Investigation of Multi user signal detection in Large scale MU-MIMO Systems

Submitted in partial fulfillment of the requirements for the degree of

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by

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I hereby declare that the thesis entitled "Investigation of multi user signal detection in Large scale MU-MIMO Systems" submitted by me, for the award of the degree of *Bachelor of Technology in Electronics and Communication Engineering* to VIT University is a record of bonafide work carried out by me under the supervision of Prof. KALAPRAVEEN BAGADI.

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B.SAI RAM SUSHEEL
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Executive Summary

The aim of this paper is to find the required receiver bits by using one of the best techniques available. We check different types of algorithm for detection in large MIMO systems based on the complexity and performance. The key idea in our work is to generate multiple possible solutions or outputs from which we select the best one. We propose 4 different techniques namely ZF, MMSE, ML & LAS in which we compare all the results and select the best one. Complexity and BER are the factors we take into the consideration for picking up the best technique. The likelihood ascent search (LAS) achieves near-optimal BER performance in fully loaded large MIMO systems. The advantages and drawbacks of the linear detection techniques like ZF and MMSE along with some nonlinear detection techniques like ML schemes have been explained. It is observed that, the performance the ML detector is optimal at the cost of additional complexity, especially in the context of a high number of users and for higher order modulation schemes. Also, the ZF and MMSE detectors exhibit low complexity at a cost of performance. The nonlinear successive detection technique outperforms the liner techniques, but still its performance is sub-optimal due to error propagation problem. As we have come across ML technique in the above discussion we faced much complexity issues so in order to reduce the complexity and to gain better optimal performance say higher capacity and BER we considered the LAS technique. Here to the LAS technique we applied multiple inputs and have drawn conclusions from output bits estimated say we have applied different techniques to ascent search namely LAS-ZF and LAS-MMSE and have drawn mathematical results by simulating with the help of MATLAB. Here we have compared different techniques by taking boundary conditions in which the transmitted bits fall into and also the BER performance into consideration and have drawn conclusions saying that LAS-ZF and LAS-MMSE has outperformed the conventional ZF,MMSE and ML techniques. However, all these MUD schemes fail to differentiate users in the critical overload scenario, when the number of users exceed number of BS receiving antenna. Here in this work we have discussed various scenarios followed by advantages and some disadvantages of each and every techniques and have drawn conclusions saying that LAS has better spectral efficiency and lesser complexity in detection of the received signal bits.

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List of Abbreviations

AWGN	Additive white Gaussian noise
BER	Bit Error Rate
BPSK	Binary Phase Shift Keying
BS	Base Station
CCI	Co-channel Interference
CDMA	Code Division Multiple Access
CSI	Channel State Information
DL	Downlink
LOS	Line of Site
MAC	Medium access control
MU-MIMO	Multi user multiple-input multiple-output
MUI	Multiuser interference
MIMO	Multiple Input Multiple Output
ML	Maximum Likelihood
MMSE	Minimum Mean Square Error
MS	Mobile Station
MSE	Mean Square Error
MSER	Minimum Symbol Error Rate
MUD	Multiuser Detection
OFDM	Orthogonal Frequency Division Multiplexing
QPSK	Quadrature Phase Shift Keying
SDM	Space Division Multiplexing
SDMA	Space Division Multiple Access
SISO	Single Input Single Output
SNR	Signal to Noise Ratio
UL	Uplink
ZF	Zero Forcing

Symbols and Notations

$(.)^H$	Hermitian transpose
$(.)^I$	Imaginary component
$(.)^T$	Transpose
$(.)^{-1}$	Inverse
I_N	Identity matrix with size N
D_i	The ith user in the downlink channel
U_i	The ith user in the uplink channel
N	A number of antennas at the base station
N_T	A number of transmit antennas at the full-duplex base station
N_R	A number of receive antennas at the full-duplex base station
N_{DI}	A number of antennas at user Di
N_{Ui}	A number of antennas at user Ui
σ_n^2	Variance
H	Channel Matrix H
H^H	Hermitian transpose of a matrix H
H^T	Transpose of a matrix H
R	Receiving bits
T	Transmitting bits
W	(R×T) dimension weight matrix
x	(T×1) transmitted vectors
x^	(T×1) estimated transmitted vectors
y	(R×1) received vectors
y^	(R×1) noiseless received vectors

CHAPTER 1 - INTRODUCTION

1.1 MOTIVATION OF WORK

In the past two decades, mankind has witnessed the fast development of the wireless communication industry. The examples of the wireless application and service are the use of mobile phone, Internet access, wireless Local Area Network (LAN) access, gaming, message forwarding and down loading, file retrieving and transfer, large volume data transfers between mobile handsets or laptop, video downloading to a handheld entertainment product, voice exchange on mobile phones and the multimedia communication to and from other mobile devices.

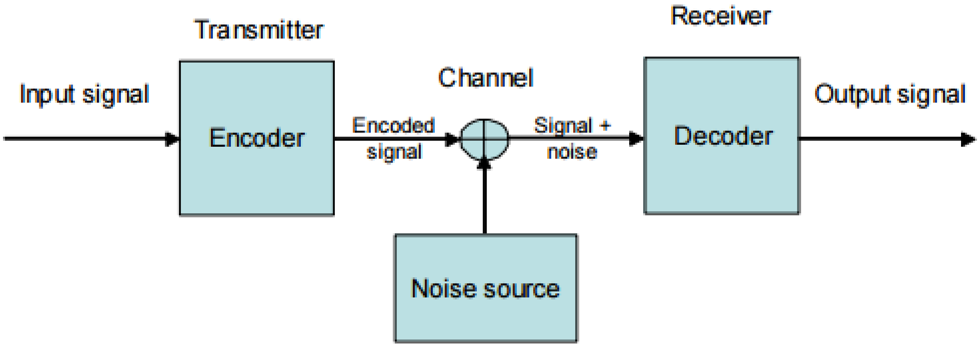


Figure 1.1 General communication model

The consequence of this expansion of the wireless communication industry is that the demand for capacity and frequency bandwidth has become increasingly high. Therefore, the available resources such as spectrum and system capacity become limited. In order to meet the ever increasing demand of high data rates and the immense growth of both mobile and fixed data traffic over finite radio resources, many modern communications technologies have been studied. Among those, the use of antenna arrays deployed at both ends of a communications link, referred to the multiple input multiple-output (MIMO) communications technique [1].It is a well-known method to offer high spectral efficiency (SE). In fact, by adding the extra spatial dimensions to a wireless link, data rate can be greatly increased. This is done by transmitting simultaneously independent information streams on different antennas, called spatial multiplexing. Another benefit brought by MIMO is transmit/receive diversity gains which mitigate channel fading to significantly enhance link reliability. Therefore, MIMO has gradually become a core component to many wireless communications standards such as LTE [2], WLAN [3] and WiMAX [4]. In current and emerging cellular networks, MIMO is realized in the form of multiuser MIMO (MU-MIMO) in the downlink (DL) and uplink (UL) channels in which a set of users is scheduled to communicate with a base station (BS) at the same time. A fading immune wireless channel can be implemented by constructing an antenna array at the transmitter or the receiver side. MU-MIMO techniques can take advantages of both spatial multiplexing gain and multiuser diversity by choosing a group of users with good channel conditions for transmission [5].

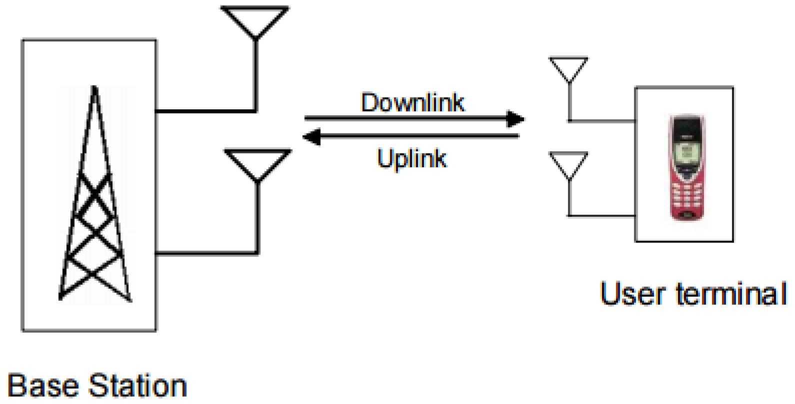


Figure 1.2 A point to point mimo communication system

Although MU-MIMO has been shown to be a promising approach to increasing Spectral Efficiency as well as the system throughput, we seem to reach the limit of capacity that MU-MIMO can provide in reality in not-so-far future. The fact is that we cannot integrate as many antennas as we want in both ends of a communications link due to several practical limitations. Also, many other issues will arise when expanding the operating bandwidth or transmit power. For example, increasing the bandwidth requires extra cost for operators in order to acquire theadditional licensed spectrum. MU-MIMO system is more robust due to high multipath richness and low correlation between the antennas on the user side. Here in this thesis we discussed about different detection techniques explaining about the complexities we face during the detection phase of each and every technique and proposing the better technique for multiple possible solutions without compromising on the better quality of service (QoS), higher network capacity, increased spectral efficiency and link reliability.

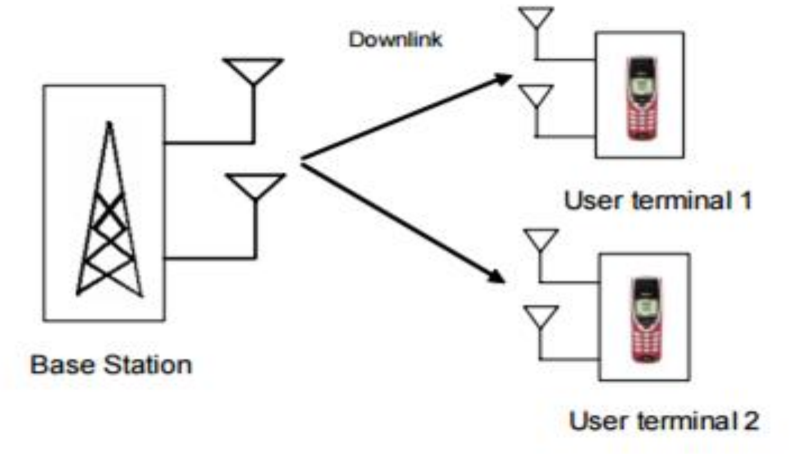


Figure 1.3 multiuser mimo downlink

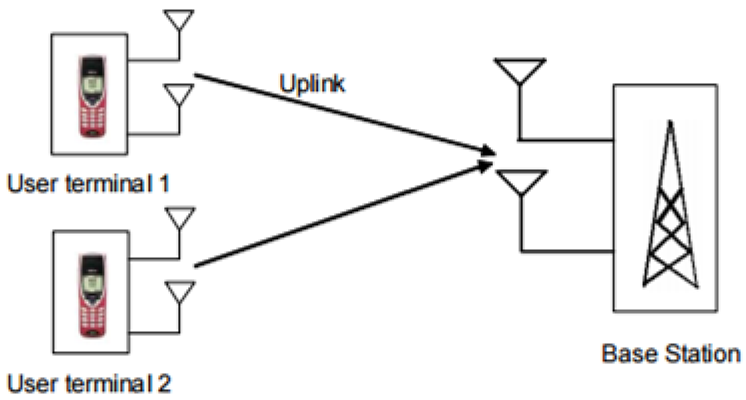


Figure 1.4 multiuser mimo uplink

1.2 LITERATURE REVIEW

Wireless radio channel is a dynamic channel in which the electromagnetic wave propagates. Comparing with wired radio channel, a mobile wireless channel is more complex in terms of random appearance of obstacles in a signal path from a transmitter to a receiver. In an urban area and outdoor environment, skyscrapers, trees as well as high density of the buildings can change a signal path significantly. The signal arriving at the receiver is not a simple case of a line-of-sight (LOS) path but the combination of the multipath signals arriving at the receiver. Similarly in the suburban area and countryside, the geographical surface of the earth such as mountains and hills can obstruct a signal; the received signal at a receiver is the combination of multi-path signals coming from a transmitter. In the situation of indoor environment, the objects in a wireless channel can vary extensively, such as floors, wall, partition in an office building, machinery etc. The complexity of a wireless channel media has brought challenge to the design of a wireless system and the analysis of the system performance. Two major things we consider are channel capacity and BER.

Capacity of wireless channel

It is known that Shannon capacity [C. E. Shannon, 1948] is defined as the maximum data rate over a channel with asymptotically small error probability. Figure 1.1 shows a typical communication system: the input signal is encoded by an encoder and then is transmitted from the transmitter; the signal traverses through the communication channel; the signal received at the receiver is the combination of the signal from the transmitter and the noise contributed from any sources on the way to the receiver, such as channel noise and thermal noise from the receiver; finally the output signal is the decoded signal from the receiver. The detected output signal should be realistic copy of the input signal, otherwise detection error occurs. In a typical wireless system with a discrete-time additive white Gaussian noise (AWGN) channel, the relationship between the output signal and input signal can be expressed as $y = x + n$, (2.17) where y denotes the output signal at time t, x denotes the input signal and n denotes the AWGN noise at time t. That is, the output of the system is the summation of input x and AWGN noise n. Assume that B is the channel bandwidth in Hz, the noise n is Gaussian distributed with zero mean and variance 2 σ, average value of the received power is Pr in Watts and the received signal-to-noise ratio (SNR) is the ratio of PrB to the power of the noise 2 σ in Watts, Shannon capacity in bits per second (bps) of such a channel is equal to

$$C = B \log (1 + SNR).$$

Probability of message error and Bit Error Rate (BER)

In a wireless communication system, the digital signal can be sent in the form of message (or symbol) in bits [A]. Assume that the total number of combination of K bits information is M, i.e., $M = 2^K$ and each input message 1: m f i or i = M is K bits information, i.e., m is sent every T second therefore the transmission data rate of the system is bits per second (bps). The message is then modulated via signal modulation. The modulated signal during the time interval [0, T) is sent through the channel. The signal arriving at the receiver is then decoded and the receiver obtains the best estimation of the input message. There are various modulation and demodulation methods and their usage depends on the system design requirement. The rule of thumb for the receiver design is to minimize the probability of message error, which is defined as

$$P_e = \sum_{i=1}^{M} p(\hat{m}_i \neq m_i | m_i \ sent) p(m_i \ sent),$$

Where p (m, si) is the probability of correct message estimation at the receiver when the input message is sent; the probability of incorrect message estimation at the receiver when the input message is sent. If the input signals are the binary phase-shift keying (BPSK) messages, the probability of message error is the probability of bit error that is also called bit error rate (BER). The relationship between the probability of bit error and the probability of message error can be expressed approximately as

$$P_b \approx \frac{P_e}{\log_2 M} .$$

Many factors can contribute to the probability of message error of wireless system; such as channel fading, transmit power, inter-symbol interference and any source of noises.

To improve the performance of the wireless system, it is desirable to attain the system capacity close to Shannon capacity and at the same time to maintain the probability of message error low in the system design. The multiple-input multiple output (MIMO) antenna technique is one of the methods to achieve these goals. The MIMO wireless system is the main focus of this thesis.

Single user – MIMO system and channel capacity

We consider a narrowband point-to-point (single user) wireless MIMO system with M transmit antennas and N receive antennas. In a multiple antenna system, a multiplexing gain can be achieved by decomposing the MIMO channel into parallel channels and multiplexing different data streams onto these channels. The multiplexing gain can only be obtainable in the MIMO system, which is proportional to the number of transmit-antenna pairs that is min (N, M). Assume that H (t) is the channel gain between the transmitter and receiver at any time instance t. The channel matrix has dimension of N×M and the matrix element hij represents the gain from transmit antenna j to receive antenna j. The received signal at the receiver can be expressed as

$$\boldsymbol{y}(t) = \boldsymbol{H}(\mathrm{t})\boldsymbol{x}(t) + \boldsymbol{n}(t),$$

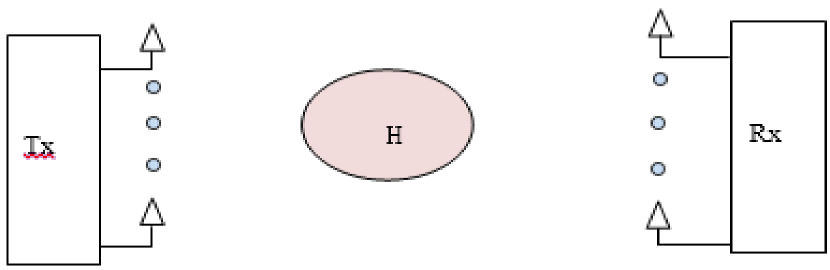


Figure 1.5 MIMO typical block diagram

Where y (t) is the received signal column vector with N element, x (t) is the input (transmitted) signal column vector with M dimension, n (t) is the additive noise which is a column vector with N dimension. Assuming R denotes the rank of channel matrix H and a MIMO channel is decomposed R parallel independent channels, an R-fold dada rate increase can be achieved by multiplexing different data onto different channels in comparison with the single antenna input and single antenna output (SISO) system. In this thesis, white Gaussian noise is assumed, that is, the entries of the noise vector are independent, identically distributed (i.i.d) with zero mean and variance matrix $\sigma^2 x$, where I is the identity matrix with N×N dimension. In the remainder of this thesis, the time index (t) is often omitted

A useful matrix operation used in decomposing the MIMO system is the singular value decomposition (SVD) of the channel matrix H. The SVD matrix manipulation is expressed as:

$$\boldsymbol{H} = \boldsymbol{U} \boldsymbol{\Sigma} \boldsymbol{V}^H ,$$

where U is an N × N unitary matrix, V is an M × M unitary matrix, H V is the Hermitian of the matrix V and $\sum$ is an N × M diagonal matrix of singular values $\{\sigma_i\ \}$ of H. Assuming λi is the ith largest eigenvalue of H HH , the singular value σ_i is equal to $\sqrt{\lambda}_i$ this singular value property holds. If both transmitter and receiver have perfect channel information, the MIMO channel can be decomposed into independent parallel channels. To estimate and optimize the channel capacity in MIMO system, parameters such as, channel bandwidth, the distribution of channel noise, the transmit power constraint are playing an important part in addition to the channel side information at the transmitter (CSIT) and channel side information at the receiver (CSIR). In general, different assumptions about channel side information (CSI) and about the distribution of the channel H entries lead to different channel capacities and different approaches to space-time signaling. The capacity of the discrete static channels in terms of the mutual information between channel input x and output vector y is defined as

$$C = \max_{p(\mathbf{x})} I(x;y) ,$$

Where I(x, y) denotes the mutual information between channel input and channel output and p(x) is the input distribution. Hence the capacity is that the maximum mutual information taken over all possible input distribution p(x).

Multiuser MIMO channel capacity

We have discussed single user MIMO (SU-MIMO) case in the above. The antenna arrays in the SU-MIMO system are deployed at one transmitter and one receiver. In a wireless application system such as cellular wireless system, one base station needs to support multiple users. If multiple antennas are equipped at the base station and user terminal having one or multiple antennas, the antenna arrays are across the base station and multiple users. The communication channel of such system is referred to as multiuser MIMO (MU-MIMO) channel. The distinct feature of MU-MIMO system is that the base station can communicate with multiple users simultaneously in the same frequency channel if a transmit scheme is designed by utilizing the space signature of the users in the system and the interference among users can be eliminated or

Minimized. This feature is called space division multiple access (SDMA) which refers to channel reuse within a cell due to geographical location of users.

Therefore, SDMA can improve system performance by increasing the spectral efficiency. Assume that K users are in a cellular system, the base station is equipped with M antennas and each user terminal equipped with one or more antennas, Figure 2.10 shows two kinds of channels in the MU-MIMO system, namely uplink channel (or multiple access channels) and downlink channel (broadcast channel). The system performance analysis to MUMIMO system is more complex than the performance analysis to the SUMIMO system. In the case of downlink channel, the MU-MIMO channel behaves the same as SU-MIMO if the transmitter has perfect channel information from all users, although different users experience different path loss and channel fading due to the space signature of user terminals. In comparison with SU-MIMO channel, the transmit-receive pairs in MUMIMO channel can originate from different users. In the case of uplink channel, system capacity achieved depends on if users can cooperate in encoding in the transmission stage.

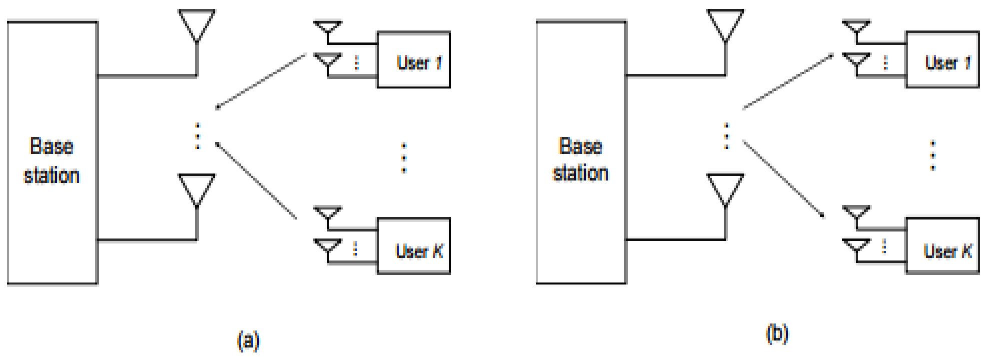


Figure 1.6 MU-MIMO channel: (a) Uplink, (b) Downlink

1.3 THESIS CONTIBUTION

It is well known that the capacity of multiple-input multiple-output (MIMO) channels grows linearly with the minimum of the number of antennas at the transmitter and the receiver sides [6]. Therefore one way to achieve very high spectral efficiency is to exploit large numbers of antennas at both the transmitter and receiver. The main bottleneck of such systems is the complexity of the receivers. A family of low complexity detectors termed Likelihood Ascent Search (LAS) detectors have been proposed in [7] for large MIMO systems. The power of the LAS detector lies in the linear average per bit complexity and the excellent BER performance in large MIMO systems (It has been proven [8] that the asymptotic BER performance of LAS detectors converges to that of maximum likelihood (ML) detector for example). The main disadvantage of LAS detectors, which is the motivation of our work, is that they need very large numbers of antennas to achieve the optimal BER performance, especially in high order modulation [8].

A conventional LAS detector [7] starts from an initial solution vector x which can be the output from any known detector such as zero-forcing for example. It then searches through a sequence of solution vectors to refine the solution with monotonic likelihood ascent. Note that the update rule (2) can be simplified and implemented more efficiently as in [7]. The LAS detector checks the candidate bits defined in the sequence of sets L(n) and updates x(n) according to (2). The LAS algorithm reaches a fixed point and terminates when there is no bit flipped in a certain period .Since the update algorithm (2) ensures monotonic likelihood ascent, it is guaranteed to converge to a local maximum likelihood (LML) point which will be the final output of the detector and will occur in a finite number of steps [9][10]. Obviously, the output LML point depends on the initial vector and the sequence of SCS. Specifying a sequence of L (n) for $n \geq 0$ and an initial vector x, one determines a particular LAS detector. L (n) should be designed such that all the bits are regularly checked in the sequence of SCS. One straightforward SCS is that each L(n) contains only one element, with element value modulo(n, L), so the detector checks all the L bits one by one in L steps. This sequence is then repeated until no bit is flipped in the last cycle. We should mention that checking (or updating) the bits in different orders may lead to different outputs. This approach to selecting the SCS has been shown to have good BER performance in the family of LAS algorithms. The likelihood ascent search (LAS) method, which performs a very simple procedure, had its main application within image restoration [47–49] and is based on Hopfield neural networks. In [50, 51], LAS was presented in the context of CDMA detection. In, [11], the same algorithm was presented in the context of large (and square) MIMO detection. What LAS does is essentially a bit-flipping procedure. At a given symbol vector, saysˆ, LAS changes one bit at a time, say bit i, and checks whether the likelihood is increased or decreased. In our system model, this is equivalent to evaluating whether the following is satisfied or not. . If it is not increased, then a different bit in sˆ is flipped and so on. If none of the bit-flips yield a likelihood ascent, the algorithm is terminated and the current symbol vector is returned as the solution. The LAS procedure has shown to converge rather fast to a solution. However, this solution is only guaranteed to be a local maximum (of the likelihood) and the global optimum may not be found. This is something that methods like Tabu search, see, try to fix. There are several variations of the LAS algorithm. An evident extension is to choose properly in which order to flip the bits to avoid getting stuck in a “wrong” local minimum and to converge fast to a global minimum [12]. Another extension is to let the number of bits flipped concurrently vary, and not flip just one bit at a time [13]. The complexity of the LAS algorithm is not fixed and it highly depends on the realization of the channel matrix and the noise.

1.4 THESIS LAYOUT

Chapter 2: This chapter will give a detailed description of Massive MIMO system models.

Chapter 3: This chapter will give a detailed description of Multi User Detection Techniques.

\Chapter 4: This chapter will discuss the proposed LAS detection technique for massive MIMO.

Chapter 5: This chapter includes the MATLAB results and discussion.

Chapter 6: This chapter presents the conclusions.

CHAPTER 2-MASSIVE MIMO SYSTEM MODEL

2.1 MASSIVE MIMO SYSTEM MODEL

Basically, the MIMO system has been categorized as Space Division Multiplexing (SDM) and Space Division Multiple Access (SDMA) for achieving different design goals in various wireless applications.

2.1.1 Space Division Multiplexing (SDM)

This system employs multiple antennas at both transmitting and receiving antennas as shown in Figure 2.1. The multiple transmitting antennas are used for either diversity gain or throughput gain (data rate gain). In the context of diversity techniques, multiple replicas of the information are transmitted through different paths, hence the SDM system is capable of exploiting both transmitter and receiver diversity to achieve reliable communications. The antennas are spaced as far apart as possible, so that the signals transmitted to or received by the different antennas experience independent fading and hence the highest possible diversity gain can be attained. Space Time Trellis Coding (STTC) [12] and Space Time Block Coding (STBC) [13] techniques are widely used to achieve the maximum possible diversity gain. However, the BER performance improvement is often obtained at the expense of a data rate loss, since STBCs and STTCs may not result additional throughput gain. As a design alternative, a specific class of SDM system was developed for improving multiplexing gain by transmitting different signal streams independently over each of the transmit antennas. This class of MIMO techniques is renowned as the Bell Labs Layered Space-Time (BLAST) scheme [14, 15]. The BLAST architecture aims to increase the system throughput in terms of the data rate that can be transmitted in a limited bandwidth.

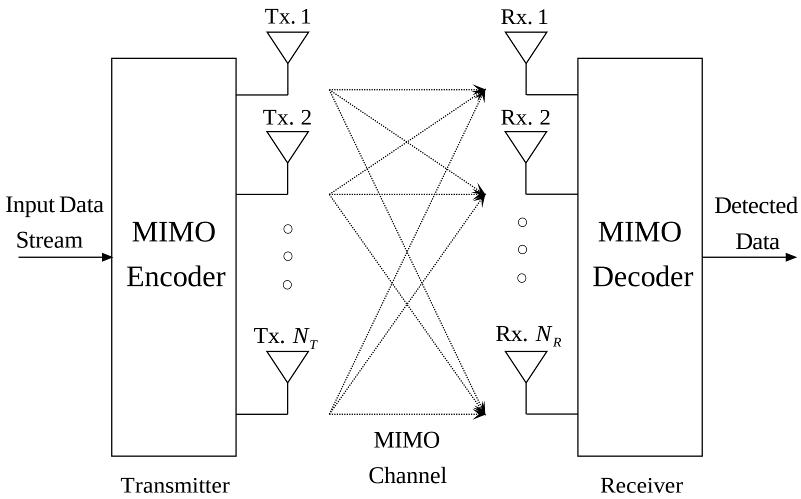


Figure 2.1 SDMmodel

2.1.2 Space Division Multiple Access (SDMA)

In contrast to the multiplexing schemes, the SDMA employs multiple users each equipped with a single transmitting antenna and an array of base station antennas [14]. SDMA exploits the unique user specific spatial signature constituted by their channel transfer function or equivalently Channel Impulse Response (CIR) for separating user's signals. This allows the system to support multiple users within the same frequency band and/or time slot, given that their CIRs are sufficiently different and are accurately measured. Spatially separated user's data streams can simultaneously access the channel in the same frequency band, provided that the locations of transmit and receive antennas are appropriately chosen. Figure 2.2 illustrates A SDMA uplink transmission scenario, where each of the *L* simultaneous users is equipped with a single transmissions antennas, while the receiver capitalizes on a *P*–element antenna front end. Space-division multiple access (SDMA) is a channel access method based on creating parallel spatial pipes next to higher capacity pipes through spatial multiplexing and/or diversity, by which it is able to offer superior performance in radio multiple access communication systems In traditional mobile cellular_network systems, the base station has no information on the position of the mobile units within the cell and radiates the signal in all directions within the cell in order to provide radio coverage. This results in wasting power on transmissions when there are no mobile units to reach, in addition to causing interference for adjacent cells using the same frequency, so called co-channel cells. Likewise, in reception, the antenna receives signals coming from all directions including noise and interference signals. By using smart antenna technology and differing spatial locations of mobile units within the cell, space-division multiple access techniques offer attractive performance enhancements. The radiation pattern of the base station, both in transmission and reception, is adapted to each user to obtain highest gain in the direction of that user. This is often done using phased array techniques.

In GSM cellular networks, the base station is aware of the distance (but not direction) of a mobile phone by use of a technique called "timing advance" (TA). The base transceiver station (BTS) can determine how far the mobile station (MS) is by interpreting the reported TA. This information, along with other parameters, can then be used to power down the BTS or MS, if a power control feature is implemented in the network. The power control in either BTS or MS is implemented in most modern networks, especially on the MS, as this ensures a better battery life for the MS. This is also why having a BTS close to the user results in less exposure to electromagnetic radiation. This is why one may be safer to have a BTS close to them as their MS will be powered down as much as possible. For example, there is more power being transmitted from the MS than what one would receive from the BTS even if they were 6 meters away from a BTS mast. However, this estimation might not consider all the Mobile stations that a particular BTS is supporting with EM radiation at any given time. In the same manner, 5th generation mobile networks will be focused in utilizing the given position of the MS in relation to BTS in order to focus all MS Radio frequency power to the BTS direction and vice versa, thus enabling power savings for the Mobile Operator, reducing MS SAR index, reducing the EM field around base stations since beam forming will concentrate RF power when it will be used rather than spread uniformly around the BTS, reducing health and safety concerns, enhancing spectral efficiency, and decreased MS battery consumption.

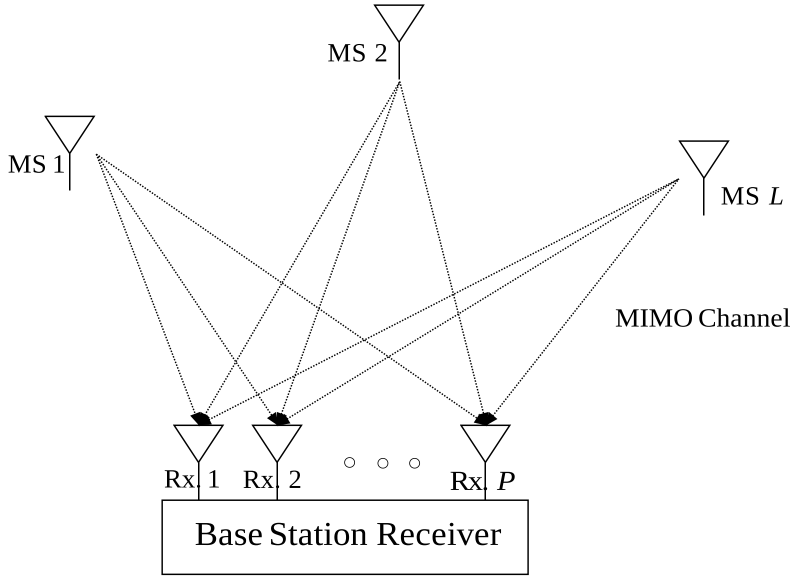


Figure 2.2 SDMA model

2.2 MU-MIMO

It is known that the capacity of a MIMO system scales linearly with the minimum of the number of antennas at transmitter and receiver. In cellular networks, the number of antennas at BSs is larger than that at users. Thus, if we increase the number of antennas at BSs but keep the one at users unchanged, the capacity is not likely greatly improved. To fully leverage the potential of MIMO communications, the idea is to serve many users at the same time which results in MU-MIMO .Due to the increasing demand for higher data rates, better quality of service (QoS), higher network capacity, increased spectral efficiency and link 7 reliability, MIMO emerges as an enabling technology which can improve the performance of wireless communications in these aspects [15]. The main benefit of MIMO is in the form of spatial multiplexing [16]. The spatial multiplexing scheme allows multiple transmit (TX) antennas to send different bit streams to multiple receive (RX) antennas in order to greatly improve the system throughput. Using a number of TX and RX antennas, the spatial multiplexing scheme can make efficient use of the spatial resource such that it can offer a linear increase in system capacity. To be more specific, if there are antennas at the transmitter, and antennas at the receiver, the channel capacity can be increase by an order of ( ). In addition, MIMO also offers the benefit of diversity gain, which increases the system reliability by mitigating multipath fading. In particular, when multiple TX antennas send the same signal to multiple RX antennas, even though the signals at some RX antennas may suffer from deep fades during the transmission, it is still possible that other RX antennas get sufficient signal quality. In this way, the symbol error rate is greatly reduced.

With the growing understanding of the theoretical knowledge of MIMO, and due to the potential of increasing the system reliability and capacity, MIMO can be considered the most important technology in modern wireless communications. However, the early research in MIMO considers only point-to-point communication, which is the case of SU-MIMO. In order to incorporate MIMO into the more practical multi-user context, more and more researchers have begun to focus on the development of MUMIMO, instead of SU-MIMO. MU-MIMO [4] is a cellular communication system which enables the simultaneous use of more than one terminal (or user) during the communication, while SU-MIMO can only afford one terminal (or user). MU-MIMO will be introduced in the following. As a key technology in wireless communication, MU-MIMO has the following potential benefits compared to SU-MIMO [17]-[19]: 8

(1) It suffers less from antenna correlation effect as compared to SUMIMO. Even though antenna correlation still affects the diversity on the per-user basis, it is not a major issue for the MU-MIMO system diversity;

(2) Spatial multiplexing gain is achieved at the base station (BS) without the need of multiple antennas equipped at the user, which reduces the cost on the terminal side;

(3) The spatial domain can offer an additional degree of freedom, which can be exploited by multiuser diversity;

(4) MU-MIMO system is more robust due to high multipath richness and low correlation between the antennas on the user side.

According to Fig. 1.1, MU-MIMO can be divided into two kinds of channels according to the direction of information transmission. In the downlink case, the M-antenna BS transmits K data streams to the K users (or terminals). This is known as the Broadcast Channel (BC). On the other hand, the uplink is called the Multiple Access Channel (MAC). The algorithms for the capacity calculation of the BC and MAC cases will be explained in detail in Chapter 3. A large amount of theoretical research has been conducted in the field of MU-MIMO. The performance of MU-

MIMO depends on three factors (1) Precoding scheme at the transmitter side; (2) Quality of the channel state information (CSI); (3) Channel characteristic and user separation .It is found that, using the interference rejection combining receiver, the capacity improvement can be maximized for the condition of small angular spread with co-polarized and closely spaced uniform linear arrays at the BS. In order to get accurate CSI, [20] proposed a feedback mechanism of using spatial correlation information from the users' channels to design codebook. In [21], the authors present a system level simulation to obtain different TX correlation performance. In [22], a joint TX-RX user scheduling scheme is proposed to help the BS have better CSI and hence optimize the channel performance.

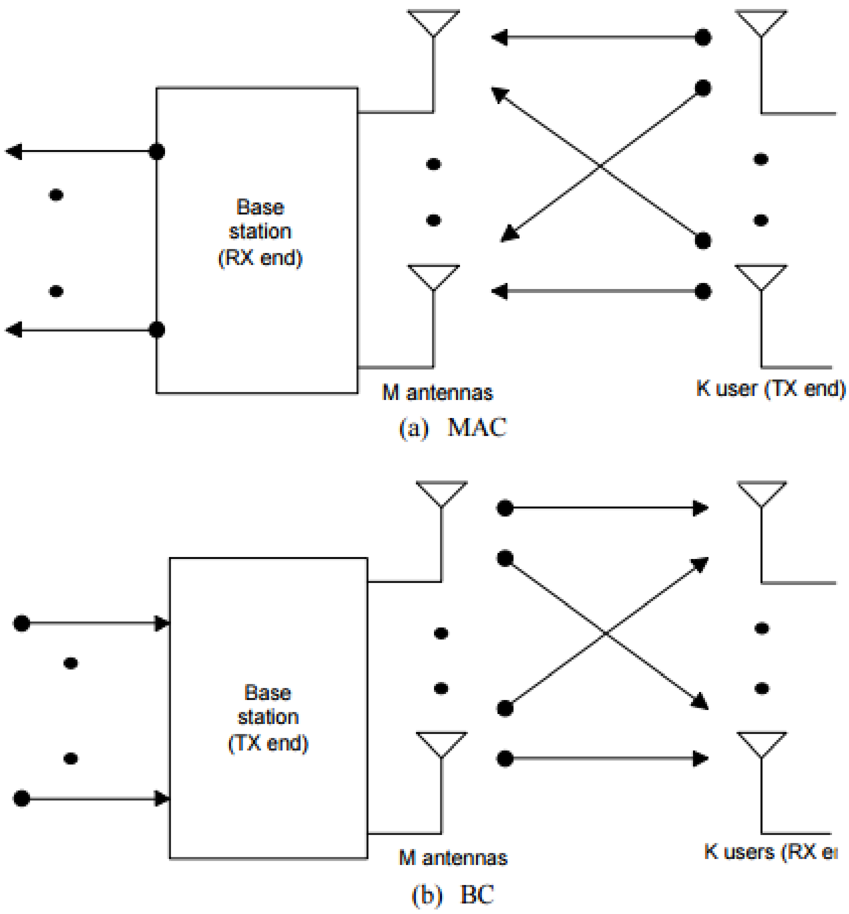


Figure 2.3 Uplink(MAC) and Downlink (BC) scenarios of MU-MIMO

CHAPTER 3 – CLASSICAL MULTIUSER DETECTION

3.1 MULTI USER DETECTION (MUD)

Because all users are considered as signals for each other, therefore, instead of users interfering with each other, they are all being used for their mutual benefit by joint detection. The multiuser channel is just the superposition of many single user channels. . Single user and multiuser spread spectrum systems have similar transmitter and receiver structures .Reduced interference leads to capacity increase of the system. It also solves the near/far problem. A cellular system has a number of mobiles which communicate with one base station (BS). The BS has to detect all the signals whereas each mobile is concerned with its own signal. This implies that the BS must know all the chip sequence. In multiuser detection, one of the main drawbacks is that of complexity. There is always a trade-off between complexity and performance of the system. Due to above mentioned two points, the main use of the multiuser detection system is for the BS, or in the reverse link (mobile to BS). The Base Station records information only on the mobiles in its own cell. This limits improvements to be expected in a MUD system. The signal received at the BS is the superposition of signals from all users, multipath components for each user's signal, and Additive White Gaussian Noise (AWGN).

3.1.1 Optimum Multiuser Detection:

The matched filter detector, described above, was believed to be the optimum detector until proved otherwise by Verdu in the early 1980's. His optimum solution jointly maximizes the likelihood functions for K users by choosing the bits {b1, b2, …, bK} that minimizes the mean square error (MSE) between the estimated received signal and the actual composite received signal, which is the sum of the received signals for all K users plus noise. It has been shown that the complexity of the optimum detector is O (2K), which increases exponentially with the number of users. In addition to complexity, the optimum detector requires a priori knowledge of the amplitudes of all K users, which is typically not available to the receiver. Although, the optimum detector has been shown to dramatically increase the capacity of the system, its complexity deems it infeasible to implement in the real world [25]. The work by Verdu gave hope that the capacity can ultimately increase using suboptimal multiuser detectors that balance between the two extreme cases of using the optimal detector or the matched filter detector. Hence, some linear multiuser detectors were proposed to accomplish that goal.

3.2.2 Linear Multiuser Detection:

Linear multiuser detectors attempt to attain as much of the capacity increase as the optimum detector while reducing the complexity of the system such that it can be implemented. They are simply linear filters that attempt to suppress MAI. In these detectors, a linear mapping (transformation) is applied to the soft outputs of the conventional detector to produce a better set of outputs to provide better performance. The two popular linear multiuser detectors are the decorrelating detector [26-28] and the Minimum Mean Square Error (MMSE) detector [29, 30]. They are highly analogous to the zero-forcing and MMSE equalizers used to combat intersymbol interference (ISI) in a single- user channel [31]. The decorrelating detector attempts to completely eliminate all MAI while the MMSE detector tries to minimize the square of the residual noise plus interference. Therefore, the decorrelating detector is a special case of the MMSE detector, where the noise is zero. The decorrelating detector has the same noise enhancement problem as the zero-forcing equalizer. It is also the decorrelating detector attempts to completely eliminate all MAI while the MMSE undefined when there are more users simultaneously using the channel than spreading chip per information bit, since it is impossible to drive the interference noise to zero in this situation [25]. The MMSE, on the other hand, requires accurate channel and user information, as does the optimum detector. Along with the channel and user knowledge, the MMSE requires a KxK matrix inversion which becomes extremely complex to evaluate as K increases the spreading factor N and the energy per bit E divided by the noise spectral density N0, respectively. Other multiuser detection techniques include nonlinear MUD, such as the Decision Feedback (DF) multiuser detector and the turbo multiuser detector, and Interference Cancellation (IC) MUD. In the following we discuss about the techniques namely Zero Forcing (ZF), Minimum Mean Square Error (MMSE) and Maximum Likelihood (ML).

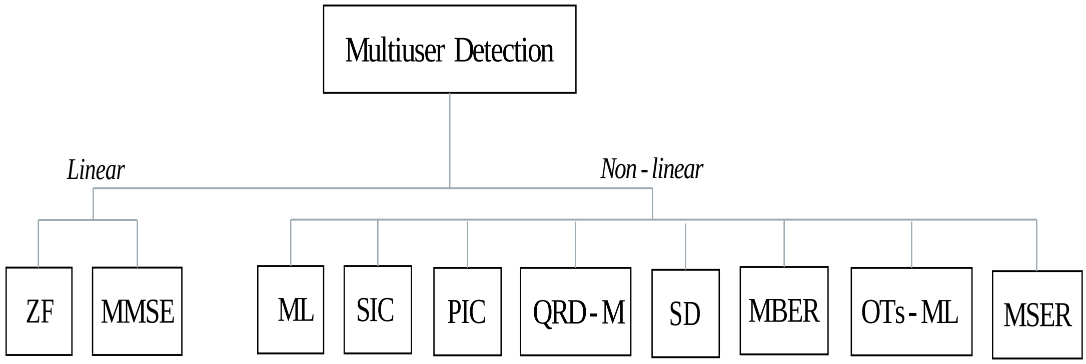


Figure 3.1 Classification of MUD schemes

3.2 Zero Forcing (ZF)

Zero Forcing refers to a form of linear equalization algorithm used in communication systems which applies the inverse of the frequency response of the channel. The Zero-Forcing applies the inverse of the channel frequency response to the received signal, to restore the signal after the channel. [1] It has many useful applications. 1n (MIMO) where knowing the channel allows recovery of the two or more streams which will be received on top of each other on each antenna. The name Zero Forcing corresponds to bringing down the intersymbol interference (ISI) to zero in a noise free case. This will be useful when ISI is significant compared to noise. In reality, zero-forcing equalization does not work in most applications, for the following reasons: Even though the channel impulse response has finite length, the impulse response of the equalizer needs to be infinitely long at some frequencies the received signal may be weak. To compensate, the magnitude of the zero-forcing filter ("gain") grows very large. As a consequence, any noise added after the channel gets boosted by a large factor and destroys the overall signal-to-noise ratio. Furthermore, the channel may have zeroes in its frequency response that cannot be inverted at all.

If the channel response (or channel transfer function) for a particular channel is H(s) then the input signal is multiplied by the reciprocal of it. This is intended to remove the effect of channel from the received signal, in particular the intersymbol interference (ISI).The zero-forcing equalizer removes all ISI, and is ideal when the channel is noiseless. However, when the channel is noisy, the zero-forcing equalizer will amplify the noise greatly at frequencies f where the channel response H (j2πf) has a small magnitude (i.e. near zeroes of the channel) in the attempt to invert the channel completely. A more balanced linear equalizer in this case is the minimum mean-square error equalizer, which does not usually eliminate ISI completely but instead minimizes the total power of the noise and ISI components in the output.

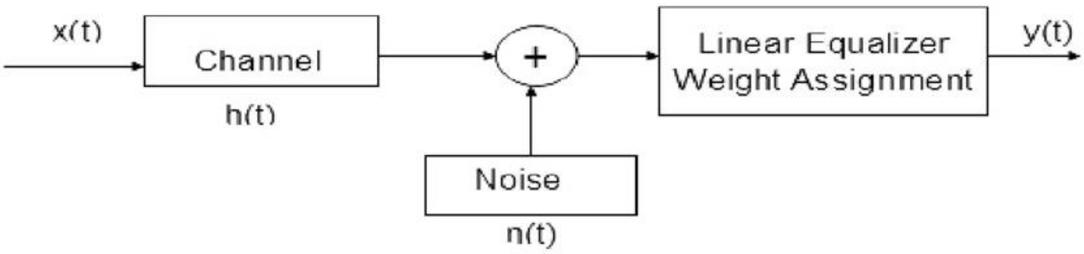


Figure 3.2 ZF block diagram

The ZF MUD scheme involves a linear transformation between the output signal and estimated channel.

$$\mathbf{y=Hx + n}$$

Y→RECEIVED SIGNAL   X→TRANSMITTED SIGNAL

H→CHANNEL MATRIX   N→NOISE

$$\boldsymbol{x} = \begin{pmatrix} \boldsymbol{x_1} \\ \boldsymbol{x_2} \\ \vdots \\ \boldsymbol{x_t} \end{pmatrix} \qquad \boldsymbol{y} = \begin{pmatrix} \boldsymbol{y_1} \\ \boldsymbol{y_2} \\ \vdots \\ \boldsymbol{y_r} \end{pmatrix}$$

$$\mathbf{H}= \begin{pmatrix} \boldsymbol{h_{11}} & \boldsymbol{h_{12}} & \cdots & \boldsymbol{h_{1t}} \\ \boldsymbol{h_{21}} & \boldsymbol{h_{22}} & \dots & \boldsymbol{h_{2t}} \\ \vdots & \vdots & \ddots & \vdots \\ \boldsymbol{h_{r1}} & \boldsymbol{h_{r2}} & \cdots & \boldsymbol{h_{rt}} \end{pmatrix}$$

The transmitted signal is detected form the least square error $\|\boldsymbol{y}-\boldsymbol{Hx}\|^2$ as:

$$\begin{aligned}\|\boldsymbol{y}-\boldsymbol{Hx}\|^2 &= (\boldsymbol{y}-\boldsymbol{Hx})^H(\boldsymbol{y}-\boldsymbol{Hx}) \\ &= -2\boldsymbol{H}^H\boldsymbol{y}+2\boldsymbol{H}^H\boldsymbol{Hx}\end{aligned}$$

The optimal minima of $\boldsymbol{x}$ can be obtained from $\partial\|\boldsymbol{y}-\boldsymbol{Hx}\|^2 \big/ \partial x = 0$. Hence,

$$\begin{aligned}-2\boldsymbol{H}^H\boldsymbol{y}+2\boldsymbol{H}^H\boldsymbol{Hx} &= 0 \\ \hat{\boldsymbol{x}} &= \left(\boldsymbol{H}^H\boldsymbol{H}\right)^{-1}\boldsymbol{H}^H\boldsymbol{y}\end{aligned}$$

In the above equation $\left(\boldsymbol{H}^H\boldsymbol{H}\right)^{-1}\boldsymbol{H}^H = \boldsymbol{H}^\dagger$, where $\hat{\boldsymbol{H}}^\dagger$ is the pseudo inverse of $\boldsymbol{H}$. Here we neglect noise in the above equation so we won't get an appropriate detection of the transmitted signal.

3.3 Minimum Mean Square Error (MMSE) MUD

In telecommunication, a Minimum Mean Square Error (MMSE) estimator is a estimator which follows an estimation method, through which it minimizes the mean square error for the fitted values of various dependent variables. The method MMSE more closely refers to the estimation in a quadratic cost function in Bayesian setting. The thinking procedure behind this Bayesian approach is to estimate stems from various practical conditions where we sometimes have some major information about the parameters which are required to be estimated.

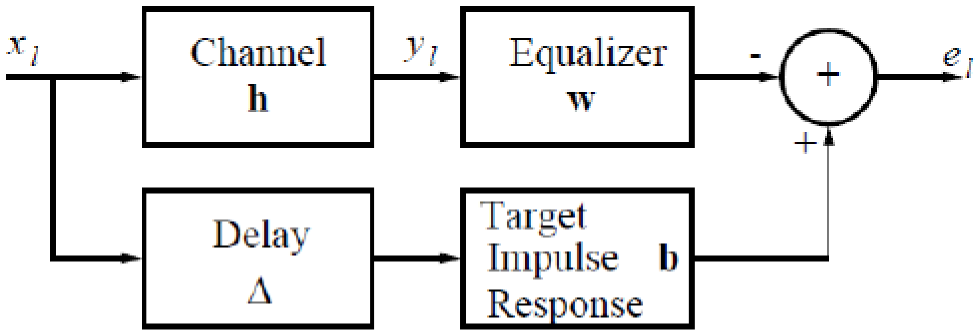


Figure 3.3 MMSE block diagram

MMSE receiver holds back both interference as well as noise components, but as far as the ZF receiver is concern, it only eliminates the interference or the noise. From this we can conclude that the Mean Square Error (MSE) is minimized. To overcome the drawback of noise enhancement of ZF, the concept of MMSE is introduced. So, we can say that, MMSE is pretentious to ZF in the presence of noise and interference.

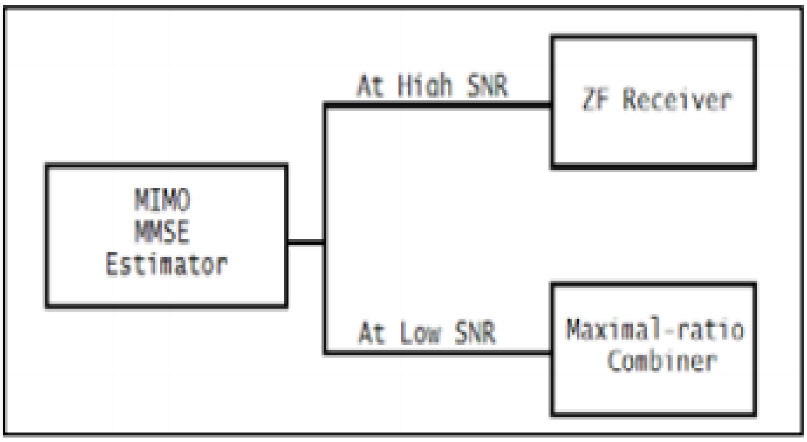


Figure 3.4 MIMO estimator

The linear MMSE MUD scheme assumes a priori knowledge of noise variance and channel covariance. In this MMSE MUD, the weight matrix '***w***' can be expressed by minimizing the mean square error, i.e. $\mathrm{MSE} = E\left[|\hat{\boldsymbol{x}} - \boldsymbol{x}|^2\right]$, where $\hat{\boldsymbol{x}}$ is the estimate of $\boldsymbol{x}$. Hence,

$$E\left[|\hat{\boldsymbol{x}} - \boldsymbol{x}|^2\right] = E\left[\left(\boldsymbol{w}^H \boldsymbol{y} - \boldsymbol{x}\right)^H \left(\boldsymbol{w}^H \boldsymbol{y} - \boldsymbol{x}\right)\right]$$

The optimal value of $\boldsymbol{w}^H$ can be obtained from $\partial E\left[\left|\hat{\boldsymbol{x}}-\boldsymbol{x}\right|^2\right]\Big/\partial \boldsymbol{w}=0$. This yield:

$$\boldsymbol{w}^H = R_{yy}^{-1}R_{yx}$$

Where $R_{yy} = E\left[\boldsymbol{y}\boldsymbol{y}^H\right]$ is the auto covariance of $\boldsymbol{y}$ and $R_{yx} = E\left[\boldsymbol{y}\boldsymbol{x}^H\right]$ is the cross covariance of $\boldsymbol{y}$ and $\boldsymbol{x}$, those are given by [56]:

$$R_{yy} = \left(\boldsymbol{H}^H\boldsymbol{H} + \sigma_n^2\boldsymbol{I}_P\right)$$

$$R_{yx} = \boldsymbol{H}^H$$

Replacing R_{yy} and R_{yx} in eq. (2.17),

$$\boldsymbol{w}^H = (\boldsymbol{H}^H\boldsymbol{H} + 2\sigma_n^2\boldsymbol{I}_P)^{-1}\boldsymbol{H}^H$$

$$\hat{\boldsymbol{x}} = (\boldsymbol{H}^H\boldsymbol{H} + 2\sigma_n^2\boldsymbol{I}_P)^{-1}\boldsymbol{H}^H\boldsymbol{y}$$

Where $(.)^H$ indicates Hermitian transpose and $\boldsymbol{I}_P$ is $\boldsymbol{P}$-dimensional identity matrix.

.

In the above equation, if SNR is high then σ_n^2 will become negligible. Hence, at higher SNR values the performance of ZF and MMSE MUDs are almost equal. In general, the received signal contains residual interference which is not Gaussian distributed due to multiuser interference. But these linear detectors assume that the received signal is corrupted by AWGN only. In addition to that, the linear detectors fail to mitigate the nonlinear degradation caused by the wireless radio environment. Hence, the requirement of a non-linear detector is essential to detect users appropriately.

3.4 MAXIMUM LIKELIHOOD (ML)

The object of the receiver is as previously stated to obtain an estimate of the message, x, from the given data in y and H. There are a wide variety of techniques for doing this but as stated in the introduction this work will only be concerned with the maximum likelihood (ML) detector and approximation thereof. The ML detector has the desirable property that, under the statistical assumptions on s given in it minimizes the probability of error. Note that minimizing the probability of error is equivalent to maximizing the probability of correctly estimating s, i.e.

$$P\,(x = \hat{x} | y, H)$$

The ML detector uses the Maximum a Posteriori (MAP) detection when all the users are equally likely to transmit. The ML detector supporting *L* simultaneous transmitting users, invokes a total of 2^{mL} metric evaluations in order to detect the possible transmitted symbol vector $\hat{x}$, where *m* denotes the number of bits per symbol. This detector calculates the Euclidean distance for all possible transmitted signal vectors and estimates the signals as expressed here [32, 33]:

$$\hat{\boldsymbol{x}} = \arg\left\{\min_{u} \left\| \boldsymbol{y} - \boldsymbol{H}\tilde{\boldsymbol{x}}_u \right\|^2 \right\},\ u = 1, 2, \ldots, 2^{mL}$$

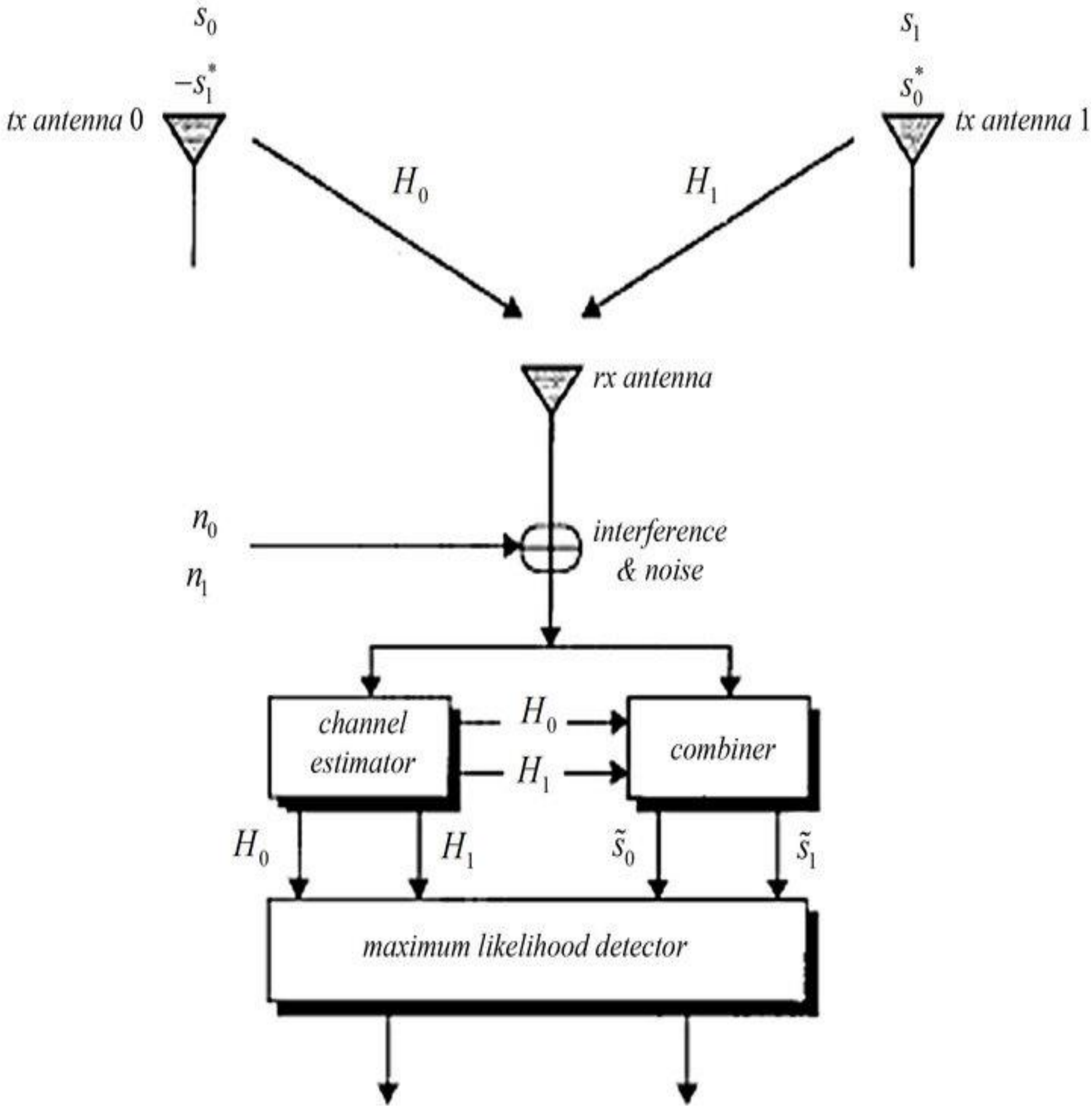


Figure 3.5 ML block diagram

Where u is the set of total metric evaluations associated with the specific modulation order and $\tilde{x}_u = \left[\tilde{x}_u^1, ..., \tilde{x}_u^L\right]^T$, $u = 1, 2, ..., 2^{mL}$ is a possible transmitted symbol. This optimal detector uses an exhaustive search for finding the most likely transmitted user's signal. Here we take every possibility into consideration check with that so that we can get the appropriated result but it is time taking process which increases complexity in detection. Hence taking complexity into consideration we don't use this detection method mostly.

CHAPTER 4-PROPOSED LAS DETECTION

4.1 PROPOSED LAS DETECTION

Here we present a low-complexity algorithm for detection in large MIMO systems based on the likelihood ascent search (LAS) algorithm. The key idea in our work is to generate multiple possible solutions or outputs from which we select the best one. We propose two possible approaches to achieve this goal and both are investigated. Computer simulations demonstrate that the proposed algorithm, Multiple Output Selection-LAS, which has the same complexity order as that of conventional LAS algorithms, is superior in bit error rate (BER) performance to LAS conventional algorithms.

It is well known that the capacity of multiple-input multiple-output (MIMO) channels grows linearly with the minimum of the number of antennas at the transmitter and the receiver sides [34]. Therefore one way to achieve very high spectral efficiency is to exploit large numbers of antennas at both the transmitter and receiver. The main bottleneck of such systems is the complexity of the receivers. A family of low complexity detectors termed Likelihood Ascent Search (LAS) detectors have been proposed in [35] for large MIMO systems. The power of the LAS detector lies in the linear average per bit complexity and the excellent BER performance in large MIMO systems (It has been proven [36] that the asymptotic BER performance of LAS detectors converges to that of maximum likelihood (ML) detector for example). The main disadvantage of LAS detectors, which is the motivation of our work, is that they need very large numbers of antennas to achieve the optimal BER performance, especially in high order modulation [36].

We consider a MIMO system with Nt transmit antennas and Nr receive antennas ($Nr \geq Nt$). The baseband system model is given by

$$y = Hx + N$$

Y→RECEIVED SIGNAL X→TRANSMITTED SIGNAL

H→CHANNEL MATRIX N→NOISE

$$\boldsymbol{x} = \begin{pmatrix} \boldsymbol{x_1} \\ \boldsymbol{x_2} \\ \vdots \\ \boldsymbol{x_t} \end{pmatrix} \qquad \boldsymbol{y} = \begin{pmatrix} \boldsymbol{y_1} \\ \boldsymbol{y_2} \\ \vdots \\ \boldsymbol{y_r} \end{pmatrix}$$

$$\mathbf{H=} \begin{pmatrix} \boldsymbol{h_{11}} & \boldsymbol{h_{12}} & \cdots & \boldsymbol{h_{1t}} \\ \boldsymbol{h_{21}} & \boldsymbol{h_{22}} & \cdots & \boldsymbol{h_{2t}} \\ \vdots & \vdots & \ddots & \vdots \\ \boldsymbol{h_{r1}} & \boldsymbol{h_{r2}} & \cdots & \boldsymbol{h_{rt}} \end{pmatrix}$$

'N' is the complex white Gaussian noise. The elements of the $Nr{\times}Nt$ channel matrix H are assumed i.i.d complex Gaussian random variables with zero mean and variance of unity.

A conventional LAS detector [35] starts from an initial solution vector *x* which can be the output from any known detector such as zero-forcing for example. It then searches through a sequence of solution vectors to refine the solution with monotonic likelihood ascent. At step *n*, the update algorithm for BPSK modulation using the LAS algorithm can be explained as follows. Given the initial vector x(0) $\in \{+1,-1\}^L$ and the search candidate sets (SCS) L(*n*) $\subseteq \{1, 2, \cdots L\}$, $\forall\ n \geq 0$, the j^{th} bit of *x*(*n* + 1) is given by

$$x_j(n+1) = \begin{cases} +1, & \text{if } x_j(n) = -1 \text{ and } M(x(n+1)) < M(x(n)) \\ -1, & \text{if } x_j(n) = +1 \text{ and } M(x(n+1)) < M(x(n)) \\ x_j(n), & \text{otherwise} \end{cases}$$

where $M(x) = ||y - Hx||^2$ is the likelihood metric for $\boldsymbol{x}$. Note that the update rule (2) can be simplified and implemented more efficiently as in [35]. The LAS detector checks the candidate bits defined in the sequence of sets L(*n*) and updates *x*(*n*) according to (2). The LAS algorithm reaches a fixed point and terminates when there is no bit flipped in a certain period.

Since the update algorithm (2) ensures monotonic likelihood ascent, it is guaranteed to converge to a local maximum likelihood (LML) point which will be the final output of the detector and will occur in a finite number of steps [37][38].

Obviously, the output LML point depends on the initial vector and the sequence of SCS. Specifying a sequence of L (n) for $n \geq 0$ and an initial vector x, one determines a particular LAS detector. L (n) should be designed such that all the bits are regularly checked in the sequence of SCS. One straightforward SCS is that each L(n) contains only one element, with element value modulo(n, L), so the detector checks all the L bits one by one in L steps. This sequence is then repeated until no bit is flipped in the last cycle. We should mention that checking (or updating) the bits in different orders may lead to different outputs. This approach to selecting the SCS has been shown to have good BER performance in the family of LAS algorithms.

4.1.1 MULTIPLE OUTPUT SELECTION-LAS ALGORITHM

An intuitive idea to improve the BER performance of conventional LAS algorithms is to generate different LML points, from which we select the best one as the final output. By doing so, we expect the probability that the output is a global maximum likelihood (GML) point is increased. We suggest the following two Multiple Output Selection-LAS (MOS-LAS) approaches to achieve this goal.

A. Multiple Initial Vectors (MIV)-LAS Algorithm

The procedure of this proposed algorithm is explained as follows: 1) Generate K initial vectors p1, p2 ⋯ pK. 2) Obtain K LML point's s1, s2 ⋯ sK by using LAS algorithm with K different initial vectors generated in 1). 3) Select the LML point with the minimum metric, i.e. ˆ s = arg min i=1, 2⋯K||y-Hsi||2. We should note that the initial vectors are not necessarily generated from known detectors but could be random vectors. Random vectors have the advantage that they do not need channel inversion and that we can save computation. In fact we show later that by using multiple random initial vectors we can achieve better BER performance and less complexity at the same time compared to conventional LAS algorithms.

B. Multiple Search Candidate Sets (MSCS)-LAS Algorithm

Another approach to obtaining multiple solutions from LAS is to use multiple SCS (MSCS) with only one initial vector. In this approach we suggest that the initial vector be obtained using MMSE, which is generally the best approach to use when only one initial vector is available in LAS. The procedure of MSCS-LAS algorithm can then be summarized as follows: 1) Obtain an initial vector p by using MMSE detector. 2) Obtain K LML points s1, s2 ··· sK by using MMSE-LAS algorithm with K different sequences of SCS as L1 (n), L2 (n), ···, LK (n). Here we update one bit each step for all the K different sequences of SCS, but with different orders. 3) Select the LML point with the minimum metric, i.e. ˆ s = arg min i=1, 2···K||y-Hsi||2. Note that we do not guarantee the K LML points obtained in step 2) are all different. The complexity of the LAS algorithm (excluding the initial vector) is mainly affected by the average number of steps required to reach to a fixed point. For MIV-LAS (except with multiple random vectors) algorithm the complexity is about K times the conventional LAS algorithms and is acceptable with small K. Because the average number of steps is very small for the LAS algorithm, using MMSE as the initial value, the complexity of the MSCS-LAS algorithm is comparable to the conventional LAS algorithms with small K (approx. K<10 from simulation results).

4.1.2 Complexity

The complexity of the LAS algorithm comprises three main components, namely, (1) computation of the initial vector x, (2) computation of H^TH, and (3) the search operation. For n_i=n_r, because of the matrix inversion involved, the complexity of computing the ZF or MMSE initial solution vector is O (n_t^3), i.e. O (n_t^2), per-symbol complexity. Likewise, H^TH can be computed in O (n_t^2), per-symbol complexity. From simulations, it has been found that the LAS search requires an average per-symbol complexity of O (n^t).So the total complexity of the algorithm is dominated by the initial solution computation rather than the search operation. The overall average per-symbol complexity is O (n_t^2), which scales well for large MIMO systems.

CHAPTER 5-SIMULATION RESULTS

5.1 RESULTS

This section presents simulation study and results by comparing the performances of classical linear and nonlinear MUD techniques in the SDMA system. All the classical MUD schemes have been investigated when all the users are transmitting 4–QAM signals. Further, as the MBER MUD is basically designed for BPSK modulation, performance of this detector is investigated when all the users are transmitting BPSK signals. The parameters of the standard wireless channels used in simulation analysis are presented in Appendix A. The performances of these detectors are evaluated with an assumption that the receiver has a perfect knowledge about the statistics of the wireless channel. The rest of the simulation parameters are provided in Table 2.1.

Table 5.1: Basic simulation parameters of the SDMA with classical MUDs

Parameters	**Value**
Number of Sub-carrier	128
Length of Guard Band	32
Number of OFDM Frames	1000
Number of Receiving Antennas (P)	4
Number of Users (L)	4
Conjugate Gradient algorithm	
Learning Rate (η)	0.08

Error Precision (β)	0.0001
Initial condition	MMSE solution
FEC Code	
FEC Scheme	Convolutional code
Code rate	1/2
polynomial	(133, 171)

The LAS algorithm reaches a fixed point and terminates when there is no bit flipped in a certain period. Since the update algorithm (2) ensures monotonic likelihood ascent, it is guaranteed to converge to a local maximum likelihood (LML) point which will be the final output of the detector and will occur in a finite number of steps [4][5]. Obviously, the output LML point depends on the initial vector and the sequence of SCS. Specifying a sequence of L (n) for $n \geq 0$ and an initial vector x, one determines a particular LAS detector. L (n) should be designed such that all the bits are regularly checked in the sequence of SCS. One straightforward SCS is that each L(n) contains only one element, with element value modulo(n, L), so the detector checks all the L bits one by one in L steps. This sequence is then repeated until no bit is flipped in the last cycle. We should mention that checking (or updating) the bits in different orders may lead to different outputs. This approach to selecting the SCS has been shown to have good BER performance in the family of LAS algorithms.

Table 5.2: Basic simulation parameters of the SDMA–OFDM with classical MUDs

Parameters	**Value**
Data frame size (N_F)	1000
Number of data frames (N_D)	1000
Modulation technique	BPSK
Number of Receiving Antennas (P)	128
Number of Users (L)	128
Channel	Rayleigh Flat Fading

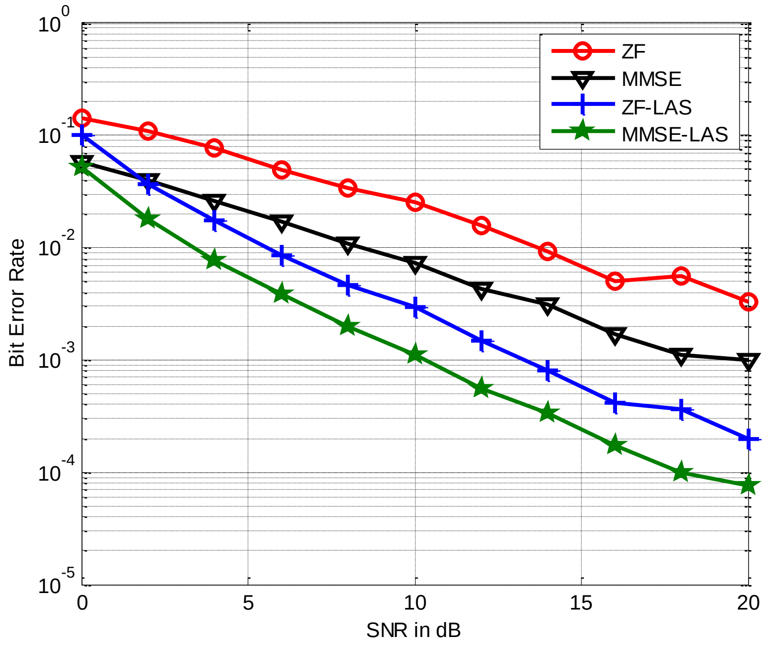


Figure 5.1: Average BER performance of all 64 users using various MUDs for a MU-MIMO system with 128 receiving antennas

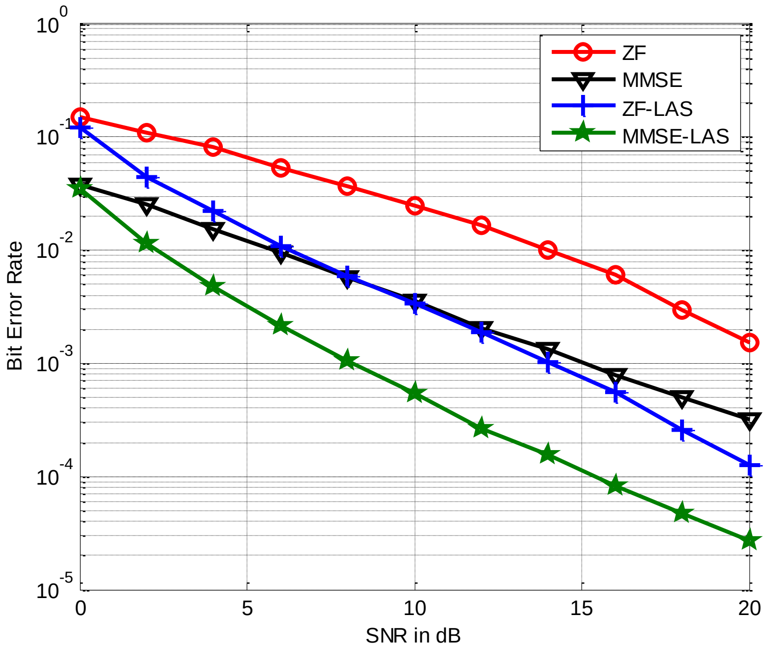
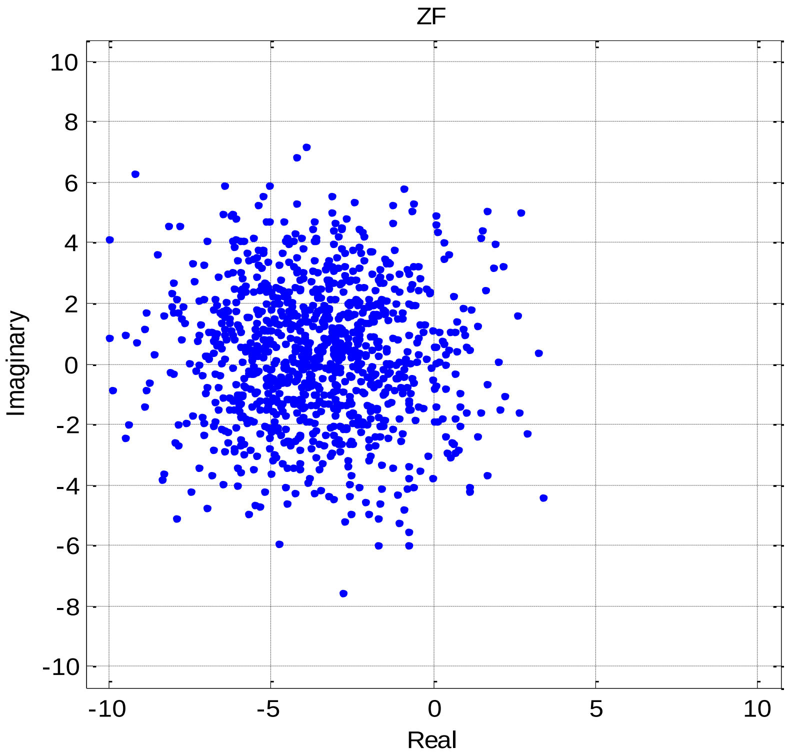
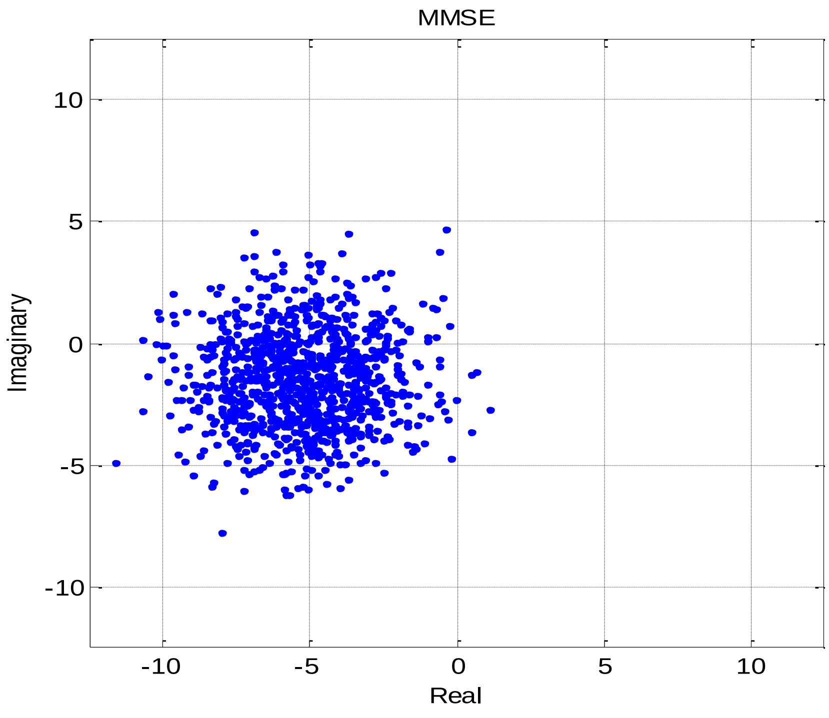


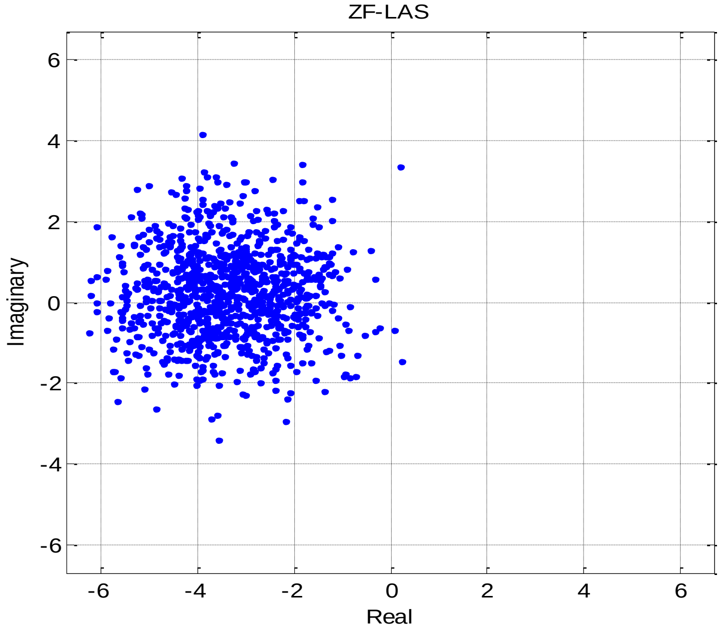
Figure 5.2: Average BER performance of all 128 users using various MUDs for a MU-MIMO system with 128 receiving antennas

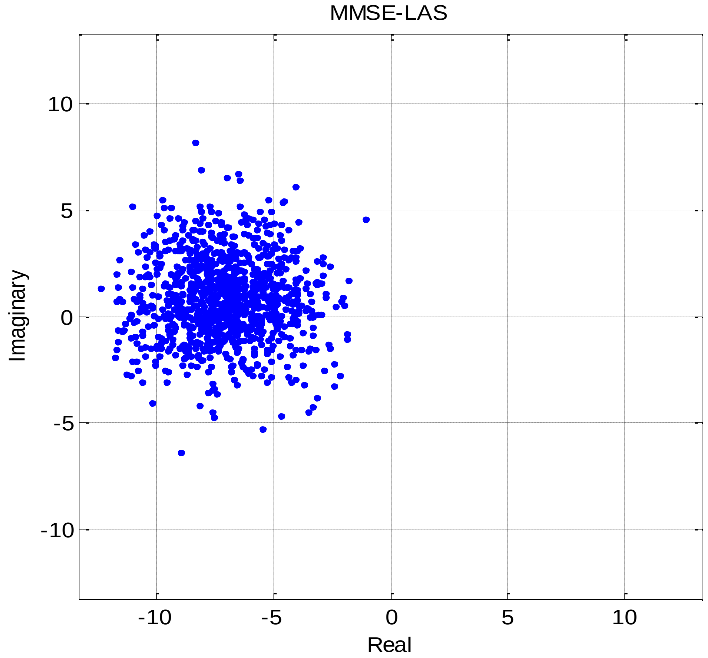

ZF
Imaginary
Real
10
8
6
4
2
0
-2
-4
-6
-8
-10
-10
-5
0
5
10

(a)


MMSE
Imaginary
Real
10
5
0
-5
-10
-10
-5
0
5
10

(b)





(d)

Figure 5.3: Estimated symbol distribution of User-1 using various MUDs when User-1 is always transmitting '–1' at 10 dB SNR value (a) ZF (b) MMSE (c) ZF-LAS (d) MMSE-LAS

Table 5.3: Complexity comparisons

Multiuser Detector	**Complexity order**
ZF	$N_F \times N_D$
MMSE	$N_F \times N_D$
ZF-LAS	$N_F \times N_D \times L$
MMSE-LAS	$N_F \times N_D \times 2^{mL}$

CHAPTER 6-CONCLUSION

6.1 CONCLUSION

The basic background of this research work including MIMO system SDM and SDMA system model is presented. Detection schemes may be invoked for the sake of separating different users at the BS in an uplink SDMA system. Different classical multiuser detection techniques have been introduced. The performance evaluation of all MUD techniques based on simulation study has been carried out over three typical wireless channel environments in order to shown their adaptability and robustness. The advantages and drawbacks of the linear detection techniques like ZF and MMSE along with some nonlinear detection techniques like ML schemes have been explained. It is observed that, the performance the ML detector is optimal at the cost of additional complexity, especially in the context of a high number of users and for higher order modulation schemes. Also, the ZF and MMSE detectors exhibit low complexity at a cost of performance. The nonlinear successive detection technique outperforms the liner techniques, but still its performance is sub-optimal due to error propagation problem. As we have come across ML technique in the above discussion we faced much complexity issues so in order to reduce the complexity and to gain better optimal performance say higher capacity and BER we considered the LAS technique. Here to the LAS technique we applied multiple inputs and have drawn conclusions from output bits estimated say we have applied different techniques to ascent search namely LAS-ZF and LAS-MMSE and have drawn mathematical results by simulating with the help of MATLAB. Here we have compared different techniques by taking boundary conditions in which the transmitted bits fall into and also the BER performance into consideration and have drawn conclusions saying that LAS-ZF and LAS-MMSE has outperformed the conventional ZF,MMSE and ML techniques. However, all these MUD schemes fail to differentiate users in the critical overload scenario, when the number of users exceed number of BS receiving antenna. Here in this work we have discussed various scenarios followed by advantages and some disadvantages of each and every techniques and have drawn conclusions saying that LAS hasbetter spectral efficiency and lesser complexity in detection of the received signal bits.

CHAPTER 7 - REFERENCES

[1]. Telatar E (1999) Capacity of multi-antenna Gaussian channels. Eur. Trans. Telecomm. 10: 585–595.

[2]. (2010). 3GPP technical specification group radio access network, evolved universal terrestrial radio access (E-UTRA): Further advancements for e-ultra physical layer aspects (release 9).

[3]. (2009). Part 11: Wireless LAN Medium Access Control (MAC) and Physical Layer (PHY) Specifications - Amendment 5: Enhancements for Higher Throughput.

[4]. (2009). Part 16: Air interface for broadband wireless access systems.

[5]. Gesbert D, Kountouris M, Heath Jr RW, Chae CB & Sälzer T (2007) Shifting the MIMO paradigm. IEEE Signal Process. Mag. 24(5): 36–46

[6] G. Foschini and M. Gans, "On limits of wireless communications in a fading environment when using multiple antennas," Wireless Personal Commune, vol. 6, no. 3, pp. 311–335, 1998.

[7] K. Vardhan, S. Mohammed, A. Chockalingam, and B. Rajan, "A low complexity detector for large mimo systems and multicarrier CDMA systems," IEEE J. Sel. Areas Commun., vol. 26, no. 3, p. 473, 2008.

[8] S. Mohammed, A. Chockalingam, and B. Rajan, "Asymptotic analysis of the performance of LAS algorithm for large MIMO detection," online arXiv, vol. 806.

[9] Y. Sun, "A family of linear complexity likelihood ascent search detectors for CDMA multiuser detection," in Proc. IEEE 6th Intl. Symp. On Spread Spectrum Tech. & App, 2000.

[10] ——, "A family of likelihood ascent search multiuser detectors: an upper bound of bit error rate and a lower bound of asymptotic multiuser efficiency," IEEE Trans. Commun., vol. 57, no. 6, pp. 1743–1752, June 2009.

[11] H. Fan, J. Murch, and R. Mow, "Near maximum likelihood detection schemes for wireless MIMO systems," IEEE Trans. Wireless Commun., vol. 3, no. 5, pp. 1427–1430, 2004.

[12] H. Lim and B. Venkatesh, “An efficient local search heuristics for asynchronous multiuser detection,” IEEE Commun. Lett., vol. 7, no. 7, pp. 299–301, 2003.

[13] J. Hu and R. Blum, “A gradient guided search algorithm for multiuser detection,” IEEE Commun. Lett, vol. 4, no. 11, pp. 340–342, 2000.

[14]. M. Jiang and L. Hanzo, “Multiuser MIMO – OFDM for Next–Generation Wireless Systems”, Proc. of the IEEE, vol. 95, pp. 1430–1469, Jul. 2007

[15] 802.22 Working Group, “IEEE 802.22 D1: draft standard for wireless regional area networks,” March 2008. [Online]. Available: http://grouper.ieee.org/groups/802/22/.

[16] A. Ghasemi and E. S. Sousa, “Collaborative spectrum sensing for opportunistic access in fading environments,” in IEEE Int. Symp. New Frontiers Dyn. Spectrum Access Netw (DySPAN 2005), Baltimore, Md, USA, pp. 131-136, Nov. 2005.

[17] A. Goldsmith, Wireless Communications, Cambridge University Press, New York, USA, 2005.

[18] A. Goldsmith, S. Jafar, I Maric and S. Srinivasa, “Breaking Spectrum Gridlock with Cognitive Radios: An Information Theoretic Perspective,” in Proc. IEEE, Vol. 97, No. 5, pp. 894-914, May 2009.

[19] A. Goldsmith, S. Jafar, N. Jindal, and S. Vishwanath, “Capacity limits of MIMO channels,” IEEE J. Sel. Areas Commun., Vol. 21, No. 5, pp. 684–702, Jun. 2003.

[20] A. J. Paulraj, D. A. Gore, R. U. Nabar and H. Bölcskei, “An overview of MIMO communications-A key to gigabit wireless,” in Proc. IEEE, Vol. 92, No. 2, pp. 198- 218, Feb. 2004.

[21] A. M. Tulino and S. Verdo, Random Matrix Theory and Wireless Communications (2004). [Online]. Available: www.nowpublishers.com.

[21] A. Narula, N. J. Lopez, M.D. Trott, and G.W. Wornell, “Efficient use of side information in multiple-antenna data transmission over fading,” IEEE J. Sel. Areas Commun., Vol. 16, No 8, pp. 1423-1436, Oct. 1998.

[22] A. Nica and R. Speicher, Lectures on the Combinatorics of Free Probability, Cambridge University Press, 2006.

[23] A. Paulraj, R. Nabar, and D. Gore, Introduction to Space-Time Wireless Communications, Cambridge University Press, Cambridge, UK, 2003.

[24] A. Sahai and D. Cabric, “Spectrum sensing: fundamental limits and practical challenges,” in IEEE International Symposium on New Frontiers in Dynamic Spectrum Access Networks (DySPAN ’05), Baltimore, Md, USA, Nov. 2005.

[25] Alexandra Duel-Hallen, Jack Holtzman and Zoran Zvonar "Multiuser Detection for CDMASystems" IEEE Personal Communications (1995-04)

[26] Peter Ang ―Multiuser Detection for CDMA Systems‖ IEEE Personal Communications (2001)

[27] J. Andrews, "Successive Interference Cancellation for Uplink CDMA," Ph.D. Dissertation, Stanford University, 2002

[28] R. Lupas, and S. Verdu, ―Near-far Resistance of Multi-user Detectors in Asynchronous Channels, ‖ IEEE J. Select Areas Commun. 38 (1990) pp. 496- 508

[29] A. Klien and B.W. Baier, ―Linear Unbiased Data Estimation in Mobile Radio Systems Applying to CDMA‖ IEEE J. Select Areas Commun. 11(1999) pp. 1058-1066

[30] Z. Zvonar, ―Multi-user Detection in Asynchronous CDMA Frequency Selective Fading Channels‖ Wireless Personal Communications, Kluwer. 3 (1996)

[31] Proakis J.G. Digital Communications, McGraw-Hill New York 1995

[32] L. Hanzo, M. Munster, B. J. Choi, T. Keller, “OFDM and MC–CDMA for Broadband Multi-User Communications, WLANs and Broadcasting”, IEEE Press/Wiley, West Sussex, 2003.

[33] S. Verdu, “Multiuser Detection”, Camb. Univ. Press, Cambridge, U.K, 1998.

[34] G. Foschini and M. Gans, “On limits of wireless communications in a fading environment when using multiple antennas,” Wireless Personal Commun, vol. 6, no. 3, pp. 311–335, 1998.

[35] K. Vardhan, S. Mohammed, A. Chockalingam, and B. Rajan, “A low complexity detector for large mimo systems and multicarrier CDMA systems,” IEEE J. Sel. Areas Commun., vol. 26, no. 3, p. 473, 2008.

[36] S. Mohammed, A. Chockalingam, and B. Rajan, “Asymptotic analysis of the performance of LAS algorithm for large MIMO detection,” online arXiv, vol. 806.

[37] Y. Sun, “A family of linear complexity likelihood ascent search detectors for CDMA multiuser detection,” in Proc. IEEE 6th Intl. Symp. On Spread Spectrum Tech. & App, 2000.

[38] ——, "A family of likelihood ascent search multiuser detectors: an upper bound of bit error rate and a lower bound of asymptotic multiuser efficiency," IEEE Trans. Commun., vol. 57, no. 6, pp. 1743–1752, June 2009.

APPENDIX

```
clc;
close all;
clear all;
Nd = 1000;                                              % number of
data symbols per frame
Ns = 1000;                                             % Number of
data frames
Nt = Nd*Ns;                                            % total
nnumber of data symbols
EbNo = 0:2:20;                                         % SNR in dB
ModOrd = 1;                                            % Modulation
Order (Number of bits per symbol)
j = sqrt(-1);                                          % Imaginary
Component
Map = modem.pskmod('M', 2^ModOrd, 'PhaseOffset', pi,
'SymbolOrder','binary', 'InputType', 'bit');% PSK
Modulation syntax
Demap = modem.pskdemod(Map);                           % PSK
Demodulation syntax
t = 8;                                                 % No of
Transmitting Users
r = 8;                                                 % No of
receiving antennas
berzf = zeros(1,Ns);bermm = zeros(1,Ns);berzflas =
zeros(1,Ns);bermmlas = zeros(1,Ns);
Errzf = zeros(1,length(EbNo));Errmm =
zeros(1,length(EbNo));Errzflas =
zeros(1,length(EbNo));Errmmlas = zeros(1,length(EbNo));
for idx = 1:length(EbNo)
    snr = EbNo(idx)+ 10*log10(ModOrd)
    sigmaS = t/(10^(0.1*snr));
    for i = 1:Ns
        s = randi([0 1],ModOrd*t,Nd);
% generation of data bits
        x = modulate(Map, s);
% generation of data symbols
        H = (randn(r,t)+j*randn(r,t))/sqrt(2);
% Rayleigh fat fading channel
        y = awgn(H*x,snr);
% Received signal vector
        xzf = inv(H'*H)*H'*y;
% Estimated signal vector using ZF receiver
        xmmse = inv(H'*H+sigmaS*eye(t))*H'*y;
% Estimated signal vector using MMSE receiver
        Dzf = demodulate(Demap,xzf);
% Estimated data bits
```

```
        Dmmse = demodulate(Demap,xmmse);
% Estimated data bits
        xinzf = real(modulate(Map, Dzf));
% generation of data symbols
        xinmm = real(modulate(Map, Dmmse));
% generation of data symbols

        for m = 1:Nd
            Y =
y(:,m);xz=xinzf(:,m);xm=xinmm(:,m);xz1=xz;xm1=xm;
            for n =1:t
                xz1(n)=-xz(n);xm1(n)=-xm(n);
                if ((norm(Y-H*xz1))^2)<((norm(Y-H*xz))^2)
                    xz(n)=xz1(n);
                end
                if ((norm(Y-H*xm1))^2)<((norm(Y-H*xm))^2)
                    xm(n)=xm1(n);
                end
            end
            xinzf(:,m)=xz;xinmm(:,m)=xm;
        end
        Dzflas = demodulate(Demap,xinzf);
        Dmmlas = demodulate(Demap,xinmm);
        berzf(i)= biterr(s, Dzf);
% BER per data frame
        bermm(i)= biterr(s, Dmmse);
% BER per data frame
        berzflas(i)= biterr(s, Dzflas);
% BER per data frame
        bermmlas(i)= biterr(s, Dmmlas);
% BER per data frame
    end
    Errzf(idx) = sum(berzf)/(Nt*t);
% Total BER per SNR
    Errmm(idx) = sum(bermm)/(Nt*t);
% Total BER per SNR
    Errzflas(idx) = sum(berzflas)/(Nt*t*idx);
% Total BER per SNR
    Errmmlas(idx) = sum(bermmlas)/(Nt*t*idx);
% Total BER per SNR
end

semilogy(EbNo,Errzf,'-ro','linewidth',2);
hold on;
semilogy(EbNo,Errmm,'-ko','linewidth',2);
hold on;
semilogy(EbNo,Errzflas,'-bo','linewidth',2);
hold on;
semilogy(EbNo,Errmmlas,'-go','linewidth',2);
grid on;
```