Design of Massive Multiuser MIMO System to Mitigate Inter Antenna Interference and Multiuser Interference in 5G Wireless Networks

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Abstract—Massive Multi-user Multiple Input Multiple Output (MU–MIMO) system is aimed to improve throughput and spectral efficiency in 5G communication networks. Inter-antenna Interference (IAI) and Multi-user Interference (MUI) are two major factors that influence the performance of MU–MIMO system. IAI arises due to closely spaced multiple antennas at each User Terminal (UT), whereas MUI is generated when one UT comes in the vicinity of another UT of the same cellular network. IAI can be mitigated by the use of a pre-coding scheme such as Singular Value Decomposition (SVD) and MUI can be cancelled through efficient Multi-user Detection (MUD) schemes. The highly complex and optimal Maximum Likelihood (ML) detector involves a large number of computations, especially when in massive structures. Therefore, the local search-based algorithm such as Likelihood Ascent Search (LAS) has been found to be a better alternative for mitigation of MUI, as it results in near optimal performance using lesser number of matrix computations. Most of the literature have been aimed at mitigating either IAI or MUI, whereas the proposed work presents SVD pre-coding and LAS MUD to mitigate both IAI and MUI. Simulation results indicate that the proposed scheme can attain near-optimal bit error rate (BER) performance with fewer computations.

Index Terms—Multi-user MIMO, inter-antenna interference, multi-user interference, likelihood ascent search

I. INTRODUCTION

The ever-rising demand for high data rate applications and the drastically increasing wireless subscribers has ignited several researchers to focus on advanced future wireless communication technologies such as Massive Multi-user Multiple Input Multiple Output (MU-MIMO) system [1], [2]. The MU–MIMO is an envisioned data transmission technique which can increase the capacity and performance of next generation 5G wireless broadcasting systems [3]. Compared with the conventional MIMO, MU–MIMO system is equipped with a large array of antennas (hundreds of antennas) at the Base Station (BS) and makes use of these antennas to serve many User Terminals (UTs) [4]. The theoretical analysis of the communication system states that the implementation of massive antennas can achieve outstanding multiplexing and diversity gains thereby providing high data rates and more reliability [5]. Practically, MU–MIMO faces several base band processing challenges such as Inter-Antenna Interference (IAI) and Multi-user Interference (MUI) [6], [7]. IAI arises as the spacing between each antenna becomes much smaller than that of the conventional half-wavelength rule. On the other hand, when more than one UTs are at proximity, the Channel Impulse Responses (CIRs) of the UTs become virtually identical and may lead to MUI. The CIR is the spatial signature of each UT in MU–MIMO system.

The near optimal performance cannot be achieved unless both IAI and MUI are moderated [8]. For eliminating the IAI and enhancing the accuracy of signal data transmission, pre-coding schemes have to be used [9]. Linear pre-coders such as Matched Filter (MF) [10], Zero–Forcing (ZF) [11] and Minimum Mean Square Error (MMSE) [12] schemes can be used in MU–MIMO systems to attain sub optimal performance with less computational complexity. On the other hand, non-linear pre-coding schemes have also been found to provide near-optimal performance [13]-[16]. However, their order of complexity increases in practice. It is quite essential to design a pre-coder with near-optimal performance and fewer mathematical computations [17]. One such pre-coding scheme is Singular Value Decomposition (SVD) [18]. It is a matrix factorization pre-coder that transforms the MIMO channel matrix into parallel sub-channels. The main aim of SVD is to eliminate the IAI at each UT such that the MIMO channel matrix of each UT can be transformed in to a number of independent coded Single Input Single Output (SISO) channels which results in improved overall spectral efficiency and reduced computational complexity [19].

At the receiver terminal, Multi-user Detection (MUD) is needed to mitigate MUI and improve the quality of data signals [20]. The main aim of MUD schemes is to retrieve the desired user's transmitted signal vector from the received signal vector by cancelling interference from the undesired UTs. In general, ZF and MMSE techniques are used for MUD and have low computational complexity in terms of matrix multiplications and additions. However, their Bit Error Rate (BER)

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performance deteriorates with an increasing number of antennas [21]. Various MUD techniques have been reported to address this issue of interference in massive MU–MIMO system [22], [23]. The neighborhood search based techniques are efficient MUD technique used for mitigating MUI. In the family of neighborhood search based techniques, the Likelihood Ascent Search (LAS) is the foremost algorithm that searches for better solution in the neighborhood of its signal space [24], [25].

The LAS uses iterative search strategy and achieves better performance over ZF and MMSE at the cost of a little extra complexity. The LAS algorithm starts with an initial solution vector, which acts as the output vector of ZF or MMSE detector and searches for the best solution vector until the advancement in ML cost function saturates [26], [27]. The classical LAS explores the solution by changing single data symbol of the initial solution among all transmitting antennas for each iteration and detects the best solution vector [28]. The main advantage of LAS is that it attains approximate optimal BER performance even when massive number of antennas are deployed [29], [30]. Although the computational complexity is slightly larger than that of linear detectors, it is much lower as compared to that of optimal ML detector.

Most of the aforementioned research articles deal with either IAI or MUI, whereas the present work deals with both IAI and MUI. In summary, this paper discusses, using SVD assisted LAS (SVD–LAS) MUD for MU–MIMO system to achieve near ML performance with affordable computational complexity.

The remaining part of the paper is organized as follows: In Section 2, the mathematical model of MU-MIMO system with SVD pre-coding is proposed. The classical MUD techniques are discussed in Section 3. The proposed SVD assisted LAS multiuser detection scheme is given in Section 4. Simulation results and the conclusion are presented in Section 5 and Section 6 respectively.

Notation: Upper-case and lower-case boldface letters denote matrices and vectors, respectively. The matrices, $\boldsymbol{I}$ and $\boldsymbol{\Sigma}$ denote identity and diagonal matrix respectively. Further, $(.)^{-1}$, $(.)^{\mathrm{T}}$, $(.)^{\mathrm{H}}$, det(.), tr(.), |.| and ||.|| represent inverse, transpose, Hermitian, determinant, trace, absolute value and norm respectively.

II. Mathematical Model of MU–MIMO System with SVD Precoding

The block diagram of the proposed MU–MIMO uplink system with SVD pre-coding is illustrated in Fig. 1. In this paper, we assume that the uplink scenario of MU–MIMO system consists of K independent UTs, each equipped with M_T transmitting antennas. Thus the total number of transmitting antennas is N_T, where $N_T = K \times M_T$. All UTs simultaneously communicate with the base station equipped with N_R receiving antennas. Since the total number of antennas at transmitter and receiver is large, the given system is treated as Massive MU–MIMO system. The BS receiver is capable of obtaining the entire Channel State Information (CSI), whereas the k^{th} UT is capable of acquiring only its own CSI over the channel between BS and k^{th} UT. The k^{th} UT cannot acquire CSI of any other UTs. Further, we assume that there is no connection or cooperation among all UTs. Initially, the k^{th} user information bit vector $\boldsymbol{d}_k = [d_{1k}, d_{2k}, ..., d_{M_T k}]^T$ where, k = 1, 2…, K is modulated by the signal mapper to generate complex un-coded data symbol vector $\boldsymbol{b}_k^c = [b_{1k}, b_{2k}, ..., b_{M_T k}]^T$. These un-coded vectors are coded as $\boldsymbol{x}_k^c$ in SVD pre-coding to mitigate inter antenna interference (IAI) existing at each UT. The coded signal vector $\boldsymbol{x}_k^c = [x_{1k}^c, x_{2k}^c, ..., x_{M_T k}^c]^T$ is transmitted through M_T transmitting antennas over a user specific complex channel $\boldsymbol{H}_k^c$. The complex signal vector arrives at the BS from K–UTs simultaneous. This is mathematically modelled as

$$\boldsymbol{y}^c = \sum_{k=1}^{K} \boldsymbol{H}_k^c \boldsymbol{x}_k^c + \boldsymbol{n}^c \tag{1}$$

where, $\boldsymbol{y}^c$ is (N_R × 1) dimensional size, $\boldsymbol{n}^c = [n_1^c, n_2^c, ..., n_{N_R}^c]^T$ is the identical independent distribution additive white Gaussian noise (AWGN) with zero mean and the covariance distribution matrix $\sigma_n^2 I_{N_R}$ The channel matrix of k^{th} UT $\boldsymbol{H}_k^c$ is a (N_R × M_T)–dimensional Rayleigh flat fading channel matrix of k^{th} UT with zero mean and unit variance. The channel coefficient matrix between the BS and k^{th} UT consisting M_T antenna is expressed as

$$\boldsymbol{H}_k^c = \begin{bmatrix} h_{11}^k & h_{12}^k & \cdots & h_{1M_T}^k \\ h_{21}^k & h_{22}^k & \cdots & h_{2M_T}^k \\ \vdots & \vdots & \ddots & \vdots \\ h_{N_R 1}^k & h_{N_R 2}^k & \cdots & h_{N_R M_T}^k \end{bmatrix} \tag{2}$$

The complex MIMO system in (1) is modelled as an identical real valued system, without loss of generality. It is as follows

$$\boldsymbol{y} = \sum_{k=1}^{K} \boldsymbol{H}_k \boldsymbol{x}_k + \boldsymbol{n} \tag{3}$$

where,

$$\boldsymbol{x}_k = \left[\Re(\boldsymbol{x}_k^c)^T \;\; \Im(\boldsymbol{x}_k^c)^T \right]^T_{(2M_T \times 1)}, \quad \boldsymbol{y} = \left[\Re(\boldsymbol{y}^c)^T \;\; \Im(\boldsymbol{y}^c)^T \right]^T_{(2N_R \times 1)}$$

$$\boldsymbol{n} = \left[\Re(\boldsymbol{n}^c)^T \;\; \Im(\boldsymbol{n}^c)^T \right]^T_{(2N_R \times 1)} \quad \boldsymbol{H}_k = \begin{bmatrix} \Re\left(\boldsymbol{H}_k^c\right) & -\Im\left(\boldsymbol{H}_k^c\right) \\ \Im\left(\boldsymbol{H}_k^c\right) & \Re\left(\boldsymbol{H}_k^c\right) \end{bmatrix}_{(2N_R \times 2M_T)}$$

Here, $\Re$ and $\Im$ represent real and imaginary components respectively.

The IAI existing at each UT can be mitigated by factorizing the CSI using SVD. In SVD, the MIMO channel matrix of each UT can be transformed in to a number of independent coded single input single output (SISO) channels. Thus, the real valued channel matrix of the k^{th} UT is decomposed as

$$\boldsymbol{H}_k = \boldsymbol{U}_k \Sigma_k \boldsymbol{V}_k^H \tag{4}$$

where, $\boldsymbol{U}_k$ is a ($2N_R \times 2M_T$) dimensional unitary matrix and $\boldsymbol{V}_k$ is a ($2M_T \times 2M_T$) dimensional unitary matrix, which satisfy the properties of $\boldsymbol{U}_k^H \boldsymbol{U}_k = I$ and $\boldsymbol{V}_k^H \boldsymbol{V}_k = \boldsymbol{V}_k \boldsymbol{V}_k^H = I$. The ($2M_T \times 2M_T$) dimensional diagonal matrix consisting of non-negative singular values that are arranged in descending order, is given as

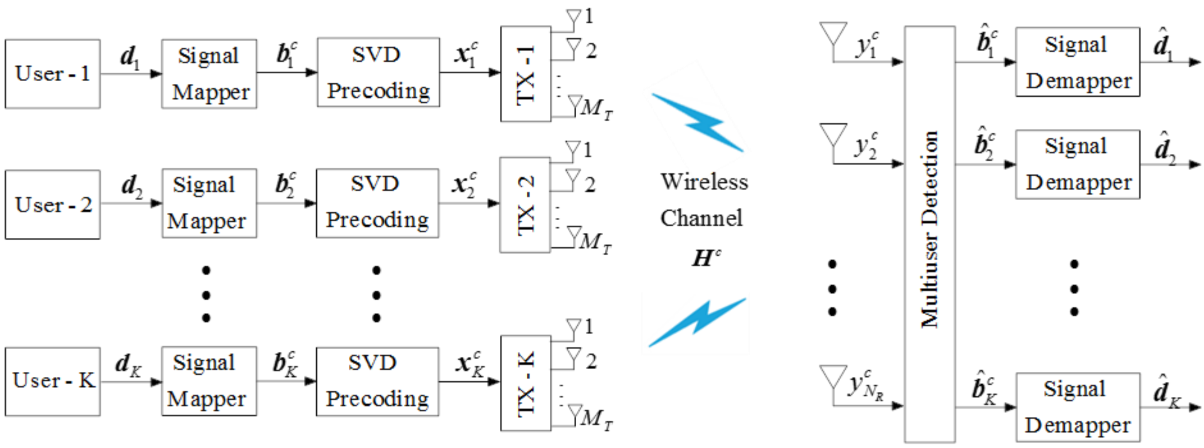

Fig. 1. Proposed uplink model of massive MU–MIMO system.

$$\Sigma_k = \begin{bmatrix} \Sigma_1^k & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \Sigma_{2M_T}^k \end{bmatrix}, \ k = 1, 2, ..., 2M_T \tag{5}$$

The received real valued signal of MU-MIMO systems given in (3) can be modified as (6) by using the SVD relation given in (4)

$$\boldsymbol{y} = \sum_{k=1}^{K} \boldsymbol{U}_k \Sigma_k \boldsymbol{V}_k^H \boldsymbol{x}_k + \boldsymbol{n} \tag{6}$$

Since x_k is a pre-coded signal vector and $\boldsymbol{V}_k$ is the unitary matrix in (6) can be re-written as

$$\boldsymbol{y} = \sum_{k=1}^{K} \boldsymbol{U}_k \Sigma_k \boldsymbol{V}_k^H \boldsymbol{V}_k \boldsymbol{b}_k + \boldsymbol{n} = \sum_{k=1}^{K} \boldsymbol{U}_k \Sigma_k \boldsymbol{b}_k + \boldsymbol{n} \tag{7}$$

where, $\boldsymbol{b}_k = \left[\Re(\boldsymbol{b}_k)^T \ \Im(\boldsymbol{b}_k)^T \right]^T$ is the ($2M_T \times 1$) dimensional real value signal vector of k^{th} UT.

For simplicity let us consider

$$\boldsymbol{U} = \left[\boldsymbol{U}_1, \boldsymbol{U}_2, ..., \boldsymbol{U}_K \right] \tag{8}$$

$$\Sigma = \text{diag}\left\{ \Sigma_1, \Sigma_2, ..., \Sigma_K \right\} \tag{9}$$

Then,

$$\boldsymbol{y} = \boldsymbol{G}\boldsymbol{b} + \boldsymbol{n} \tag{10}$$

Where, $\boldsymbol{G} = \boldsymbol{U}\Sigma$

III. Multi-user Detection of Massive MU–MIMO System

The SVD pre-coding is used at each UT of the MU–MIMO system to mitigate interference imposed by the other antennas of the same UT. The MU-MIMO still suffers from interference occurred from other transmitting UTs existing in the same network. This kind of interference is known as Multi-user Interference (MUI). This MUI can be moderated by using effective MUD schemes. The MU–MIMO system with both pre-coder and MUD is shown in Fig. 1. The key objective of MUD technique is to reconstruct the desired UT's transmitted signal vector from the received signal vector by cancelling interference from the undesired UTs in the vicinity.

Several linear detectors like Matched Filter (MF) [31], Zero–Forcing (ZF) [32] and Minimum Mean Square Error (MMSE) detectors [33] are used to minimize MUI, using less number of computations. The mathematical expressions to detect the real valued symbol vector $\hat{\boldsymbol{b}} = \left[(\hat{\boldsymbol{b}}_1)^T, (\hat{\boldsymbol{b}}_2)^T, ..., (\hat{\boldsymbol{b}}_K)^T \right]^T$ where, $\hat{\boldsymbol{b}}_k = \left[\Re(\hat{\boldsymbol{b}}_k^c)^T \ \Im(\hat{\boldsymbol{b}}_k^c)^T \right]^T$ of the different linear detectors are given as follows

$$\hat{\boldsymbol{b}}_{MF} = \boldsymbol{H}^H \boldsymbol{y} \tag{11}$$

$$\hat{\boldsymbol{b}}_{ZF} = \left(\boldsymbol{H}^H \boldsymbol{H} \right)^{-1} \boldsymbol{H}^H \boldsymbol{y} \tag{12}$$

$$\hat{\boldsymbol{b}}_{MMSE} = \left(\boldsymbol{H}^H \boldsymbol{H} + \sigma_n^2 I \right)^{-1} \boldsymbol{H}^H \boldsymbol{y} \tag{13}$$

The linear detection models given in (11) to 13) are transformed to SVD coded MU–MIMO system model as

$$\hat{\boldsymbol{b}}_{MF} = \boldsymbol{G}^H \boldsymbol{y} \tag{14}$$

$$\hat{\boldsymbol{b}}_{ZF} = \left(\boldsymbol{G}^H \boldsymbol{G} \right)^{-1} \boldsymbol{G}^H \boldsymbol{y} \tag{15}$$

$$\hat{\boldsymbol{b}}_{MMSE} = \left(\boldsymbol{G}^H \boldsymbol{G} + \sigma_n^2 I \right)^{-1} \boldsymbol{G}^H \boldsymbol{y} \tag{16}$$

These linear detectors achieve uniform Signal-to-Noise (SNR) ratios for all receivers.

The Maximum Likelihood (ML) detector is an optimal detector that estimates the transmit symbol vector from all feasible transmit vectors based on a maximum a priori criterion. Let $\boldsymbol{A} = [a_1, a_2,\ldots,a_L]$ denotes real valued signal set for the modulation scheme employed, where L is the size of signal set A. For example, signal set for BPSK is $\boldsymbol{A} = [-1, 1]$ and for 16–QAM is $\boldsymbol{A} = [-3, -1, 1, 3]$. So, L is equal to 2 and 4 respectively for BPSK and 16–QAM. Then the solution for ML is obtained from

$$\hat{\boldsymbol{b}}_{ML} = \arg\min_{s \in A^{2N_T}} \|\boldsymbol{y} - \boldsymbol{Hs}\|^2 \quad (17)$$

where, $\boldsymbol{A}^{2N_T}$ is the set of all possible candidates of the $2N_T$ – element real-valued transmitted data vector. The size of $\boldsymbol{A}^{2N_T}$ depends on the specific modulation scheme employed.

The ML has exponential computational complexity, hence it is difficult to implement for massive MIMO systems. So, there is a clear trade-off between linear and ML detectors in terms of performance and complexity. To balance this, the proposed LAS detection is suggested for MU–MIMO system with SVD pre-coding which is briefly described in section IV.

IV. Proposed LAS Detection for MU–MIMO System With SVD Precoding

It is well known that the capacity of the MIMO channel increases linearly with the number of antennas at the transmitter and the receiver terminals. One way to achieve high spectral efficiency is to deploy large numbers of antennas at both BS and UTs. The major drawback of such systems is their receiver complexity. Therefore, Likelihood Ascent Search (LAS) detector is recommended for large MIMO systems. The main feature of LAS detector is, it provides linear average per-bit complexity with satisfactory BER performance, especially for massive structures. The LAS algorithm explores a sequence of bit vectors until it reaches a fixed point. The sequence of bit vectors is designed based on the LAS update rule. The LAS starts with initial solution vector (solution of ZF or MMSE detectors), it searches superlative solution vector from its neighborhood vectors and calculates the best neighborhood solution by computing the ML detector. If the neighborhood solution vector is lesser than ML cost function, then it is chosen as the new initial vector. The iteration process repeats until it reaches local minima and this vector is declared as output vector. The main disadvantage of LAS detector is that it can provide acceptable performance only for a massive number of antennas. Unlike the ML detector, the LAS algorithm performs a local search for each transmitting symbol. So, it provides acceptable performance with less number of computations. Another challenge in LAS algorithm is selection of Initial vector. In order to overcome this issue, we propose SVD pre-coded LAS detection for MU –MIMO system which can mitigate both MUI and IAI.

Assume that k^{th} UT is the desired user and the initial solution of LAS algorithm is chosen as the real valued output vector of ZF or MMSE detector. Then, the n^{th} symbol of initial solution is replaced with all possible entities of the signal set $\boldsymbol{A}$ and the remaining symbols of ZF or MMSE are left unaltered. The entity that will give minimum ML cost value which is given in (17) is replaced with n^{th} symbol of initial solution. This process is continued for remaining $(2N_T - 1)$ symbols.

Let $\hat{\boldsymbol{b}} = \left[(\hat{\boldsymbol{b}}_1)^T, (\hat{\boldsymbol{b}}_2)^T, \ldots, (\hat{\boldsymbol{b}}_K)^T\right]^T = \left[\hat{b}_1, \hat{b}_2, \ldots, \hat{b}_{2N_T}\right]^T$ be the real valued output vector obtained from ZF or MMSE detectors. The LAS algorithm employed for detecting n^{th} data symbol of un-coded MU–MIMO system is expressed as

$$\hat{b}_{n,LAS} = \arg\min_{p_n \in A} \|\boldsymbol{y} - \boldsymbol{Hp}\|^2, \; n = 1, 2, \ldots, 2N_T \quad (18)$$

Similarly, The LAS algorithm employed for detecting n^{th} data symbol of SVD aided MU–MIMO system is expressed as

$$\hat{b}_{n,SVD-LAS} = \arg\min_{p_n \in A} \|\boldsymbol{y} - \boldsymbol{Gp}\|^2, \; n = 1, 2, \ldots, 2N_T \quad (19)$$

The $(2N_T \times 1)$ dimensional trail vector $\boldsymbol{p} = [p_1, p_2, \ldots, p_{2N_T}]^T$ is defined as

$$\boldsymbol{p}_i = \begin{cases} \boldsymbol{p}_n \in A & if \; i = n \\ \hat{b}_i & if \; i \neq n \end{cases}, \text{ where } i = 1, 2, \ldots, 2N_T \quad (20)$$

Thus, the number of ML cost function evaluations that are required to detect all users is $L \times 2N_T$.

The algorithm of the proposed SVD assisted LAS detector for MU–MIMO system is given as follows:

Algorithm: 1. The Proposed SVD Assisted LAS Detector

1: **Inputs :** $\boldsymbol{y, H, x, b, G, U, V, p}$
2: **Output:** $\hat{b}$
3: *Initialization n=1& i=1*
4: $\boldsymbol{x}_k \leftarrow \boldsymbol{V}_k \boldsymbol{b}_k$; preprocessing at k^{th} User
5: $\left[\boldsymbol{U}_k \boldsymbol{\Sigma}_k \boldsymbol{V}_k^H\right] \leftarrow$ SVD of $\boldsymbol{H}_k$
6: *Compute G & y*
7: $\hat{\boldsymbol{b}}_{MMSE} \leftarrow \left(\boldsymbol{G}^H\boldsymbol{G} + \sigma_n^2 I\right)^{-1} \boldsymbol{G}^H \boldsymbol{y}$
output of SVD based MMSE Detector
8: $\boldsymbol{p} \leftarrow \hat{\boldsymbol{b}}_{MMSE}$; initial solution for LAS detector
where, $\boldsymbol{p} = [p_1, p_2, \ldots, p_{2N_T}]^T$
9: for n=1 to $2N_T$; do
10: $\text{Cost}_{prev} \leftarrow \|\boldsymbol{y} - \boldsymbol{Gp}\|^2$
11: **for** i=1 to $2N_T$; do
12: $\boldsymbol{p}_n = A$
13: $\text{Cost}_{next} \leftarrow \|\boldsymbol{y} - \boldsymbol{Gp}\|^2$

if $\text{Cost}_{next} \le \text{Cost}_{Prev}$
$\boldsymbol{p}_i = \hat{b}_i$
end
$\text{Cost}_{prev} \leftarrow \text{Cost}_{next}$
end
end
Choose "p" as solution of SVD assisted LAS MUD

V. Simulation Results

In this section, the performance of the proposed SVD assisted LAS detector for MU-MIMO system will be discussed. Simulation results obtained by the proposed detector are compared with that of conventional MMSE, SVD-MMSE, MMSE-LAS detectors with respect to BER. These comparisons are drawn based on evaluation of BER of UT1. The uplink model of MU-MIMO system consists of a BS receiver with multiple antennas and each UT consisting of one multiple antennas. The wireless channel between UTs and BS is assumed to be Rayleigh flat fading channel. The simulation parameters of proposed Massive MU–MIMO system are summarized in Table I.

TABLE I: Simulation Parameters

Parameters	Description
Number of user terminals (UTs) (K)	15
Number of antennas per each UT (M_T)	8
Number of receiving antennas (N_T)	128
Number of symbols per data frame	1000
Number of data frames	100
Type of modulation scheme	BPSK,16–QAM

A. *Performance Analysis*

The BER performances of various detectors while varying Signal-to-Noise Ratio (SNR) are compared and plotted in Fig. 2 and Fig. 3. The BERs are evaluated when each UT is modulated by BPSK and 16–QAM signal mappers as shown in Fig. 2 and Fig. 3 respectively. From these figures, it is observed that the performance of un-coded MMSE detector is poor as it can mitigate neither MUI nor IAI. On the other hand, the SVD pre-coding helps remove IAI and LAS detection is used to moderate MUI.

As the number of UTs considered is more than the number of antennas per each UT, the effect of MUI is more significant than IAI. As evidenced in Fig. 2 and Fig. 3 the performance of MMSE–LAS detectors is better than the performance of SVD–MMSE detectors. Furthermore, it is observed that SVD assisted MMSE–LAS detector is more suitable for MU–MIMO as it nullifies both IAI and MUI. This improvement can be seen in both Fig. 2 and Fig. 3. However, the results show all these detectors perform well for BPSK modulation rather than for 16–QAM modulation.

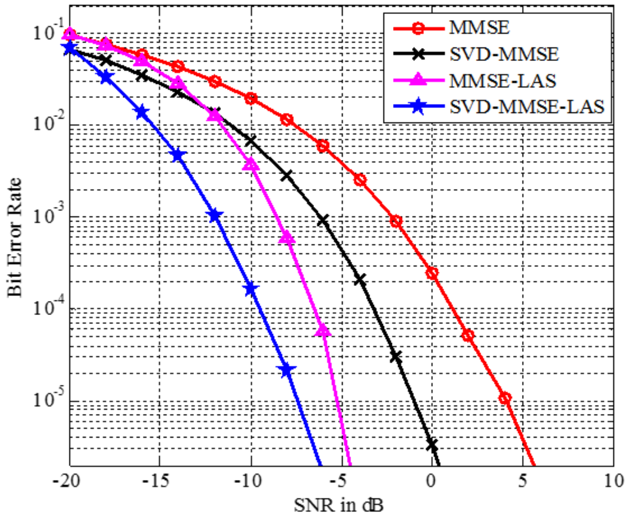

Fig. 2. BER comparison of various detectors considering BPSK modulation

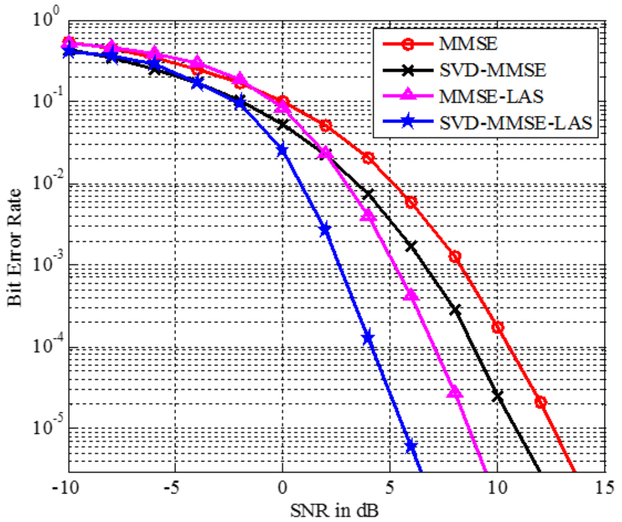

Fig. 3. BER comparison of various detectors considering 16–QAM modulation

For example, at 10^{-5} BER floor, while using BPSK modulation, the SNR required for un-coded MMSE detector is 4 dB and the SNR values required for SVD–MMSE, MMSE–LAS and SVD assisted MMSE–LAS detector are –1 dB, –5 dB and –7 dB, respectively. Similarly, for the same BER floor while using 16–QAM modulation, the SNR required for un-coded MMSE detector is 13 dB and the SNR values required for SVD–MMSE, MMSE–LAS and SVD assisted MMSE–LAS detector are 11 dB, 8 dB and 6 dB, respectively.

The BER performances of various detectors while varying number of UTs with respect to BPSK and 16–QAM modulation techniques are shown in Fig. 4 and Fig. 5, respectively. The SNR values considered for BPSK and 16–QAM modulated schemes are –10 dB and 0 dB, respectively. As the number of UTs in the network increases the corresponding MUI also increases and hence all detectors show high error in results. As shown in Fig. 4 and Fig. 5, the results of using LAS algorithm are more prominent while accommodating large number of UTs, as it is mainly useful for mitigating MUI which increases with number of UTs. The performance of MMSE–LAS is more or less same, as compared to that of SVD–MMSE with fewer number of UTs. Thus, when the number of UTs increases, the performance of MMSE–LAS is better than SVD–MMSE detector. Above all, the SVD assisted MMSE–LAS shows its superiority among all other techniques even in cases of high MUI.

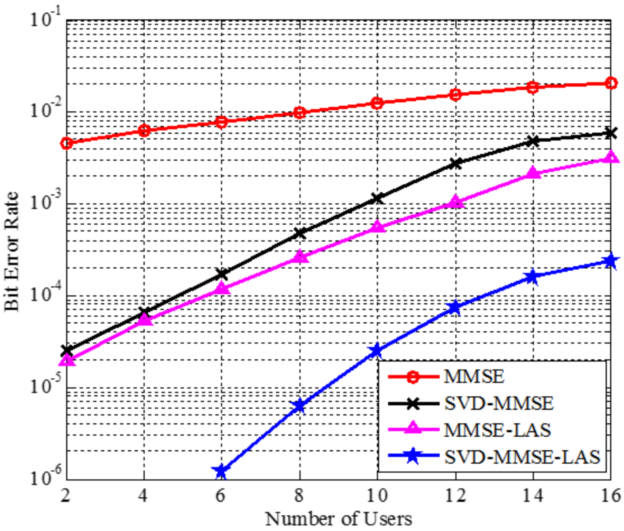

Fig. 4. BER comparison of various detectors for different number of users while each user's signals are modulated by BPSK mapper

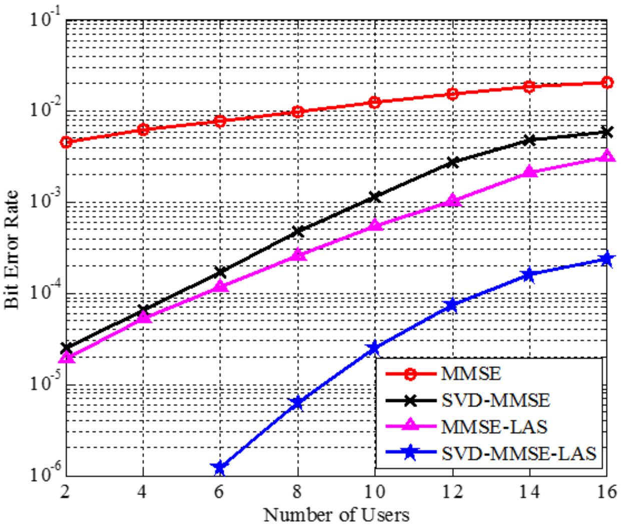

Fig. 5. BER comparison of various detectors for different number of users while each user's signals are modulated by 16–QAM mapper

For example, while accommodating 10 users modulated by BPSK, the un-coded MMSE result is 0.0123 BER, whereas the SVD–MMSE, MMSE–LAS and SVD assisted MMSE–LAS results are 0.00113625, 0.000541325 and 0.00002516 BERs, respectively, as seen in Fig. 4. Similarly, while accommodating 10 users modulated by 16–QAM, the un-coded MMSE result is 0.0615 BER, whereas the SVD–MMSE, MMSE–LAS and SVD assisted MMSE–LAS results are 0.1193526, 0.006352 and 0.0015261 BERs, respectively, as observed in Fig. 5.

B. *Complexity Analysis*

In this section, the complexity of proposed SVD assisted LAS algorithm is analysed in terms of ML cost function and number of numerical computations as presented in Table II and Table III.

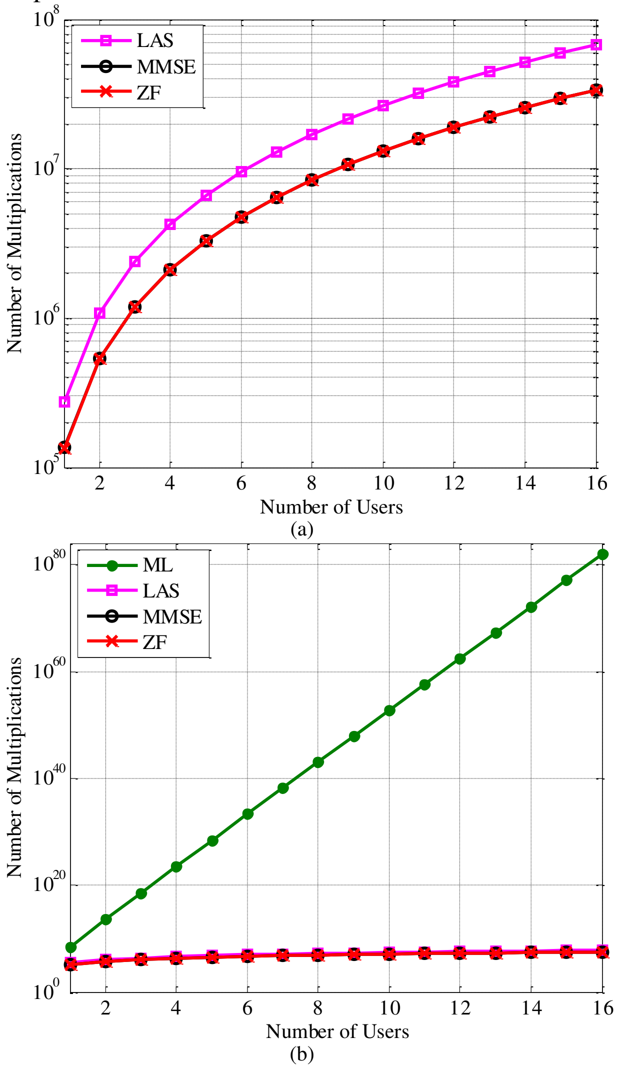

Fig. 6. Complexity comparison of various detectors for different number of users (a) without ML (b) with ML

In conventional MIMO system, the order of computational complexity is $O\left(M^3\right)$, where M is the dimensions of the matrix. However, in massive MU–MIMO structure, the usage of a large number of antennas results in higher matrix complexity which is undesirable. So, we propose SVD assisted LAS detector to limit the order of computational complexity to $O\left(M^2\right)$. In this paper, the complexity of the proposed scheme is compared with that of the optimal ML detector and is presented in Table II. From Table II, it is evident that the proposed scheme needs lesser number of matrix computations than that of the optimal ML detector. The computational complexities of BPSK and 16–QAM modulation schemes for the proposed algorithm are 4.8×10^2 and 9.6×10^2 , respectively. However, for optimal

ML detector, it requires $2^{240} \approx 10^{72}$ and $4^{240} \approx 10^{148}$, respectively. Thereafter the computational complexity in terms of matrix multiplications and additions of various detectors is illustrated in Table III. The total number of computations required for matrix operations are as follows.

TABLE II: COMPUTATIONAL COMPLEXITY COMPARISON

Detector	Order of complexity	Complexity of BPSK	Complexity of 16–QAM
Optimal MLD	$L^{2N}{}_{T}$	$2^{240}\approx10^{72}$	$4^{240}\approx10^{148}$
Proposed SVD–LAS	$L\times2N_T$	4.8×10^2	9.6×10^2

TABLE III: COMPLEXITY COMPARISON OF VARIOUS DETECTORS IN TERMS OF MULTIPLICATIONS AND ADDITIONS

MUD	**Operations**	**Computational Complexity**	**Numerical complexity for BPSK**	**Numerical complexity for 16-QAM**
ZF	Multiplications	$4N_TN_R\ (4N_T+1)$	2.955×10^7	2.955×10^7
	Additions	$2N_T\ (8N_TN_R–2N_T–1)$	2.943×10^7	2.943×10^7
MMSE	Multiplications	$4N_T\ (4N_TN_R+N_T+N_R)$	2.961×10^7	2.961×10^7
	Additions	$2N_T\ (8N_TN_R–1)$	2.949×10^7	2.949×10^7
Proposed SVD–LAS	Multiplications	$4N_T\ (4N_TN_R+N_T+N_R)+4LN_TN_R\,(2N_T+1)$	5.480×10^7	8.834×10^7
	Additions	$2N_T\,(8N_TN_R–1)+4LN_T\,(4N_TN_R+2N_T–1)$	80427×10^7	14.791×10^7
Optimal ML Detector	Multiplications	$2L^{2N}{}_{T}N_R\,(2N_T+1)$	1.090×10^{77}	$\approx 6.169\times10^{148}$
	Additions	$L^{2NT}(4N_TN_R+2N_T–1)$	$\approx 1.089\times10^{77}$	$\approx 6.167\times10^{148}$

The total number of matrix multiplications required for the conventional schemes such as ZF and MMSE are $4N_TN_R\ (4N_T+1)$ and $4N_T\ (4N_TN_R+N_T+N_R)$, respectively. The total number of additions required is $2N_T\ (8N_TN_R–2N_T–1)$ and $2N_T\ (8N_TN_R–1)$, respectively. Similarly, the optimal ML detector needs $2L^{2N}{}_{T}N_R\,(2N_T+1)$ multiplications and $L^{2NT}\ (4N_TN_R+2N_T–1)$ additions. However, the proposed SVD assisted LAS algorithm requires only $4N_T\ (4N_TN_R+N_T+N_R)+4LN_TN_R\ (2N_T+1)$ multiplication operations and $2N_T\ (8N_TN_R–1)+4LN_T\ (4N_TN_R+2N_T–1)$ additions, which is significantly lower than those required for optimal ML detector.

Additionally, the number of multiplications required with increased number of UTs is evaluated and plotted in Fig. 6. From Table III and Fig. 6, it is observed that, the complexity of proposed SVD assisted LAS is slightly higher than the linear methods and it is nominal while comparing with that of optimal ML detector.

VI. CONCLUSION

In this paper, an SVD precoded MMSE based LAS detector has been proposed for uplink scenario of massive MU–MIMO system. In this proposed scheme, the SVD precoding technique is used to mitigate IAI in UTs. The MUI due to multiple UTs in the network is put in check by using the LAS algorithm. From simulation studies, it is observed that the proposed SVD assisted MMSE based LAS technique provides approximetly 2 dB, 5dB and 8dB SNR gain over MMSE–LAS, SVD–MMSE and conventational MMSE detection techniques, respectively. Moreover, it has been proved that the SVD assisted LAS scheme achieves near optimal BER performance while needing fewer computations than optimal ML based detector. Hence, the proposed scheme appears to be a promising option for the design of practical massive MU–MIMO system.

CONFLICT OF INTEREST

The authors declare no conflicts of interest

AUTHOR CONTRIBUTIONS

Naga Raju Challa conducted the research including formulating idea, performance evaluation to the final manuscript. Kalapraveen Bagadi is the corresponding author. He supervised this work by investing a full guidance to conduct this research. However, both authors had approved the final version.

REFERENCES

[1] A. Chockalingam and B. S. Rajan, *Large MIMO Systems*, 1st ed., Cambridge University Press, U.K.: 2014, ch. 1, pp. 1-12.

[2] E. G. Larsson, O. Edfors, F. Tufvesson, and T. L. Marzetta, “Massive MIMO for next generation wireless systems,” *IEEE Commun. Magazine*, vol. 52, no. 2, pp. 186-195, February 2014.

[3] L. Lu, G. Y. Li, A. L. Swindlehurst, A. Ashikhmin, and R. Zhang, “An overview of massive MIMO: Benefits and challenges,” *IEEE Journal. Select. Topic. Signal Process*, vol. 8, no. 5, pp. 745-758, October 2014.

[4] R. S. Kshetrimayum, *Fundamentals of MIMO Wireless Communications*, 1st ed., Cambridge University Press, U.K.: 2017, ch. 1, pp. 3-6.

[5] Y. Liu, J. Liu, Q. Wu, Y. Zhang, and M. Jin, “A near-optimal iterative linear precoding with low complexity for massive MIMO systems,” *IEEE Commun. Letters*, vol. 23, no. 6, pp. 1105-1108, June 2019.

[6] C. Tang, Y. Tao, Y. Chen, C. Liu, L. Yuan, and Z. Xing, “Approximate iteration detection and precoding in massive MIMO,” *China Commun*, vol. 15, no. 5, pp. 183-196, May 2018.

[7] N. Fatema, G. Hua, Y. Xiang, D. Peng, and I. Natgunanathan, "Massive MIMO linear precoding: A survey," *IEEE System Journal*, vol. 12, no. 4, pp. 3920-3931, December 2018.

[8] K. P. Bagadi and S. Das, "Minimum symbol error rate multiuser detection using an efficient invasive weed optimization for MIMO/SDMA-OFDM system," *Int. J. of Commun. Sys.*, vol. 27, no. 12, pp. 3837-3854, Dec. 2014.

[9] A. H. Mehana and A. Nosratinia, "Diversity of MIMO linear precoding," *IEEE Trans. Infor. Theory*, vol. 60, no.2, pp. 1019-1038, February 2014.

[10] K. P. Bagadi, V. Annepu, and S. Das, "Recent trends in multiuser detection techniques for SDMA–OFDM communication system," *Physical Commun*, vol. 20, pp. 93-106, September 2016.

[11] D. Lee, "Performance analysis of zero-forcing precoded scheduling system with adaptive modulation for multiuser-multiple input multiple output transmission," *IET Commun*, vol. 09, no. 16, pp. 2007-2012, November 2015.

[12] X. He, Q. Guo, J. Tong, J. Xi, and Y. Yu, "Low-complexity approximate iterative LMMSE detection for large-scale MIMO systems," *Digital Signal. Process*, vol. 60, pp. 134-139, January 2017.

[13] C. V. R. Kumar and K. P. Bagadi, "Design of MC-CDMA receiver using radial basis function network to mitigate multiple access interference and nonlinear distortion," *Neu. Comp. and Appl.*, vol. 31, no. 2, pp. 1263–1273, Feb. 2019.

[14] A. Hindy and A. Nosratinia, "Ergodic fading MIMO dirty paper and broadcast channels: Capacity bounds and lattice strategies," *IEEE Trans. Wireless. Commun*, vol. 16, no.8, pp. 5525-5536, August 2017.

[15] C. V. R. Kumar and K. P. Bagadi, "MC–CDMA receiver design using recurrent neural networks for eliminating multiple access interference and nonlinear distortion," *Int. J. of Commun. Sys.*, vol. 30, no. 16, pp. 1–13, May 2017.

[16] L. Gopal, Y. Rong, and Z. Zang, "Tomlinson-Harashima precoding based transceiver design for MIMO relay systems with channel covariance information," *IEEE Trans. Wireless. Commun*, vol. 14, no. 10, pp. 5513-5525, October 2015.

[17] R. M. Fukuda and T. Abrão, "Linear, quadratic, and semidefinite programming massive MIMO detectors: Reliability and complexity," *IEEE Access*, vol. 7, pp. 29506-29519, March 2019.

[18] W. A. Shehab and Z. Al-qudah, "Singular value decomposition: Principles and applications in multiple input multiple output communication system," *Int. Journ. Comput. Network. Commun*, vol. 9, no. 1, pp. 13-21 January 2017.

[19] W. Liu, L. L. Yang, and L. Hanzo, "SVD-assisted multiuser transmitter and multiuser detector design for MIMO systems," *IEEE Trans. Veh. Technol*, vol. 58, no. 2, pp. 1016-1021, February 2009.

[20] N. R. Challa and K. Bagadi, "Design of near-optimal local likelihood search based detection algorithm for coded large-scale MU-MIMO system," *Int. J. of Commun. Syst.*, Apr. 2020.

[21] D. C. Araújo, *et al*, "Massive MIMO: Survey and future research topics," *IET Commun*, vol. 10, no. 15, pp. 1938-1946, October 2016.

[22] M. Mandloi and V. Bhatia, "Error recovery based low-complexity detection for uplink massive MIMO systems," *IEEE Wireless. Commu. Lett*, vol. 6, no. 3, pp. 302-305, June 2017.

[23] Y. Le, Q. He, and R. S. Blum, "Limited-Complexity receiver design for passive/active MIMO radar detection," *IEEE Trans. Signal. Process*, vol. 67, no. 12, pp. 3258-3271, June 2019.

[24] K. V. Vardhan, *et al*., "A low-complexity detector for large MIMO systems and multicarrier CDMA systems," *IEEE Journal. Select. Area. Commun*, vol. 26, no. 3, pp. 473-485, April 2008.

[25] P. Li and R. D. Murch, "Multiple output Selection-LAS algorithm in large MIMO systems," *IEEE Commun. Letters*, vol. 14 no. 5, pp. 399-402, May 2010.

[26] S. Agarwal, A. K. Sah and A. K. Chaturvedi, "Likelihood-based tree search for low complexity detection in large MIMO systems," *IEEE Wireless. Commun. Letters*, vol. 6, no. 4, pp. 450-453 May 2017.

[27] A. K. Sah and A. K. Chaturvedi, "An unconstrained likelihood ascent based detection algorithm for large MIMO systems," *IEEE Trans. Wireless. Commun*, vol. 16, no. 4, pp. 2262-2273, April 2017.

[28] L. Li, W. Meng, and C. Li, "Semidefinite further relaxation on likelihood ascent search detection algorithm for high-order modulation in massive MIMO system," *IET Commun*, vol. 11, no. 6, pp. 801-808, April 2017.

[29] N. R. Challa and K. Bagadi, "Lattice reduction assisted likelihood ascent search algorithm for multiuser detection in massive MIMO system," in *Proc. 15th IEEE India Council International Conference INDICON*, Coimbatore, India, December 16-18, 2018.

[30] A. K. Sah and A. K. Chaturvedi, "Sequential and global likelihood ascent search based detection in large MIMO systems," *IEEE Trans. Commun*, vol. 66, no. 2, pp. 713-725, October 2018.

[31] S. A. Khudhair and M. J. Singh, "Review in FBMC to enhance the performance of 5G networks," *J. of Commun*. vol. 15, no. 5, pp. 415-426, May 2020.

[32] G. Gaspard and D. S. Kim, "Optimal sensing and interference suppression in 5G cognitive radio networks," *J. of Commun*, vol. 15, no. 4, pp. 303-308, April 2020.

[33] S. Pramono, E. Triyono, and B. B. Subagio, "Performance of leakage based precoding scheme for minimizing interference," *J. of Commun*, vol. 15, no. 2, pp. 214-220, February 2020.

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