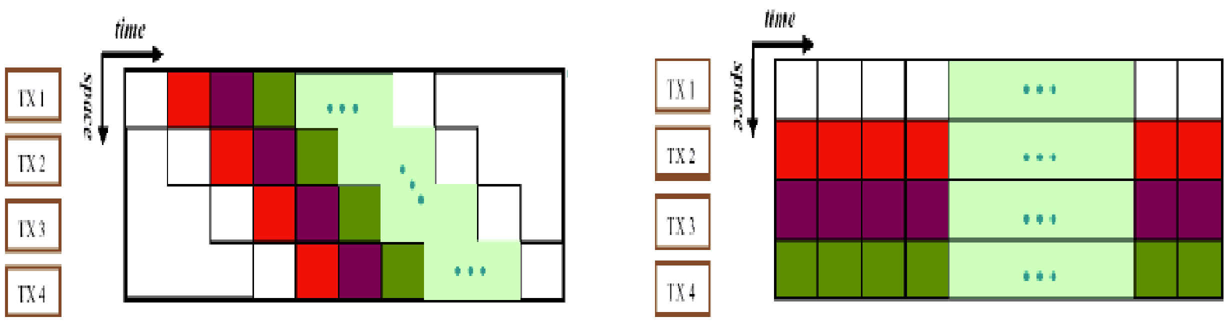
The main concept of SM is to provide simultaneous transmissions of M information streams in the same frequency band from M transmit antennas. However, by using such a transmission method, a constraint is introduced where the number of receive antennas must be equal or greater than the number of transmit antennas ($N \geq M$) in order to separate and detect the M transmitted signals. Spatial multiplexing primarily leads to multiplexing gain with the gain factor equal to the minimum number of Transmit (Mt) or Receive (Mr) antenna [16, 28, 30].

The most known spatial multiplexing schemes are the BLAST family which includes Vertical-BLAST, Diagonal-BLAST, and Turbo-BLAST. The acronym BLAST stands for “Bell Laboratories Layered Space-Time” [52].

Vertical Bell Lab Layered Space Time (V-BLAST): as the name suggests, this is an invention of Bell Labs, V-BLAST sends M bit flows out by mutually independent antennas after they are encoded, mapped and interleaved, so that the diversity gain is fully tapped, and each flow of message can be tested separately. Optimal V-BLAST requires MT transmit and MR receive antenna for full Multiplexing gain, it provides multiplexing gain with no diversity gain [24, 53].

Diagonal Bell Lab Layered Space Time (D-BLAST): D-BLAST transmits encoded and interleaved codeword in a rotated manner across the entire MT antennas. It achieves this by introducing delays of 1 symbol between the start of each codeword across the antennas thereby spreading out the codeword in time and space. D-BLAST achieves diversity and multiplexing gain but that comes at the expense of wasted space-time dimension [24, 52].

Diagonal Bell Laboratories Layered Space-Time architecture (D-BLAST) is one of the spatial multiplexing schemes to approach the theoretical capacity limit of multiple -input multiple -output (MIMO) systems. However, due to its complex coding procedure, Vertical Bell Laboratories Layered Space-Time architecture (V-BLAST) has been proposed as a simplified version. In V-BLAST, channel coding may be applied to individual antennas (sub-layers), corresponding to the data stream transmitted from each transmit antenna, while in D-BLAST coding processing is applied not only across the time but also to each sub-layer, which implies higher complexity [52,53]. The simple comparison between D-BLAST and V-BLAST is shown at Fig.2.5.



(a) (b)

Fig 2.7 Transmit coding scheme comparison between (a) D-BLAST and (b) V-BLAST

From the above figure, we can see that the essential difference between D-/V-BLAST is the vector encoding process. In D-BLAST system, redundancy between the sub-streams is introduced by using specialized inter-sub-stream block coding, and code blocks organized along diagonals in space-time leads higher spectral efficiencies. On the other hand, in V-BLAST system, demultiplexing followed by independent bit-to-symbol mapping of each sub-stream, so no coding is required. From these implemental advantages of V-BLAST, we will focus on the aspect of V-BLAST among several spatial multiplexing methods [52, 16].

2.6 MIMO receivers

2.6.1 Maximum Likelihood (ML) receiver

It is well known that theoretically, maximum likelihood detection algorithm is the optimum method of recovering the transmitted signal at the receiver. ML receiver is a method that compares the received signals with all possible transmitted signal vectors which is modified by channel matrix **H** and estimates the transmitted symbol vector **x** according to the Maximum Likelihood principle , which is given as[42].

$$\hat{X} = \arg_{\mathrm{X}_k \varepsilon \{\mathrm{X}_1,\dots,\mathrm{X}_{\mathrm{NT}}\}} \min \left\| \mathrm{Y} - \mathrm{H}X_k \right\|^2 \tag{2.12}$$

Where $\hat{X}$ is the estimated symbol vector. The ML receiver searches through the entire vector constellations for the most probable transmitted signal vector. However, since the complexity increases exponentially with the number of transmit antennas, it is very difficult to use the receiver in practice, which is the main disadvantage of this method [17, 27, 28]. For example, in the case of 4 transmit antennas and 16-QAM transmission, a total of 16^4 = 65536 comparisons per symbol is required to be enumerated for each transmitted symbol. Therefore, the complexity of ML receiver is high and even prohibitive when many antennas or high order modulation schemes are used [11].

2.6.2 Zero Forcing (ZF) linear receiver

The MIMO version of the ZF receiver acts similarly to a ZF equalizer in frequency selective channels. The MIMO channel is inverted at the receiver in order to totally suppress the interference from other transmitted symbols. The output of the ZF filter is thus only a function of the symbol to be detected and the noise. It is then fed into a ML decoder which estimates the transmitted symbol. The complexity of ZF decoding is similar to SISO ML decoding, but the inversion step is responsible for the noise enhancement [11].

The ZF receiver is a linear receiver. It behaves like a linear filter and separates the data streams and thereafter independently decodes each stream. We assume that the channel matrix H is invertible and estimate the transmitted data symbol vector as [42, 28].

$$\hat{X} = (H^H H)^{-1} HX = H^{\dagger} X \tag{2.13}$$

Where † represents pseudo inverse, since an inverse of H can only exist if the columns of H are independent, it is assumed that H = Hv (i.e., the entries are i.i.d). The noise in the separated streams is correlated and consequently the SNRs are not independent [42].

2.6.3 Minimum Mean Square Error (MMSE) linear receiver

ZF receiver eliminates the interference but enhances noise. This might not be significant at high SNR, but at low SNR, it is both sensible and practical to design a filter maximizing the global signal to noise plus interference ratio (SINR). One possibility is to minimize the total resulting noise [11].The solution of the linear MMSE is given by [11, 42].

$$\hat{\mathbf{X}} = \left(\frac{\mathbf{I}_{\mathbf{M_R}}}{\mathbf{SNR}} + \mathbf{H}^{\mathbf{H}}\mathbf{H}\right)^{-1} \mathbf{H}^{\mathbf{H}}\mathbf{Y} \tag{2.14}$$

In above equation, the superscript H denotes the complex conjugate transpose. I_{M_R} is M_R X M_R identity matrix and SNR is the signal-to-noise ratio of each data stream. The ZF receiver perfectly separates the cochannels' signals at the cost of noise enhancement. The MMSE receiver, on the other hand, can minimize the overall error caused by noise and mutual interference between the cochannel signals [42, 28].

2.6.4 Adaptive MIMO linear receiver

In ZF and MMSE the information of the channel response is obtained from the channel measurement or channel estimation to set the equalizer. For Adaptive algorithms, instead of estimating the channel, equalizer taps are automatically adjusted by periodically sending training symbols and allowing the equalizer taps to adjust its parameters in response to these known symbols and corresponding received signals. The next two chapters discuss detail of these adaptive algorithms.

CHAPTER

3 ADAPTIVE ARRAY SYSTEMS

3.1 Overview of adaptive array systems

Adaptive array antenna systems have undergone enormous growth and development in the past few years. A major reason for the progress is their ability to automatically respond to an unknown interference environment by steering nulls and reducing side lobe levels in the direction of the interference, while keeping desired signal beam characteristics. A system with adaptive antenna arrays and processors can perform filtering thus reducing the sensitivity of the receiving system to interfering noise sources [10].

Generally located at a base station, a smart antenna system combines an antenna array with digital signal processing capability to transmit and receive in an adaptive, spatially sensitive manner. In other words, such a system can automatically change the directionality of its radiation pattern in response to its signal environment. Smart antennas also known as adaptive array antennas, multiple antennas and recently MIMO are antenna arrays with smart signal processing algorithms. It is used to identify spatial signal signature such as the direction of arrival (DOA) of the signal, and used to calculate beamforming vectors, that track and locate the antenna beam on the mobile/target. This can dramatically increase the performance characteristics (such as capacity, BER) of wireless System [1, 2].

Adaptive beam forming algorithms are classified into two groups, known as non blind adaptive algorithms and blind adaptive algorithms. Non blind algorithms use a training signal d (n) to update its complex weight vectors. LMS, RLS, SMI etc algorithms are categorized as non blind algorithms. Blind algorithms do not require any training sequence to update its complex weight vectors .CMA, MCMA, SCMA and DD are categorized as blind algorithms. A classification of such adaptive array algorithms is shown in Figure 3.1 [2, 9].

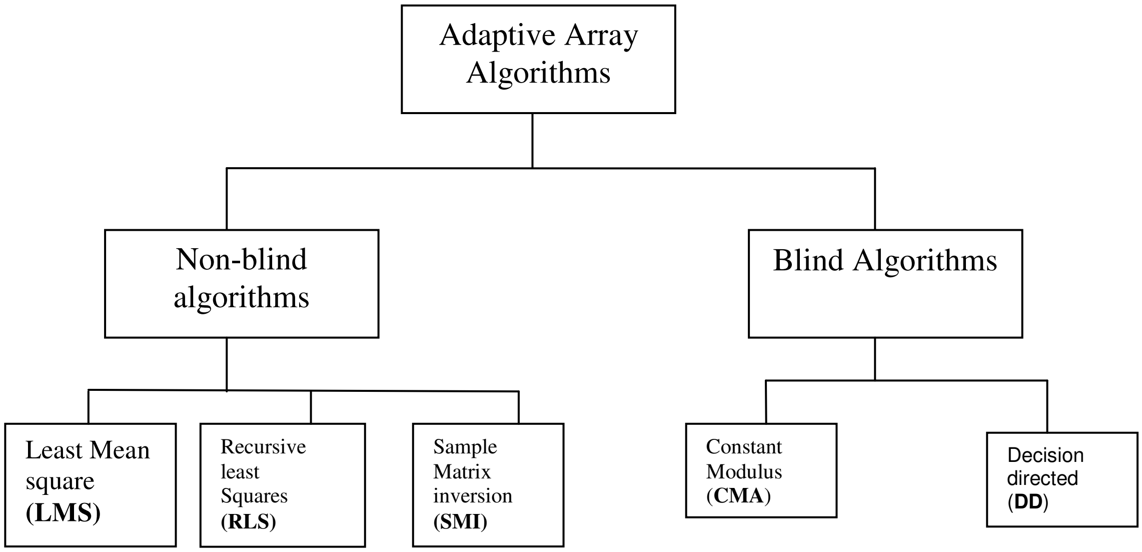


Fig. 3.1 Classification of adaptive array algorithms

The remainder of this chapter is organized as follows: In the next section, some background on non blind adaptive array algorithms such as LMS, RLS, SMI are given and their adaptation techniques are discussed. Then, in Section 3.3, the Blind adaptive array algorithms such as CMA and MCMA are considered. Finally, some considerations in Selection of Adaptive Array Algorithms are given in Section 3.4.

3.2 Nonblind adaptive algorithms

In a non-blind adaptive algorithm, a training signal, d (n), which is known to both the transmitter and receiver, is sent from the transmitter to the receiver during the training period. The beamformer in the receiver uses the information of the training signal to compute the optimal weight vector, W_{opt}. After the training period, data is sent and the beamformer uses the weight vector computed previously to process the received signal. If the radio channel and the interference characteristics remain constant from one training period until the next, the weight vector, the optimal weight (W_{opt}), will contain the information of the channel and the interference, and their effect on the received signal will be compensated in the output of the array[1, 6, 27, 49].

3.2.1 Least Mean Square (LMS) algorithm

The least-mean-square (LMS) is a search algorithm in which a simplification of the gradient vector computation is made possible by appropriately modifying the objective function. The LMS algorithm, as well as others related to it, is widely used in various applications of adaptive filtering due to its computational simplicity [9].

The LMS algorithm is by far the most widely used algorithm in adaptive filtering for several reasons. The main features that attracted the use of the LMS algorithm are low computational complexity, proof of convergence in stationary environment, unbiased convergence in the mean to the Wiener solution, and stable behavior when implemented with finite-precision arithmetic. The convergence analysis of the LMS presented here utilizes the independence assumption [7, 6, 9].

For the LMS algorithm it is necessary to have a reference signal d[n] representing the desired filter output. The difference between the reference signal and the actual output of the transversal filter is the error signal as in [7, 9].

$$e[n] = d[n] - W^H[n]Y[n] \tag{3.1}$$

From the method of steepest descent, the weight vector equation is given as in [9]

$$W(n+1) = W(n) + \frac{1}{2}\mu\,[-\Delta\,(E\,\{e^2(n)\}\,)] \tag{3.2}$$

Where μ is the step-size parameter, (0< μ <1), and controls the convergence characteristics of the LMS algorithm; $e^2(n)$ is the mean square error between the beamformer output y(n) and the reference signal which is given by[1,40].

$$e^2(n)=[d^*(n) - W^H\,Y(n)]^2 \tag{3.3}$$

The gradient of the vector in the above weight update equation can be computed as:

$$\nabla_W \left(\mathrm{E}\left\{e^2(n)\right\}\right) = -2\mathrm{r} + 2\mathrm{RW}(n) \tag{3.4}$$

In the method of steepest descent the biggest problem is the computation involved in finding the values r and R matrices in real time. The LMS algorithm on the other hand simplifies this by using the instantaneous values of covariance matrices r and R instead of their actual values i.e.

$$\mathrm{R}(n) = \mathrm{E}\{\mathrm{Y}(n) Y^H(n)\} \tag{3.5}$$

$$\mathrm{r}(n) = \mathrm{E}\{ d^*(n) Y(n)\} \tag{3.6}$$

Where R is the autocorrelation of the received signal, r is the cross correlation of the received signal and the reference signal [9].

Therefore the weight update can be given by the following equation,

$$\mathrm{W}(n+1) = \mathrm{W}(n) + \mu \mathrm{Y}(n) \left[d^*(n) - Y^H(n) W(n)\right] \tag{3.7}$$

$$= \mathrm{W}(n) + \mu \mathrm{Y}(n)\, e^*(n) \tag{3.8}$$

The LMS algorithm is initiated with an arbitrary value W (0) for the weight vector at n=0. The successive corrections of the weight vector eventually leads to the minimum value of the mean squared error.

3.2.3 Convergence and stability of LMS algorithm

The step-size parameter or the convergence factor μ is the basis for the convergence speed of the LMS algorithm. The LMS algorithm initiated with some arbitrary value for the weight vector is seen to converge and stay stable for:

$$0 < \mu < 1/\lambda_{max} \tag{3.9}$$

Where λ_{max} is the largest eigenvalue of the correlation matrix R, the convergence of the algorithm is inversely proportional to the eigenvalue spread of the correlation matrix R. When the eigenvalues of R are widespread, convergence may be slow. The eigenvalue spread of the correlation matrix is estimated by computing the ratio of the largest eigenvalue to the smallest eigenvalue of the matrix. If μ is chosen to be very small then the algorithm converges very slowly. A large value of μ may lead to a faster convergence but may be less stable around the minimum value [7, 10, 47].

The upper bound obtained for the value of μ is important from the practical point of view, because it gives us an indication of the maximum value of μ that could be used in order to achieve convergence of the coefficients. However, the given upper bound is somewhat optimistic due to the approximations and assumptions made. In most cases, the value of μ should not be chosen close to the upper bound [51].

To solve convergence and stability contradict a variable step size is introduced [47]. We can increase the stepsize to improve the speed of convergence in the period of convergence and decrease the step-size to improve the accuracy of convergence after the period of convergence. The algorithm based on the adaptive variable step-size formula is given by [47] is:

$$\mu = \frac{(\mu_{max} - \mu_{min}) X (generation_{max} - g_i)}{generation_{max} + \mu_{min}} \tag{3.10}$$

Where μ_{max} is the maximum step, μ_{min} is the minimum of step size, $generation_{max}$ is the maximal number of iterations, g_i is the ith iteration. In the above formula, μ_{max}, μ_{min} and $generation_{max}$ are all fixed value. The step factor will be corrected continually when the current number of iterations is constant change. In this case, the step size can be adjusted adaptively. It would be increased during the beginning period and deceased during the process of convergence [47].

3.2.3 Sample Matrix Inversion (SMI)

The LMS algorithm discussed in the previous section is a continuously adaptive algorithm and has a slow convergence when the eigen values of the covariance matrix are widespread. When the transmission is discontinuous, a block adaptive approach would give a better performance than a continuous approach. One such algorithm is the Sample Matrix Inversion (SMI), which provides good performance in a discontinuous traffic. However, it requires that the number of interferers and their positions remain constant during the duration of the block acquisition [9, 30].

The SMI algorithm has a faster convergence rate since it employs direct inversion of the covariance matrix R. Let us recall the equations for the covariance matrix R and the correlation matrix r as [9].

$$\mathrm{R} = \mathrm{E}[\mathrm{Y}(\mathrm{n}) Y^{H}(n)] \tag{3.11}$$

$$\mathrm{r} = \mathrm{E}[\mathrm{d}(\mathrm{n}) \mathrm{Y}(\mathrm{n})] \tag{3.12}$$

If a priori information about the desired and the interfering signals is known, then the optimum weights can be calculated directly by using the Weiner solution given [9].

$$W_{Opt} = R^{-1}\mathrm{r} \tag{3.13}$$

However, in practice signals are not known and the signal environment keeps changing. Therefore optimal weights can be computed by obtaining the estimates of the covariance matrix R and the correlation matrix r, by time averaging from the block of input data. The estimates of the matrices over a block size N2-N1 are given by

$$\widehat{\mathrm{R}} = \frac{1}{N_2 - N_2 + 1} \sum_{\mathrm{i}=\mathrm{N}_1}^{\mathrm{N}_2} \mathrm{Y}(\mathrm{i}) \mathrm{Y}^{\mathrm{H}}(\mathrm{i}) \tag{3.14}$$

$$\hat{\mathbf{r}} = \frac{1}{N_2 - N_2 + 1} \sum_{\mathrm{i}=\mathrm{N}_1}^{\mathrm{N}_2} \mathrm{d}^{*}(\mathrm{i}) \mathrm{Y}^{\mathrm{H}}(\mathrm{i}) \tag{3.15}$$

Where N_1 and N_2 form the lower and the upper limit of the observation interval. The weight vector can now be estimated by the following equation:

$$\widehat{W} = \hat{R}^{-1}\hat{r} \tag{3.16}$$

Based on the above discussion the weights will be updated for each incoming block. There is always a residual error in the SMI algorithm since it is based on estimation. This error is usually greater when compared to the LMS error. The error due to estimates can be computed by the following equation as [9].

$$\mathrm{e} = \hat{R}^{-1}\hat{r} - \widehat{W} \tag{3.17}$$

The stability of the SMI algorithm depends on the ability to invert the large covariance matrix. In order to avoid a singularity of the covariance matrix, a zero- mean white Gaussian noise is added to the array response vector. It creates a strong additive component to the diagonal of the matrix. In the absence of noise in the system, a singularity occurs when the number of signals to be resolved is less than the number of elements in the array [2, 7, 9].

Since SMI employs direct matrix inversion the convergence of this algorithm is much faster compared to the LMS algorithm. However, huge matrix inversions lead to computational complexities that cannot be easily overcome [9].

3.2.4 Recursive Least Square (RLS) algorithm

As was mentioned in the previous section, the SMI technique has several drawbacks. Even though the SMI method is faster than the LMS algorithm, the computational burden and potential singularities can cause problems. However, we can recursively calculate the required correlation matrix and the required correlation vector. Recall that in Eqs (3.12) and (3.13) the estimate of the correlation matrix and vector was taken as the sum of the terms divided by the block length K. When we calculate the weights in Eq. (3.14), the division by K is cancelled by the product $\bar{R}^{-1}xx$ (k) $\bar{r}$(k)[9]. Thus, we can rewrite the correlation matrix and the correlation vector omitting K as [9].

$$\hat{\mathbf{R}}_{YY}(k)=\sum_{i=1}^{k} \bar{Y}(i)\bar{Y}^{H}(i) \tag{3.18}$$

$$\hat{\mathbf{r}}(k)=\sum_{i=1}^{k} d^{*}(i)\bar{Y}^{H}(i) \tag{3.19}$$

Where k is the block length and last time sample k and $\hat{R}_{xx}$(k), $\hat{r}$(k) is the correlation estimates ending at time sample k. summations of (Eqs. (3.16) and (3.17)) use rectangular windows, thus they equally consider all previous time samples. Since the signal sources can change or slowly move with time, we might want to deemphasize the earliest data samples and emphasize the most recent ones. This can be accomplished by modifying Eqs. (3.16) and (3.17), such that we forget the earliest time samples. This is called a weighted estimate [9, 7, 10].

Thus

$$\hat{\mathbf{R}}_{\mathbf{YY}}(\mathbf{n})=\sum_{i=1}^{k} \alpha^{k-i}\bar{\mathbf{Y}}(i)\bar{\mathbf{Y}}^{H}(i) \tag{3.20}$$

$$\hat{\mathbf{r}}(\mathbf{n})=\sum_{i=1}^{k} \alpha^{k-i}\mathbf{d}^{*}(i)\bar{Y}^{H}(i) \tag{3.21}$$

Where α is the forgetting factor.

The forgetting factor is also sometimes referred to as the exponential weighting factor [7]. α is a positive constant such that $0 \leq \alpha \leq 1$.When $\alpha = 1$, we restore the ordinary least squares algorithm. α = 1also indicates infinite memory. Let us break up the summation in Eqs. (3.18) and (3.19) into two terms: the summation for values up to i = k−1 and last term for i = k.

$$\hat{R}_{YY}(n)=\alpha\sum_{i=1}^{k-1}\alpha^{k-1-i}\bar{Y}(i)\bar{Y}^{H}(i)+\bar{Y}(n)\bar{Y}^{H}(n)$$

$$=\ \alpha\,\hat{R}_{YY}(n-1)+\bar{Y}(n)\bar{Y}^{H}(n) \qquad (3.22)$$

$$\hat{r}(n)=\alpha\sum_{i=1}^{k-1}\alpha^{k-1-i}\ d^{*}(i)\bar{Y}^{H}(i)+d^{*}(n)\bar{Y}^{H}(n)$$

$$=\alpha\,\hat{r}(n-1)+d^{*}(n)\bar{Y}^{H}(n) \qquad (3.23)$$

Thus, future values for the array correlation estimate and the vector correlation estimate can be found using previous values. Not only can we recursively calculate the most recent correlation estimates, we can also use Eq. (3.20) to derive a recursion relationship for the inverse of the correlation matrix. The next steps follow the derivation in. The inverse of equation 3.20 is given by [9, 23].

$$\hat{\mathbf{R}}_{YY}^{-1}(n-1)=\alpha^{-1}\,\hat{\mathbf{R}}_{YY}^{-1}(n-1)-\frac{\alpha^{-2}\,\hat{\mathbf{R}}_{YY}^{-2}(n-1)\bar{Y}(n)\bar{Y}^{H}(n)\hat{R}_{YY}^{-1}(n-1)}{1+\alpha^{-1}\,\widehat{\bar{Y}^{H}R}_{YY}^{-1}(n-1)\bar{Y}(n)} \qquad (3.24)$$

We can simplify Eq. (3.22) by defining the gain vector $\hat{g}(k)$ given by

$$\hat{g}(n)=\frac{\alpha^{-1}\,\hat{\mathbf{R}}_{YY}^{-2}(n-1)\bar{Y}(n)\bar{Y}^{H}(n)\hat{\mathbf{R}}_{YY}^{-1}(n-1)}{1+\alpha^{-1}\,\widehat{\bar{Y}^{H}R}_{YY}^{-1}(n-1)\bar{Y}(n)} \qquad (3.25)$$

Thus

$$\hat{R}_{YY}^{-1}(n-1)=\alpha^{-1}\,\hat{R}_{YY}^{-1}(n-1)-\hat{g}(n)\alpha^{-1}\,\bar{Y}^{H}(n)\hat{R}_{YY}^{-1}(n-1) \qquad (3.26)$$

Now we can derive a recursion relationship to update the weight vectors. The optimum Wiener solution is repeated in terms of the iteration number *n* and we can substitute Eq. (3.20) yielding

$$\hat{W}(n)=\hat{R}_{YY}^{-1}(n)\hat{\mathbf{r}}(n)$$

$$=\alpha^{-1}\,\hat{R}_{YY}^{-1}(n)\hat{\mathbf{r}}(n-1)+\hat{R}_{YY}^{-1}(n)\bar{Y}(n)d^{*}(n) \qquad (3.27)$$

Finally, using eq.(3.24) and eq.(3.25) we get the following eq. given by[1,7,9].

$$\hat{W}(n)=\hat{W}(n-1)+\hat{g}(n)[d^{*}(n)-\bar{Y}^{H}(n)\hat{W}(n-1)] \qquad (3.28)$$

The advantage of the RLS algorithm over SMI is that it is no longer necessary to invert a large correlation matrix. The recursive equations allow for easy updates of the inverse of the correlation matrix. The RLS algorithm also converges much more quickly than the LMS algorithm.

3.3 Blind adaptive algorithms

Sending training symbols at the beginning to initialize the receiver can be impractical and not effective for some applications. The correct sampling point has to be known in order to extract the training symbols before the equalizer converges. However, trained algorithms need information from training sequences to converge. In addition to the above issues, the training sequence will also consume bandwidth. So, in some cases, it is desirable to estimate the channel without the aid of training sequence and the method is called blind algorithms [7, 9, 10]. Some commonly known blind algorithms are investigated in this section.

3.3.1 Constant Modulus Algorithms (CMA)

Many adaptive beamforming algorithms are based on minimizing the error between a reference signal and the array output. The reference signal is typically a training sequence used to *train* the adaptive array or a desired signal based upon an a priori knowledge of nature of the arriving signals. In the case where a reference signal is not available one must resort to an assortment of optimization techniques that are blind to the exact content of the incoming signals [9].

Many wireless communication and radar signals are frequency-or phase-modulated signals. Some examples of phase and frequency modulated signals are FM, PSK, FSK, QAM. This being the case, the amplitude of the signal should ideally be a constant. Thus the signal is said to have a constant magnitude or modulus. However, in fading channels, where multipath terms exist, the received signal is the composite of all multipath terms. Thus, the channel introduces an amplitude variation on the signal magnitude. Frequency selective channels by definition destroy the constant modulus property of the signal. If we know that the arriving signals of interest should have a constant modulus, we can devise algorithms that restore or equalize the amplitude of the original signal [1, 9].

Dominique Godard [50] was the first to capitalize on the constant modulus (CM) property in order to create a family of blind equalization algorithms to be used in two-dimensional data communication systems. Specifically, Godard's algorithm applies to phase modulating waveforms. Godard used a cost function called a dispersion function of order p and, after minimization, the optimum weights are found. The Godard cost function is given by [1, 9, 50].

$$Z(n)=W^{H}Y[n] \tag{3.29}$$

$$J(n)=E[(|Z(n)|^{p}-R_{p})^{q}] \tag{3.30}$$

Where p is the positive integer and q is the positive integer = 1 [9].Godard showed that the gradient of the cost function is zero when R_p is given by [1, 9, 33].

$$R_{p}=\frac{E[|S(n)|^{2p}]}{E[|S(n)|^{p}]} \tag{3.31}$$

Where is the zero-memory estimate of $Z(n)$. This cost function's optimization results in the filter coefficients update which equalize only the symbol amplitude, without depending on the carrier phase, and also it is differentiated to the derivative at which an LMS type algorithm is obtained. The resulting error signal and update equation for the equalizer coefficients are given by [9, 33].

$$\mathbf{e(n)}=\mathbf{Z(n)}|\boldsymbol{Z}(n)|^{p-2}(\mathbf{R_{p}}-|\boldsymbol{Z}(n)|^{p}) \tag{3.32}$$

This error signal can replace the traditional error signal in the LMS algorithm to yield

$$\overline{\mathbf{w}}(n+1)=\overline{\mathbf{w}}(n)+\mu\mathbf{Y}(n)\,\mathbf{Z(n)}|\boldsymbol{Z}(n)|^{p-2}(\mathbf{R_{p}}-|\boldsymbol{Z}(n)|^{p})$$
$$\overline{\mathbf{w}}(n+1)=\overline{\mathbf{w}}(n)+\mu\mathbf{e}^{*}(n)\mathbf{Y}(n) \tag{3.33}$$

The p = 1 case reduces the cost function to the form

$$J(n)=E[(|\mathbf{Z}(n)|-R_{1})^{2}] \tag{3.34}$$

Where

$$R_{1}=\frac{E[|S(n)|^{2}]}{E[|S(n)|]} \tag{3.35}$$

If we scale the output estimate S(n) to unity, we can write the error signal in Eqn. (3.24) as

$$e(n)=\left(Z(n)-\frac{Z(n)}{|Z(n)|}\right) \quad (3.36)$$

Thus the weight vector, in the $p = 1$ case, becomes

$$\bar{w}(n+1) = \bar{w}(n)+\mu\left(1-\frac{1}{|Z(n)|}\right) Z^{*}(n)\bar{Y}(n) \quad (3.37)$$

3.3.2 Modified Constant Modulus Algorithm (MCMA)

The CMA (Constant Modulus Algorithm) algorithm expects constellations with a constant amplitude, which degrades the equalization performance when an M-QAM (M>4) modulation is used since it has multi-modulus property. In order to improve the performance of the CMA for M-QAM (M>4), a multi-modulus algorithm, called MCMA (Modified Constant Modulus Algorithm), has been proposed in [29, 48]. In this algorithm the cost function for CMA (3.22) is modified to consider the real and imaginary parts separately. The modified cost function is written as [48].

$$J^{mcma}(n)=J_R(n)+J_I(n) \quad (3.38)$$

Where $J_R(n)$ and $J_I(n)$ are the cost functions for the real- and imaginary parts of the equalizer output $y(n) = y_R(n) + j\,.y_I(n)$ respectively and they are defined as[48].

$$J_R(n)=E\{(|R\{Z(n)\}|^2 - R_R)^2\} \quad (3.39)$$

$$J_I(n)=E\{(|I\{Z(n)\}|^2 - R_I)^2\} \quad (3.40)$$

Assuming the input data are complex numbers with two dimensions, R_R and R_I are the real constants determined for the real and imaginary parts of the source signals respectively

$$R_R=\frac{E[R|S(n)|^4]}{E[R|S(n)|^3]} \quad (3.41)$$

$$R_I=\frac{E[I|S(n)|^4]}{E[I|S(n)|^3]} \quad (3.42)$$

Where R{s(n)} and I{s(n)} denote the real and imaginary part of source signals s(n) respectively.The tap weights vector is updated using SGD to optimize the cost function

$$W(n+1)=W(n)-\mu e(n)Y^H(n) \quad (3.43)$$

Where the error signal $e(n) = e_R(n) + j\, e_I(n)$ is given by

$$e_{R(n)}=R\{Z(n)\}(|R\{Z(k)\}|^2-R_R) \tag{3.44}$$

$$e_{I(n)}=I\{Z(n)\}(|I\{Z(k)\}|^2-R_I) \tag{3.45}$$

3.4 Selection of adaptive array algorithms

For one adaptive array, there may exist several adaptive algorithms that could be used to adjust the weight vector. The choice of one algorithm over another is determined by various factors:

1. **Rate of convergence**. This is defined as the number of iterations required for the algorithm, in response to stationary input, to converge to the optimum solution. A fast rate of convergence allows the algorithm to adapt rapidly to a stationary environment of unknown statistics.

2.**Tracking.** When an adaptive algorithm operates in a non stationary environment, the algorithm is required to track statistical variations in the environment.

3.**Robustness**. In one context, robustness refers to the ability of the algorithm to operate satisfactorily with ill-conditioned input data. The term robustness is also used in the context of numerical behavior.

4. **Computational requirements**. Here the issues of concern include:

- ✓ The number of operations (i. e., multiplications, divisions, and dditions/subtractions) required to make one complete iteration of the algorithm,
- ✓ the size of memory locations required to store the data and the program, and
- ✓ The investment required to program the algorithm on a computer or a DSP processor. Since there exists a mapping between the narrowband beamformer and the FIR filter [1].

The table below summarizes pros and cons of different adaptive array algorithms.

Table 3.1.: Advantages and disadvantages of Adaptive Algorithms

Algorithms	Advantages	Disadvantages
LMS	Always converges,	Require training sequence
SMI	Always converges ,Faster than LMS	Require training sequence, computationally complex
RLS	Always Converges ,10 times Faster than LMS	Require training sequence and Rxx^{-1}
CMA	Doesn't Require training sequence	Theoretically may not converge

Table 3.2.: Performance of MIMO receivers [15]

Algorithm	Complexity	Convergence	Tracking
LMS	Low	Slow	Poor
MMSE	Very High	Fast	Good
RLS	High	Fast	Good

CHAPTER

4 PERFORMANCE ANALYSIS OF ADAPTIVE ARRAYS FOR MIMO SYSTEMS

In this chapter, we provide some background on adaptive arrays for MIMO systems. We explain a System model of Adaptive arrays for MIMO systems in section 4.1. In the next sections, some introduction on Channel State Information, LMS for MIMO, and SMI for MIMO systems are discussed. Then SMI-CMA and LMS-CMA for MIMO systems are introduced in section 4.5 and 4.6 respectively. Finally in section 4.7 Complexity comparison of MIMO receivers are described.

4.1. System Model of adaptive array MIMO systems

A general block diagram of MIMO systems is illustrated in Figure 4.1, where MIMO encoder and MIMO decoder accommodate various MIMO coding/decoding schemes, such as Alamouti, singular value decomposition (SVD) and space-time block coding (STBC). By applying different coding/decoding schemes, the self interfering MIMO channel can be converted into a set of parallel sub-channels, over which separate data streams are transmitted.

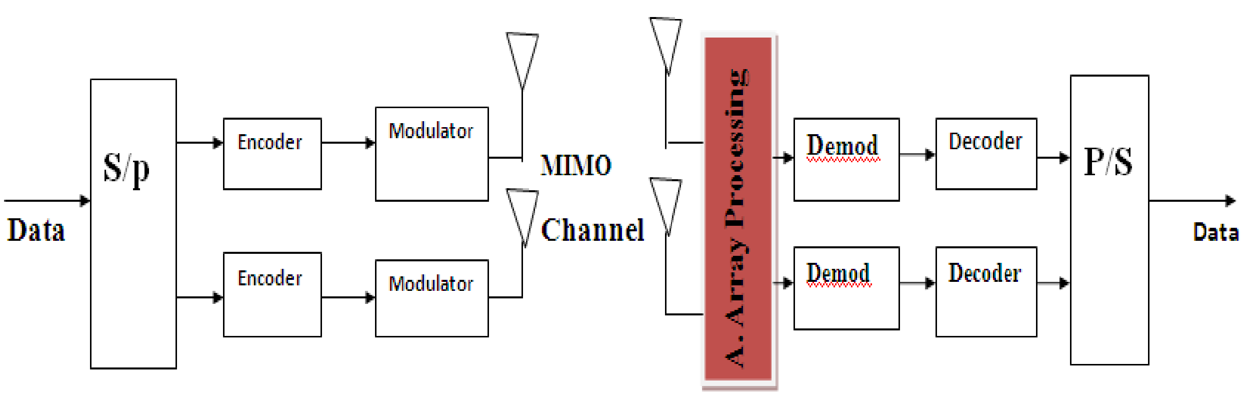


Fig 4.1 MIMO transmission system Model

The Adaptive array processing at the receiver side is used to receive in an adaptive, spatially sensitive manner with digital signal processing capability. In other words, it can automatically change the directionality of its radiation pattern in response to its signal environment. In this thesis work we use these adaptive arrays processing for channel estimation.

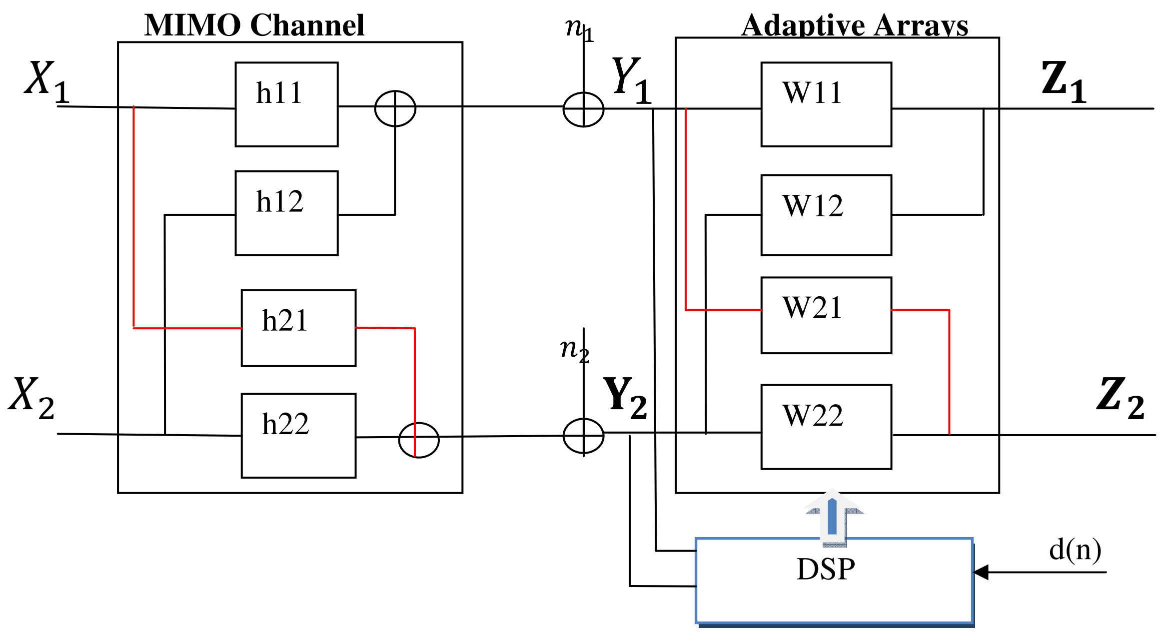


Fig 4.2 MIMO systems and adaptive array receiver

As it has been studied in chapter three there are many adaptive array algorithms that can be used for MIMO systems. However, for this thesis work we have selected LMS, SMI algorithms due to their simplicity and convergence properties. In addition to this we have evaluated performance of blind and non blind combined algorithms such as LMS-CMA and SMI-CMA in order to achieve advantages of blind and non blind algorithms. In all cases we have considered 2x2 MIMO systems.

4.2 Channel State Information (CSI)

An important factor when deriving transmission strategies for MIMO systems is the availability of channel knowledge at the transmitter. The transmitter is said to have full Channel State Information (CSI) if the instantaneous channel **H** is known at the transmitter. Full or partial CSI can be obtained by either a feedback channel or in a TDD system with time duplex distance shorter than the channel coherence time by directly applying the CSI from the receive channel estimate. A feedback channel is already implemented in some systems for a fast power control which provides the transmitter with partial CSI [9].

4.3 LMS for MIMO systems

In the MIMO case filter taps are updated independently based on different equalized signals from each receiving antennas. The equalize signal can be expressed as [48].

$$Z_m(n)=\sum_{j=1}^{M} Y_j(n)W_{j,m}(n) \tag{4.1}$$

Where M denotes the number of receiving antennas, Y_j is the vector of received symbols at j^{th} receiving antenna and W_{jm} is the estimated weights and it can be written.

$$W_{j,m} = \begin{bmatrix} w_{1,1} & w_{2.1} & \cdots & w_{M,1} \\ \vdots & & \ddots & \vdots \\ w_{1,M} & w_{2,M} & \cdots & w_{M,2} \end{bmatrix} \tag{4.2}$$

Where M denotes the number of receiving antennas, error and filter updating process is expressed as [48, 51].

$$\mathbf{Z_m(n)= Y_k W_{mn}\ (n)} \tag{4.3}$$

$$\mathbf{e_m(n) = Z_m(n) - X_n(n)} \tag{4.4}$$

$$\mathbf{W_m(n+1) = W_m(n) - \mu \nabla_W J_{lms}} \tag{4.5}$$

Where n, m stands for the n^{th} transmitting and m^{th} receiving antenna respectively, $\boldsymbol{\mu}$ is the stepsize parameter that controls the convergence speed of the LMS algorithm and. $\nabla_W \mathbf{J_{lms}}$ is the gradient of the cost function that is to be minimized, Here n = m and the MSE cost function can be written as:

$$\mathbf{J_{lms}} = E\{|e_m(n)|^2\}$$
$$= E\{|Z_m(n) - X_n(n)|^2\}$$
$$= E\{|Y_k W_m - X_n(n)|^2\} \tag{4.6}$$

Where Y_k is the k^{th} row vector of receiver and $\mathbf{W}_m$ is m^{th} column vector of equalizer matrix

Therefore, for 2x2 MIMO systems the equalized signals from eqn.4.1 (M=2) are given by

$$Z_1 (n) = W_{11}Y_1 + W_{12}Y_2 \tag{4.7}$$

$$Z_2 (n) = W_{21}Y_1 + W_{22}Y_2 \tag{4.8}$$

And from eqn. 4.4 and 4.5

$$e_1 (n) = Z_1 (n) - X_1 (n) \tag{4.7a}$$

$$e_2 (n) = Z_2 (n) - X_2 (n) \tag{4.7b}$$

$$W_{11} (n+1) = W_{11} (n) - 2\mu\, e_1 (n)\, Y1 \tag{4.8a}$$

$$W_{12} (n+1) = W_{12} (n) - 2\mu\, e_1 (n)\, Y1 \tag{4.8b}$$

$$W_{21} (n+1) = W_{21} (n) - 2\mu\, e_2 (n)\, Y2 \tag{4.8c}$$

$$W_{22} (n+1) = W_{22} (n) - 2\mu\, e_2 (n)\, Y2 \tag{4.8d}$$

4.4 SMI for MIMO systems

The detail study of this algorithm has been presented in chapter three. Here we will state when the transmission is single user MIMO system using the estimated matrices over a block size N2-N1 using training signal as eqn (3.14), (3.15). From eqn (3.16) the weight vector are described as follow.

$$\mathbf{\widehat{W}} = \mathbf{\widehat{R}^{-1}\hat{r}} \tag{4.9}$$

Using this estimated weight vector we can calculate the estimated received signals for 2x2 MIMO systems as follows:

$$Z_1 (n) = W_{11}Y_1 + W_{12}Y_2 \tag{4.10}$$

$$Z_2 (n) = W_{21}Y_1 + W_{22}Y_2 \tag{4.11}$$

Where $W_{j,M}$ is 2x2 vector matrix which is the same as eqn. (4.2).

4.5 CMA for MIMO systems

Among all blind equalization algorithms, the constant modulus algorithm is a popular, low complexity blind algorithm used for channel equalization and inters symbol interference (ISI) suppression for constant modulus signals. One limitation of the conventional CMA algorithm is that, it is incapable of distinguishing one user data from another in MIMO detection applications; and so it fails to lock on the desired user signal. There are different proposed solutions to solve CMA for MIMO systems limitations. One of the simplest and commonly used methods is adding a cross-correlation term to the CMA cost function to get the cross correlation CMA (CC-CMA) algorithm [3, 33, 48].

Hence, CMA for MIMO weight updating process is given by [48].

$$Zm(n) = Y_k W_m(n) \tag{4.12}$$

$$Wm\ (n+1) = Wm(n) - \mu Z_m(n)(|Z_m(n)|^2 - Rcma) Y_k^H \tag{4.13}$$

Where W_m (n+1) is the m^{th} column weight vector and Z_m(n) is the m^{th} estimated signal (denoted by $\hat{X}$), Y_k is the K^{th} row vector of received matrix and R_{cma} is defined as eqn.(3.35).

But the minimization of (3.30) does not ensure the recovery of all source signals in a MIMO system because it may converge to recover the same source signal at many outputs. In order to solve this problem, a cross-correlation term is introduced due to its computational simplicity [3]. Then (3.30) for 2 x 2 MIMO is rewritten as [33, 48].

$$J(w) = Z_m(n)(|Z_m(n)|^2 - Rcma) Y_k^H + \sum_{i=1}^{m-1} \hat{r}_{mi}(n) Z_i(n) Y_k^H \tag{4.14}$$

Where $\hat{r}_{mi}$ (n) = $E[Z_m(n) Z_i^*(n)]$ is the cross-correlation between the m^{th} and the i^{th} equalizer outputs and prevents the extraction of the same signal at many outputs.

Then from eqn. 3.22, 3.23 (where p=2 and q=1) and eqn. 4.10, 4.11 the error and weight updating are given by:

$$e_1 (n) = |Z_1 (n)|^2 - R_1 (n) \tag{4.15a}$$

$$e_2 (n) = |Z_2 (n)|^2 - R_2 (n) \tag{4.15b}$$

$$W_{11} (n+1) = W_{11} (n) - 2\mu\, e_1 (n)\, Y1 \tag{4.16a}$$

$$W_{12} (n+1) = W_{12} (n) - 2\mu\, e_1 (n)\, Y1 \tag{4.16b}$$

$$W21 (n+1) = W21 (n) - 2\mu\, e2 (n)\, Y2 + r_{12} Z_1 Y_2 \tag{4.16c}$$

$$W22 (n+1) = W22 (n) - 2\mu\, e2 (n)\, Y2 + r12\, Z_1 Y_2 \tag{4.16d}$$

Where r_{12} is cross-correlation between the equalized signal from receiver antenna 1 and receiver antenna 2.

4.5 SMI-CMA for MIMO systems

This section used Adaptive algorithm which combines the SMI and CMA algorithms to improve the convergence speed with small bit error rate (BER). In this case SMI initialize the weights by using some training signals and the adaptation process continues blindly to recover the desired signal. The estimated weight is calculated as eqn. (4.9) for some known training data.

$$\widehat{W} = \widehat{R}^{-1} \hat{r} \tag{4.17}$$

Where, $\hat{R}^{-1}$ and $\hat{r}$ are 2x2 vector matrix for 2x2 MIMO system and correlation of few training samples. Using this initialized weight we update the weights using constant modulus algorithm, without using training signal, as follow:

$$Z_1 (n) = W_{11} Y_1 + W_{12} Y_2 \tag{4.18a}$$

$$Z_2 (n) = W_{21} Y_1 + W_{22} Y_2 \tag{4.18b}$$

$$e_1 (n) = |Z_1 (k)|^2 - R_1 (n) \tag{4.19a}$$

$$e_2 (n) = |Z_2 (k)|^2 - R_2 (n) \tag{4.19b}$$

$$W11 (n+1) = W11 (n) - 2\mu\, e1 (n)\, Y1 \tag{4.20a}$$

$$W12 (n+1) = W12 (n) - 2\mu\, e1 (n)\, Y1 \tag{4.20b}$$

$$W21 (n+1) = W21 (n) - 2\mu\, e2 (n)\, Y2 \tag{4.20c}$$

$$W22 (n+1) = W22 (n) - 2\mu\, e2 (n)\, Y2 \tag{4.20d}$$

The number of data for SMI training depends on the required performance. Detail flow chart of these algorithms is stated below:

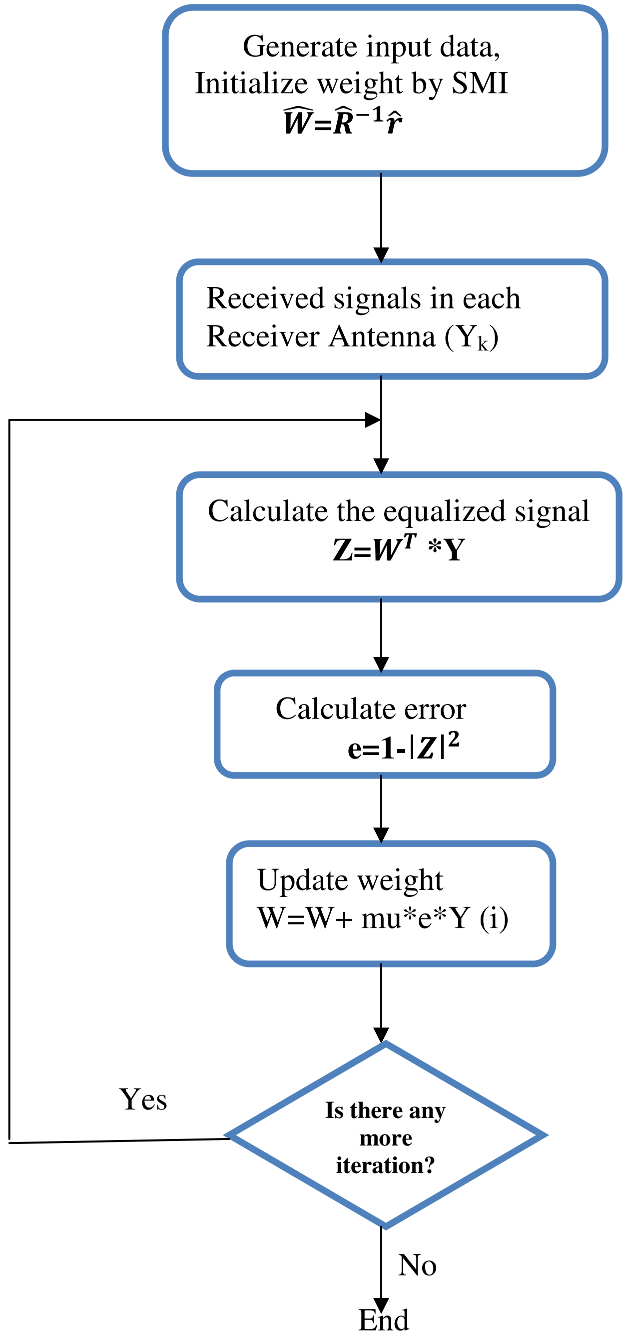


Fig.4.3 Flow chart of SMI-CMA Algorithm

4.6 LMS-CMA for MIMO systems

As described in section 4.5 using this combined algorithm help to achieve both advantages of LMS and CMA (blind and nonblind algorithms). In this case, first the weights are initialized as Zeros or ones which are commonly used initializations in LMS algorithm. Then weight updating and error calculations are trained for few samples of data using LMS algorithm that can be used as an initial value for CMA.

Therefore, using eqns. (4.7a and 4.7b) calculating the error and the initial weight vector using LMS (non blind) Algorithm are given as follows;

LMS error calculation for few samples:

$$e_1 (n) = Z_1 (n) - X_1 (n) \tag{4.21a}$$

$$e_2 (n) = Z_2 (n) - X_2 (n) \tag{4.21b}$$

And the weights are updated using LMS (non blind) Algorithm as eqns. (4.8a-4.8d).

Then for the remaining data the weights and errors are calculated using CMA algorithm using eqns. (4.15a and 4.15b)

$$e1 (n) = |Z_1 (k)|^2 - R1 (n) \tag{4.21a}$$

$$e2 (n) = |Z_2 (k)|^2 - R2 (n) \tag{4.21b}$$

The weight updating is the same as LMS algorithm eqns.(4.8a-4.8d) except the error here is given by the above eqns.(4.21a and 4.21b). Flow graph of this algorithm is stated in the following page:

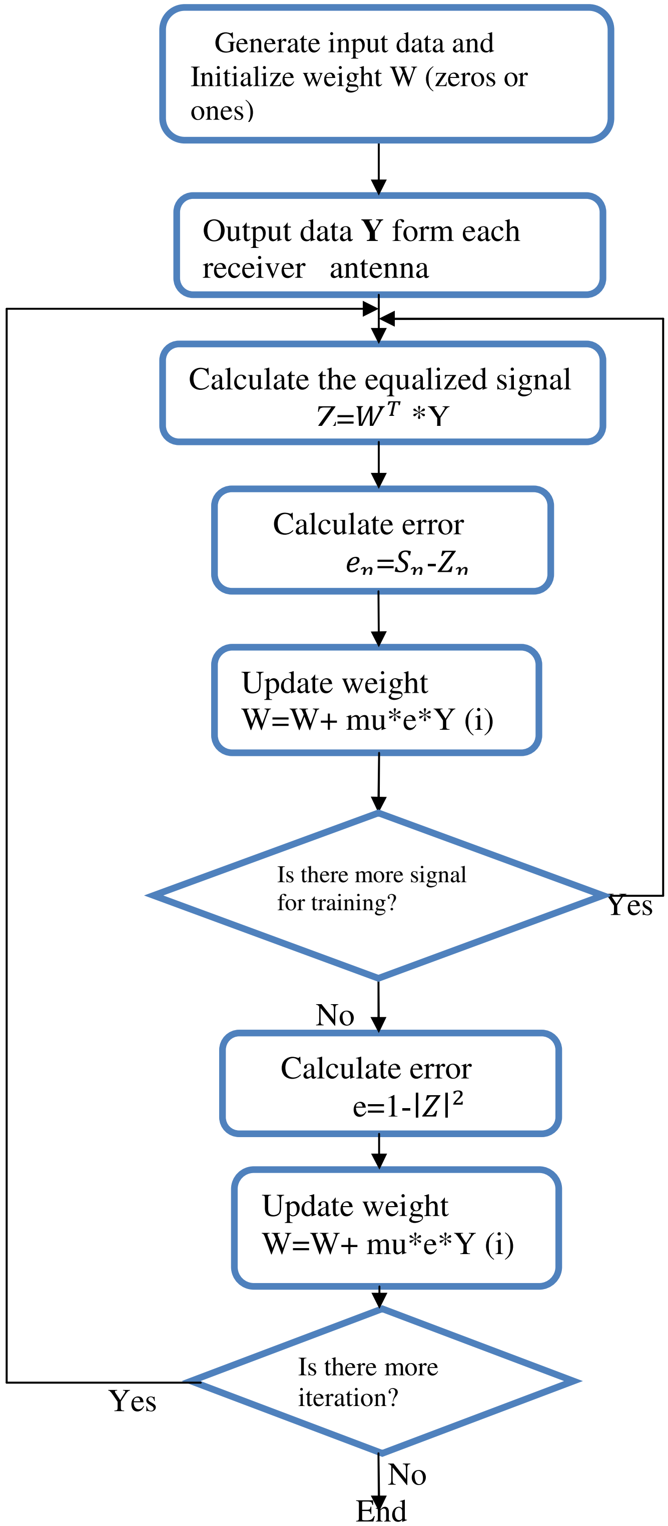


Fig.4.2 Flow chart of LMS-CMA

4.7 Complexity Comparison of MIMO receivers

Since, there are always tradeoffs between the performance of the algorithms and their computation complexity. It is important and necessary to make a complexity comparison between different algorithms and try to find an algorithm that might achieve the best balance [31].

Table 4.1 Complexity Comparison per weight update for different algorithms.

Algorithm	Multiplications	Additions
CMA	$2(4N+3)N$	$(9N+2)N$
LMS	$(8N+2)N$	$(9N+2)N$
RLS	$4N^2(7+N)$	$32N^2+6N+1$
ZF/MMSE	$12N^3$	$12N^3-4N^2+N$

In Table (4.1), N is the number of receiving and transmitting antennas. From this table it can be seen that LMS has the lowest computational complexity. But the RLS algorithm has a faster convergence speed but much higher complexity which is shown in the above table.

CHAPTER

5 SIMULATIONS AND RESULTS

In this chapter Simulation results and discussions on the performances of adaptive arrays and other MIMO receivers under fading channels are presented. In section 5.1 simulation parameters and assumptions are stated. MIMO capacity, convergence of adaptive algorithms, comparison of selected adaptive algorithms interms of BER are discussed in section 5.2, 5.3 and 5.4 respectively. Finally simulation results and discussions of comparison of these adaptive algorithms and other linear receivers are described in section 5.5.

5.1 Simulation parameters

Some of the simulation parameters used for performance evaluation of adaptive array MIMO systems is shown in table 5.1.

Table 5.1 simulation parameters

Number of users	1(single user MIMO)
Number of transmit antennas × Number of receive antennas	(2 × 2)
Number bits	20000
Data Modulation /Demodulation	BPSK
Propagation Model	Flat fading channel
Number of runs	100
Step-size	0.008
Software	MATLAB
Noise	AWGN
Channel type	Static

5.2 Capacity of MIMO Systems

5.2.1 Capacity of MIMO systems Channel unknown to the transmitter

As we have discussed in chapter two, capacity of MIMO systems increase linearly with number of transmitting and receiving antennas. The result below shows that the normalized MIMO capacity for unknown channel to the transiting antenna.

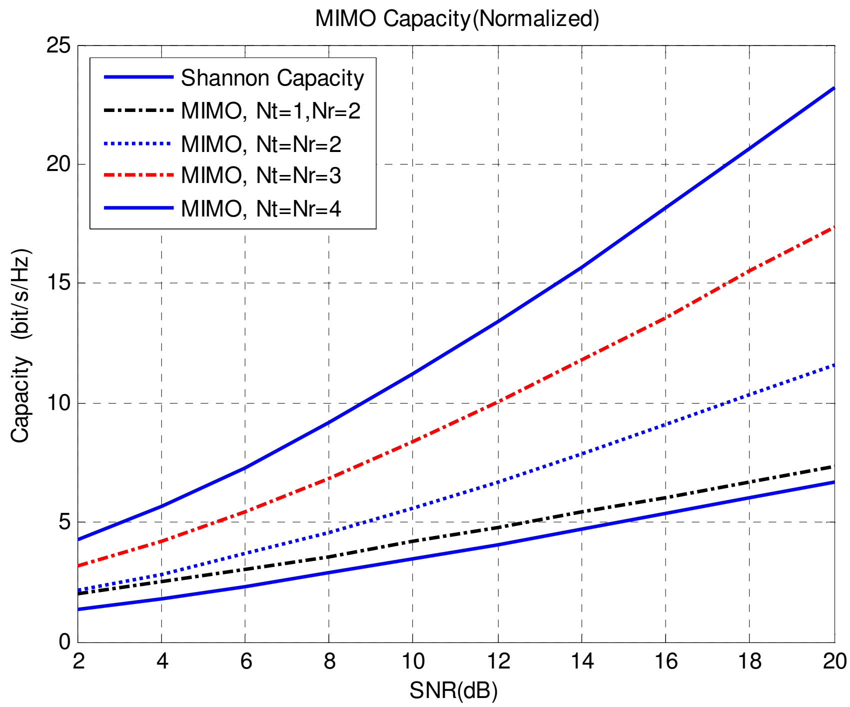


Fig.5.1 capacity of MIMO systems for unknown channel to the transmitter

The capacity for different signal-to-noise-ratios, with one, two, three and four receiver and transmitter antennas are shown. It is clear that when increasing the number of antennas from 1 to 4 the capacity is significantly increased linearly (fig 5.2) while in SIMO case the capacity increase logarithmically relative to SISO system.

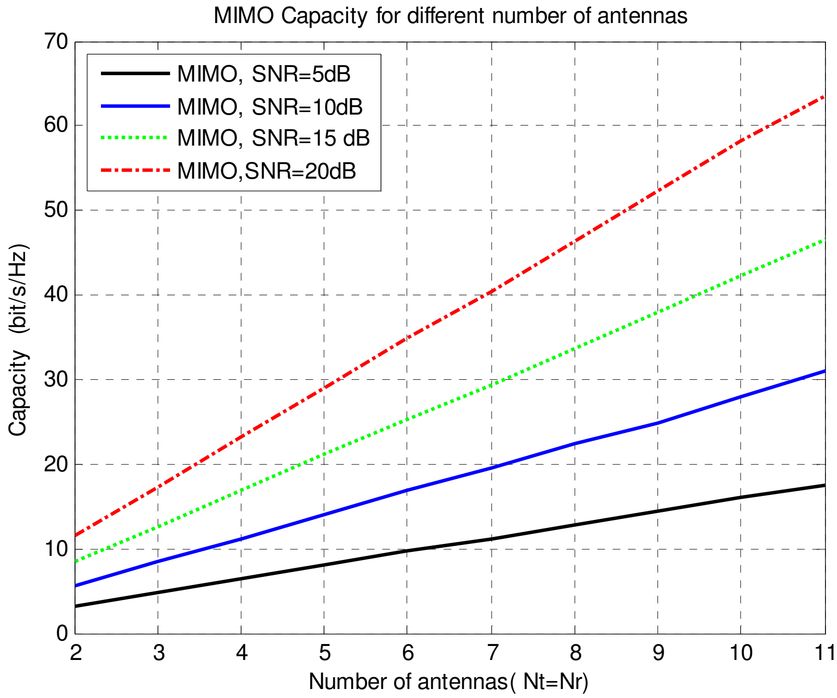


Fig.5.2 capacity of MIMO systems for different number of antennas

5.2.1 Capacity of MIMO system with channel known to the transmitter

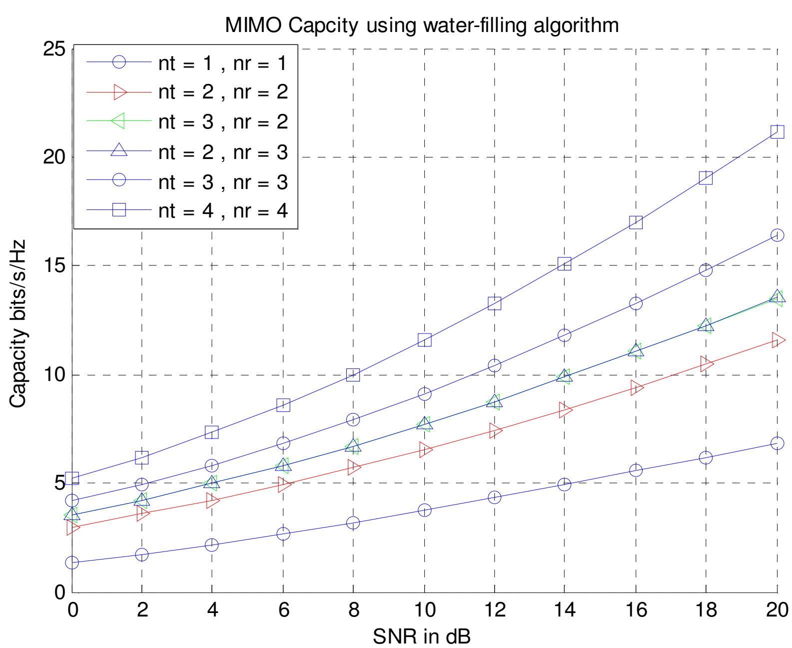


Fig 5.3 Capacity of MIMO system using water-filling algorithm

As stated above the capacity increase with the number of antenna and when we have and the result is same with and which shows that on increasing number of antennas at either side of the MIMO system will have same effect in rising the capacity. The difference is when the channel is known at the transmitter we can use water-algorithm to gain better capacity than unknown channel. From the simulation result we can see that water filling algorithm has better performance than unknown channel at lower SNR.

5.3 BER performance of STBC (2x2 Alamouti)

In chapter two detail calculation of 2x2 Alamouti STBC is described. Simulation result in figure 5.4 shows that STBC in Rayleigh channel has better performance than the theoretical AWGN BER for SISO system at low SNR.

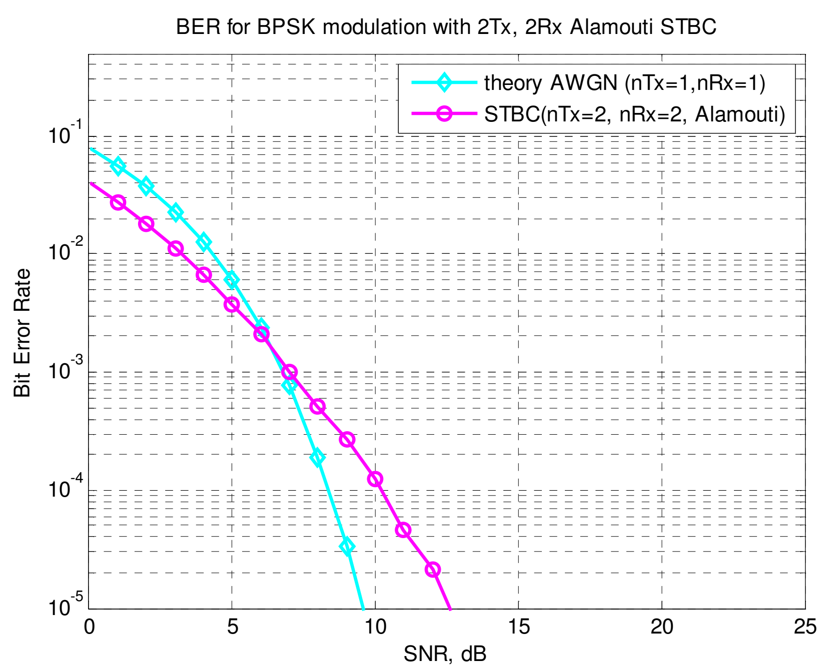


Fig 5.4 BER performance of STBC (Alamouti)

5.4 Convergence of adaptive array algorithms

5.4.1 Convergence comparison of LMS and CMA

As stated in chapter three SMI and LMS converge faster than CMA for comparison purpose we have simulated LMS and CMA under non fading channel with AWGN.

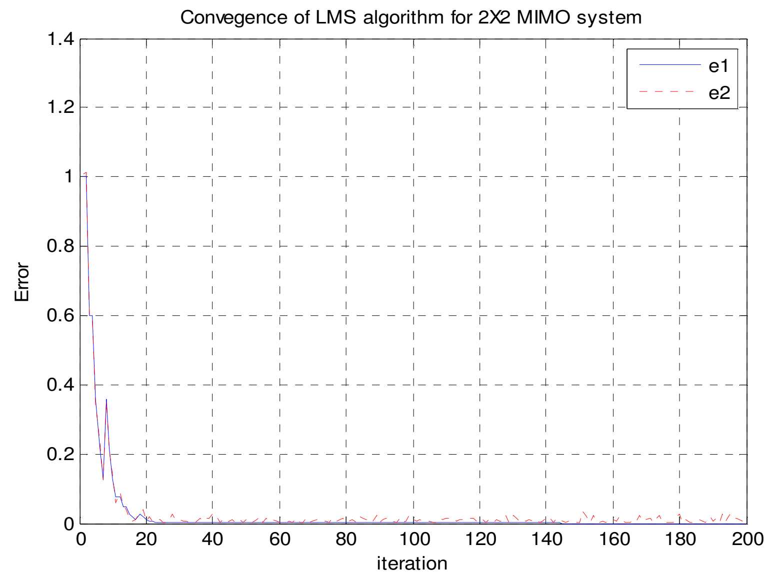


Fig 5.5 Convergence of LMS algorithm for 2x2 MMO systems

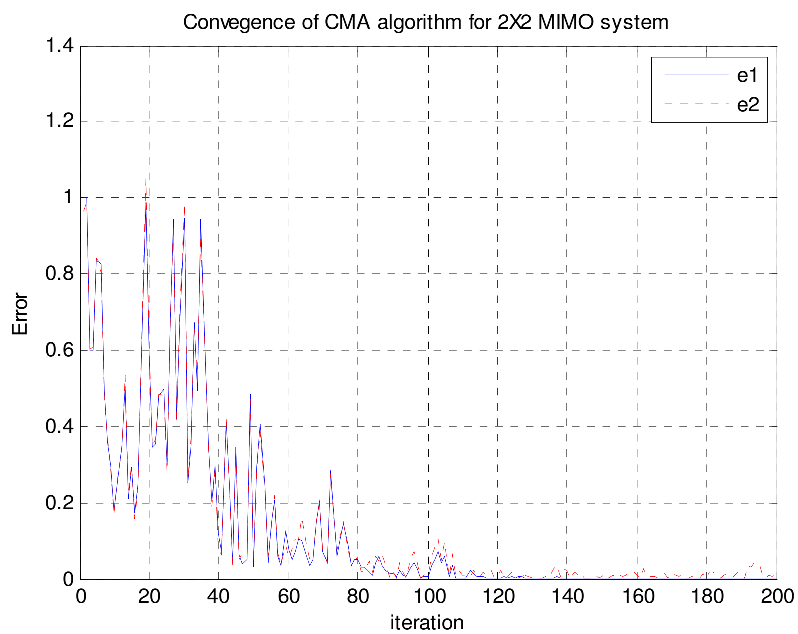


Fig 5.6 Convergence of CMA algorithm for 2x2 MMO systems

The simulation result of fig 5.5 and 5.6 shows that the error in LMS algorithm for 2x2 MIMO systems converges faster than CMA algorithm using step-size 0.1 so as to see the learning curve difference clearly.

5.4.2 Convergence and stability of the LMS algorithm for different step-size

As we discussed in chapter there convergence and Stability of LMS algorithm depends on the selection of step size parameter, the following simulation results shows the effect of large and small step size parameter on convergence and stability of LMS algorithm. We have taken three cases 0.2, 0.02, 0.002 and 0.008.

5.4.2.1 Convergence and stability of LMS algorithm for step-size 0.2

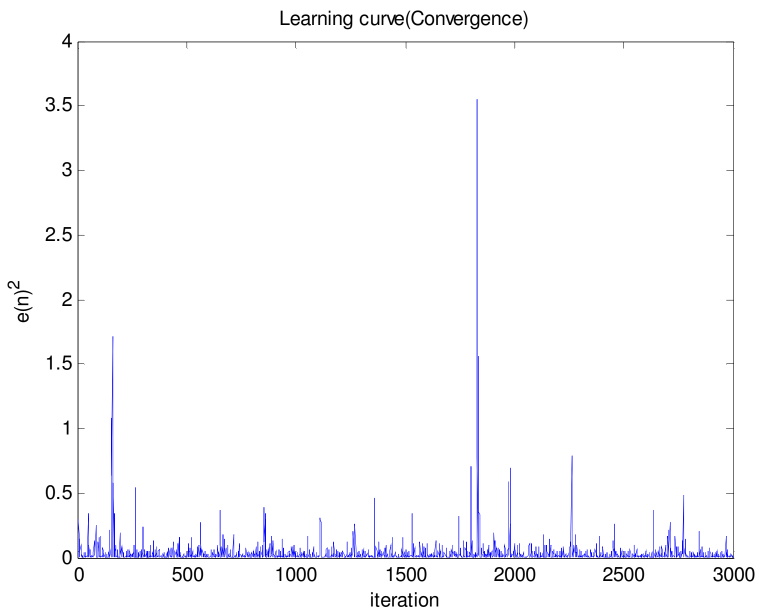


Fig.5.7 convergence and stability of LMS for step size 0.2

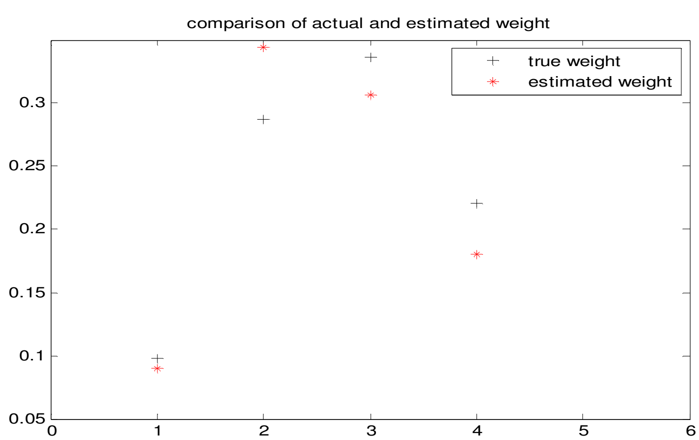


Fig 5.8 Comparison of Actual and estimated weights (0.2)

From fig 5.7 and 5.8, we see that the error converges soon but it causes instability (large error after convergence) that results poor estimated weight (fig 5.8). Most of the estimated weights are by far different from the true value.

5.4.2.1 Convergence and stability of LMS algorithm for step-size 0.02

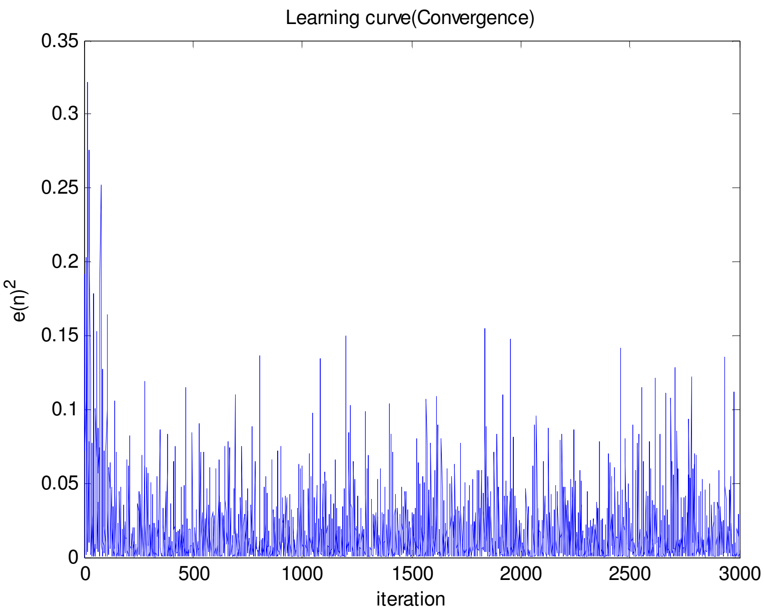


Fig 5.9 Comparison of Actual and estimated weights (0.02)

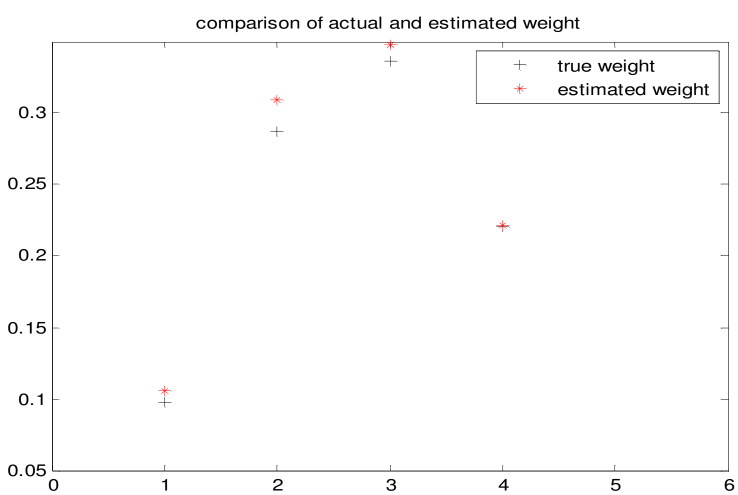


Fig 5.10 Comparison of Actual and estimated weights (0.02)

Fig (5.9 and 5.10) shows that step size 0.02 has better stability with slow convergence rate than the larger step size 0.2.

5.4.2.3 Convergence and stability of LMS algorithm for step-size 0.002

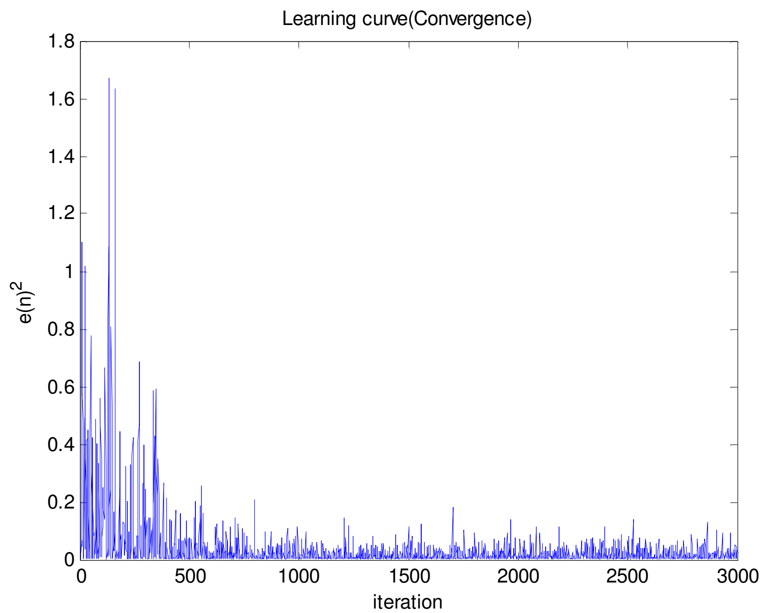


Fig 5.11 Comparison of Actual and estimated weights (0.002)

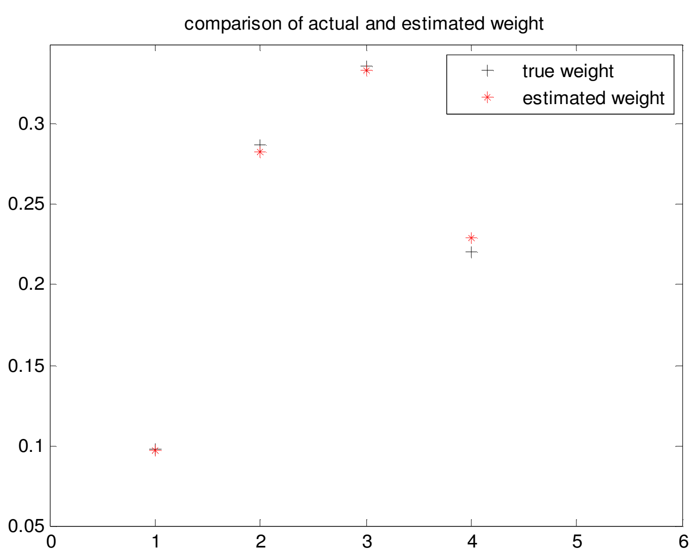


Fig 5.12 Comparison of Actual and estimated weights (0.002)

LMS algorithm with step size 0.002 has good performance in terms of the estimated weight (fig 5.12) and slow convergence rate.

5.4.2.4 Convergence and stability of LMS algorithm for step-size 0.008

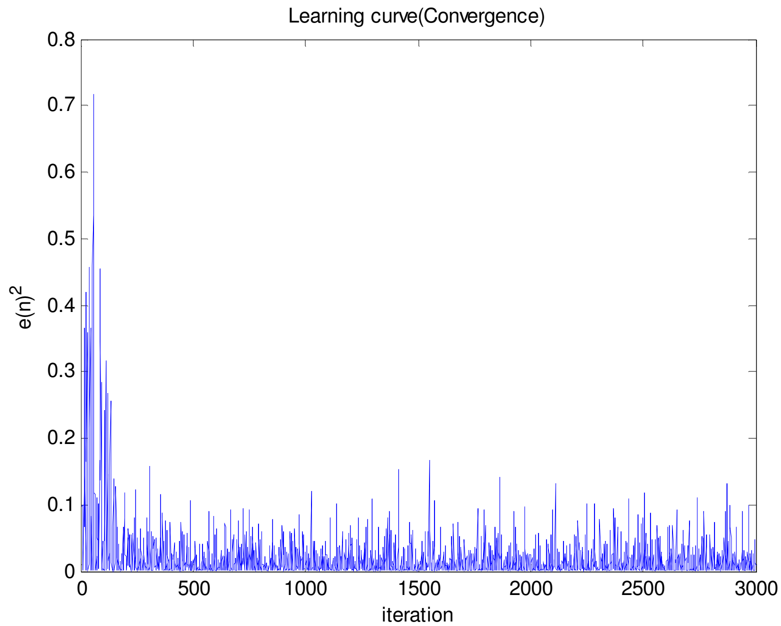


Fig 5.13 Comparison of actual and estimated weights (0.008)

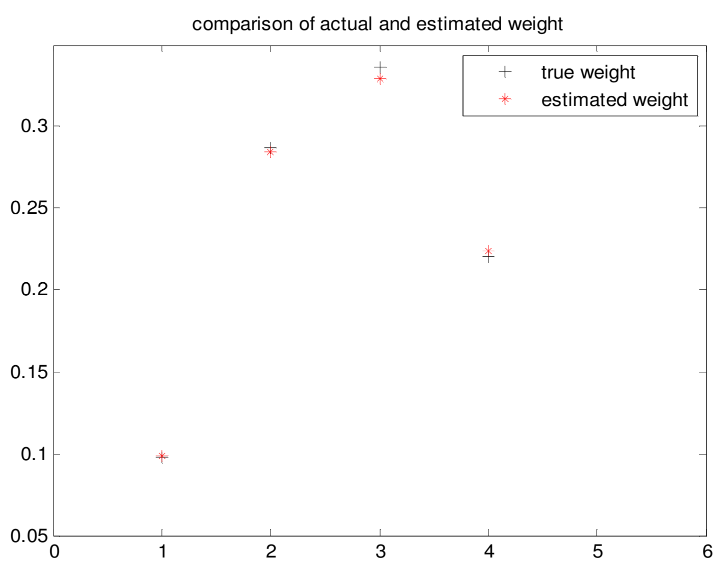


Fig 5.14 Comparison of actual and estimated weights (0.008)

Generally form the above comparisons we clearly see that the appropriate step size for our simulation results is between 0.02 and 0.002. Therefore for the next simulations 0.008 step size will be appropriate choice as shown in the above figures (5.13 and 5.14).

5.5 Comparison of Selected adaptive array algorithms

5.5.1 Performance Comparison of SMI and LMS

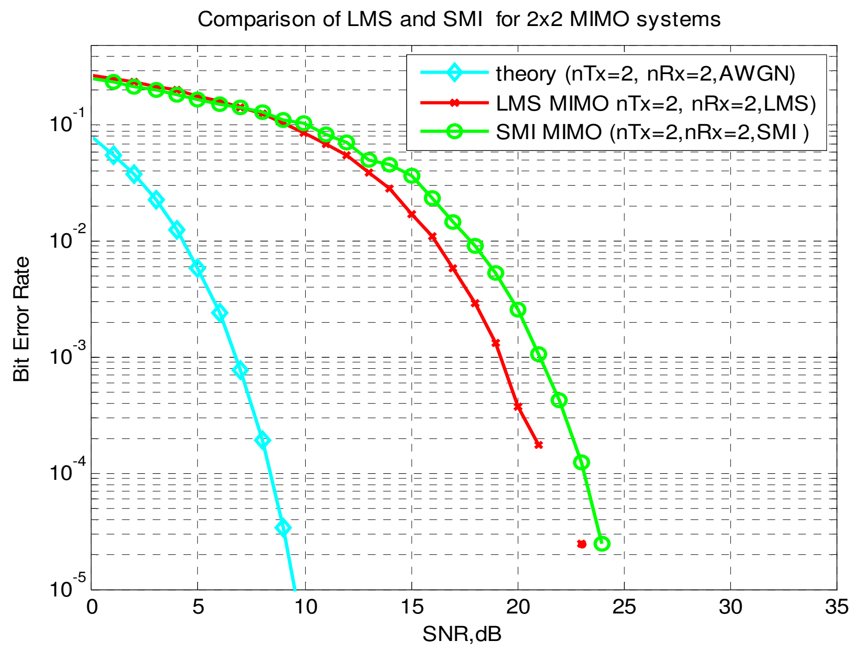


Fig 5.15 BER comparison of SMI and LMS

The above simulation result compares the performance of SMI and LMS algorithms for 2X2 MIMO systems. As shown in fig 5.15 BER performance of LMS is the same with SMI for low SNR (for SNR less than 10dB). For SNR greater than 10 dB LMS performs better than SMI.

5.5.2 Performance comparison of LMS and LMS-CMA

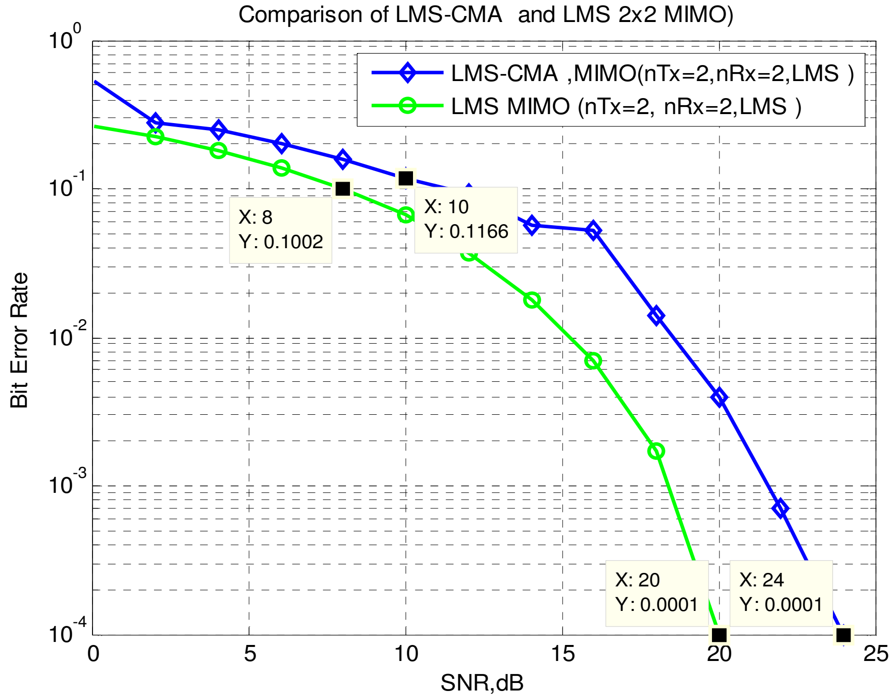


Fig 5.16 BER performance comparison of LMS and LMS-CMA

From Figure 5.16, we see that the BER performance of LMS is higher than the combined algorithm LMS-CMA. This is due to the minimization of number of nonblind training data from 10 % to 3.75% at the cost of from 2-4dB SNR. Then we can choose LMS-CMA if we want to minimize the number of training data with this SNR cost.

5.5.3 Performance of LMS-CMA and SMI-CMA

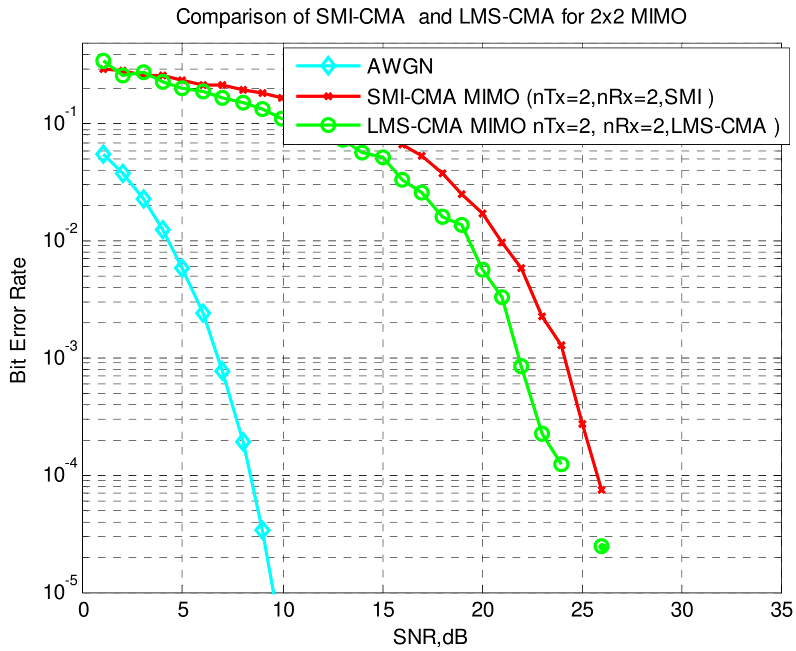


Fig 5.17 BER performance comparison of LMS and LMS-CMA

5.6 Comparison of adaptive arrays with other MIMO linear receivers

5.6.1 BER performance of LMS and ZF

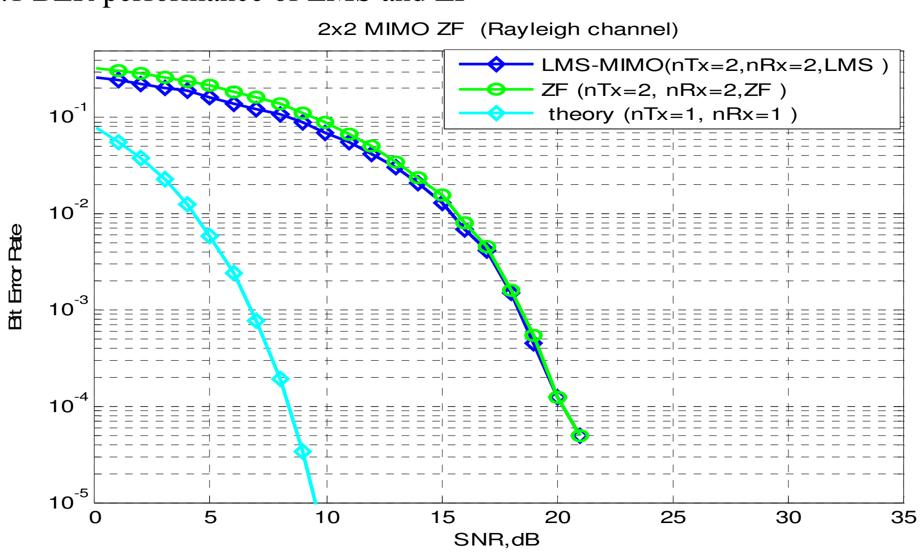


Fig 5.18 BER performance comparison of LMS and ZF

As shown fig 5.18, the LMS algorithm has lower BER of better performance than ZF linear receiver. However, as SNR increase ZF approaches to LMS algorithm.

5.6.2 BER performance of LMS and MMSE

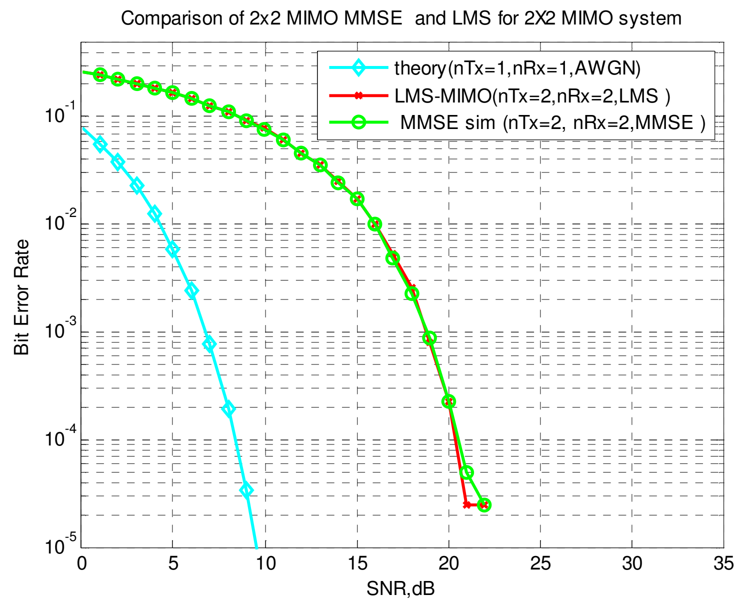


Fig 5.19 BER performance comparison of LMS and MMSE

5.6.3 BER performance of LMS, ZF and MMSE

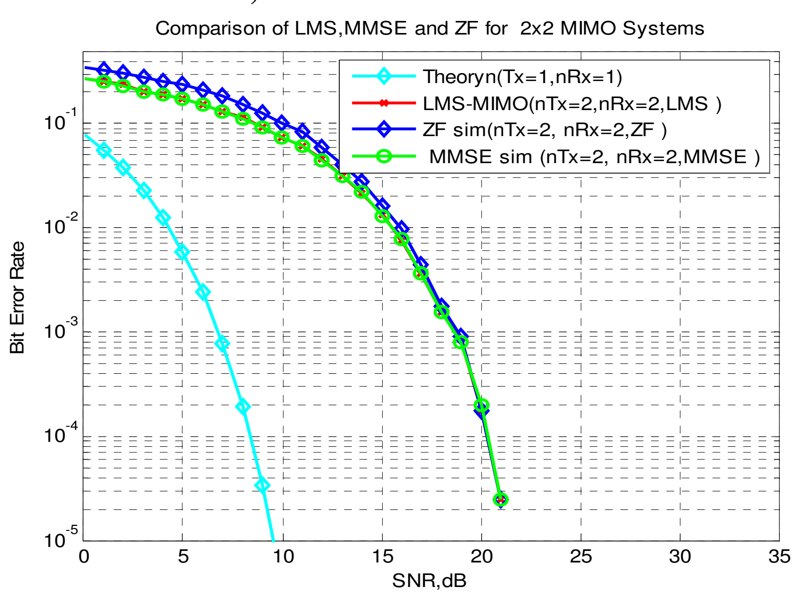


Fig 5.20 BER performance comparison of LMS, ZF and MMSE

Performance of LMS and linear MIMO receivers (ZF and MMSE) is illustrated in Figures 5.18, 5.19 and 5.20. Bit error rate (BER) curves for transmission using two transmit antennas and two receiving antenna are shown in this figure. The BER curve for the one transmit and one receives antenna (1 Tx-1Rx) case is also plotted for reference. The following observations can be made from the performance plots.

- LMS algorithm has the same BER performance as MMSE linear receiver.
- ZF has large BER performance than LMS and MMSE.
- At high SNR ZF approaches to MMSE and LMS in static flat fading channel.

CHAPTER

6 CONCLUSION AND RECOMMENDATIONS FOR FUTURE WORK

6.1 Conclusion

MIMO is one of the future wireless technologies. So many ongoing researches are done to improve its performance and complexity. In this thesis adaptive array processing have been analyzed and evaluated for MIMO wireless communication systems. For this, different MIMO adaptive array receivers and transmission techniques are thoroughly studied for 2 x 2 MIMO systems.

In Chapter three, different non blind and blind adaptive arrays algorithms are described and their detail algorithms are analyzed. Comparison based on their advantages and disadvantages are stated in table 3.1. Comparison of Adaptive arrays with other linear MIMO receivers (ZF and MMSE) interms of Complexity, convergence, and tracking are described in table 3.2. From Table 3.1 we can see that non blind algorithms converges faster than blind algorithms but they need training signal while blind algorithms converges slowly and doesn't Require training signal. Table 3.2 show that MMSE and RLS has good tracking and fast convergence in contrast to LMS algorithm that has poor tracking with slow convergence rate. However, LMS has low complexity (easy and simple to implement) while MMSE and RLS have high and very high complexity respectively.

In chapter four the system is modeled and performance of algorithms is evaluated. Then simulation results of the model are described in chapter five with the following conclusions:

The capacity of MIMO system with known channel state information and unknown channel state information (CSI) at the transmitter is evaluated the transmitter with known CSI using water filling algorithm has larger capacity than the transmitter with unknown CSI Fig (5.1, 5.2 and 5.3). MIMO transmission techniques such as spatial multiplexing and spatial diversity (2x2 alamouti STBC) are used for high data rate and reliable communication.

LMS has converged faster than CMA Fig. (5.5, 5.6) but it has a cost of bandwidth. From the result of Figures (5.7- 5.12), we have seen that LMS algorithm convergence depends on step size parameters. For large step size LMS algorithm converges fast but it has a stability problem. Therefore an optimal choice of step size parameter based on eqns. (3.9 and 3.10) is necessary to have better performance interms of convergence and stability.

Finally, from simulation results of comparison of selected algorithms for MIMO systems we can see that LMS has better BER performance than SMI (Fig. 5.15). We can minimize the number of training sequence by 62.5% with a cost of 2- 4dB using combined algorithms such as LMS-CMA (we can utilize blind and non blind advantages with some cost in SNR). Moreover, results for Comparison of adaptive arrays with other linear MIMO receivers shows that LMS algorithm in slow fading channel has the same BER performance with MMSE and better BER performance than ZF.

6.2 Recommendations for future work

Adaptive array technology has opened numerous areas for future work which could be done to better understand performance of Adaptive array processing for MIMO systems. Some of the areas are as follows:

- Performance evaluation of adaptive array for interference mitigation and signal separation in MIMO systems, this is to evaluate interference mitigation and signal separation of adaptive arrays advantages of adaptive arrays for MIMO systems
- Performance evaluation of Adaptive array MIMO systems for different fading channels
- Performance evaluation of adaptive arrays for MIMO systems with different Doppler speed/non stationary environment.
- Utilizing interference mitigation and channel estimation adaptive arrays ; this is how we can utilize both advantages at a time or their tradeoffs

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