Collaborative Learning based Symbol Detection in Massive MIMO

Arijit Datta, Manekar Tushar Deo and Vimal Bhatia
Discipline of Electrical Engineering
Indian Institute of Technology Indore
Madhya Pradesh, India

***Abstract*—Massive multiple-input multiple-output (MIMO) system is a core technology to realize high-speed data for 5G and beyond systems. Though machine learning-based MIMO detection techniques outperform conventional symbol detection techniques, in large user massive MIMO, they suffer from maintaining an optimal bias-variance trade-off to yield optimal performance from an individual model. Hence, in this article, collaborative learning based low complexity detection technique is proposed for uplink symbol detection in large user massive MIMO systems. The proposed detection technique strategically ensembles multiple fully connected neural network models utilizing iterative meta-predictor and reduces the final estimation error by smoothing the variance associated with individual estimation errors. Simulations are carried out to validate the performance of the proposed detection technique under both perfect and imperfect channel state information scenarios. Simulation results reveal that the proposed detection technique achieves a lower bit error rate while maintaining a low computational complexity as compared to several existing uplink massive MIMO detection techniques.**

***Index Terms*—Massive MIMO, collaborative learning, deep learning, maximum likelihood.**

I. Introduction

Massive multiple input multiple output (MIMO) is one of the key technologies of 5G and beyond wireless communication systems to realize the ever-growing demand for high speed data with high spectral efficiency [1]. In massive MIMO, where hundreds of base station (BS) serve few tens of users, both spatial diversity and spatial multiplexing are achieved. Spatial multiplexing yields high data rate and spatial diversity improves reliability. However, in uplink massive MIMO, the received signal at the BS suffers from inter-user interference and noise. The inter-user interference becomes severe when the number of active users scale up in the system and thereby it makes the symbol detection at the BS challenging. Hence, to practically achieve the benefits of massive MIMO, optimal detection of massive MIMO symbols at the received is utmost important.

Maximum likelihood (ML) detection performs an exhaustive search and is capable to optimally detect the symbols. However, the computational complexity of ML detection exponentially increases with the users. Hence, ML detection is practically unfeasible for massive MIMO systems with large number of users. Sphere decoder (SD) reduces the computational complexity of ML detection by searching withing a fixed radius hyper-sphere. However, SD is practically realizable upto 32×32 MIMO systems. The algorithm proposed in [2] utilizes Dijkstra instead of depth first tree search (DFTS)[3] as used in fixed sphere decoder (FSD)[4]. However, the above algorithm exhibits high computational complexity as compared to conventional linear detectors such as minimum mean square error (MMSE) and not practically suitable for massive MIMO systems.

Due to channel hardening phenomena, the Gram matrix formed from massive MIMO channel matrix becomes diagonally dominant. Hence, linear detection techniques like minimum mean square error (MMSE) yields optimal bit error rate performance for massive MIMO systems. However, MMSE involves high dimensional matrix inversion and posses cubic order computational complexity in terms of the number of users. Hence, due to cubic order computational complexity, linear detectors like MMSE is also not practically convenient for large user massive MIMO systems.

Existing detection techniques for uplink massive MIMO detection can be classified into two categories a) approximate matrix inversion based techniques and b) matrix inversion less iterative techniques. Newton iteration (NI) [5], Improved newton iteration (INI) [6] and Diagonal band newton iteration (DBNI) [5] are approximate matrix inversion based techniques which provides near-optimal BER performance. However, the computational complexity of approximate matrix inversion based techniques significantly increases with the number of iteration. Matrix inversion less iterative techniques such as Richardson iteration (RI) [7], joint steepest descent Jacobi iteration (JSDJI) [8] and iterative sequential detection (ISD) [9] outperforms approximate matrix inversion based techniques. However, the performance of both approximate matrix inversion based techniques and matrix inversion less iterative techniques substantially degrades with the increas in the number of users in the massive MIMO systems. Hence, design of low complexity symbol detection technique for uplink massive MIMO system with large number of users is cruicial to realize the potential benefits of massive MIMO.

Wireless communication systems targeted for 5G and beyond demands a more robust, accurate, flexible and faster detection techniques. Implementation of deep learning (DL) and deep neural networks (DNN) for symbol detection in massive MIMO systems has proven to be a viable candidate that can fulfill the shortcomings of conventional detectors [10]. DNN architectures deliver promising accuracy with flexible and low computational complexity. Furthermore, DL and DNN based models are also more natural to apply on hardware as compared to several state-of-art detectors for uplink massive MIMO systems. Hence, DL and DNN based detection models have gained prominence among communication and signal processing researchers for low complexity robust symbol detection in massive MIMO systems.

The total error associated with DL and DNN based detection composed of bias, variance and irreducible error [11], [12]. Though the irreducible error term cannot be removed by any model, there exists an optimizable trade-off between the bias and the variance term. An individual machine learning model with low bias exhibits high variance and vise versa. However, an optimal detection scheme must maintain a favorable trade-off between the bias and variance, keeping both the parameters as low as possible. Collaborative learning [13], [14] is a machine learning paradigm in which multiple models, their leanings and predictions are combined in a strategic manner to generate more optimal results. As ensembling operation has variance-reducing effect, the goal of ensembling based collaborative learning is to smooth the variance term from multiple models with approximately fixed bias term and yield an near-optimal detection technique. Hence, collaborative learning needs to be explored for achieving superior performance based on existing DL and DNN based detection models for uplink symbol detection in massive MIMO.

Contributions: In this article, we explore ensembling based collaborative learning with iterative prediction for robust and low complexity symbol detection in uplink massive MIMO systems. The proposed detection technique stakes B fully connected neural network (FullyCon) [10] models utilizing iterative meta-predictor. Simulations are carried out to justify the viability of the proposed detection technique over several existing state-of-art detection techniques for uplink massive MIMO detection. It is observed from simulation results that the proposed detection technique performs substantially better as compared to several state-of-art uplink massive MIMO detection techniques, under both perfect and imperfect channel state information (CSI) at the BS.

Rest of the paper is organized as follows. Section II describes the uplink massive MIMO system model, ML and MMSE detection techniques. The proposed detection techniques are discussed in Section III. The simulation results are drawn and explained in Section IV. Finally, Section V concludes the paper.

Notations: Boldface uppercase and lowercase alphabets represent column vectors and matrices respectively. $(.)^T$ and $()^{-1}$ respectively denote transpose and inverse operations. The l_p norm operation is denoted as $||\ .\ ||_p$.

II. System Model and Preliminaries

In this section, the system model of massive MIMO, and maximum likelihood (ML) and minimum mean square error (MMSE) detection techniques are briefly discussed.

A. System Model

We consider an uplink massive MIMO system under slow fading scenarios, where N_t single antenna users are being served by N_t BS antennas ($N_r >> N_t$, e.g $N_r = 128$, $N_t = 16$). The received symbol vector $\tilde{\mathbf{y}}$ at the BS can be expressed as

$$\widetilde{\mathbf{y}} = \widetilde{\mathbf{H}}\widetilde{\mathbf{x}} + \widetilde{\mathbf{n}}, \quad (1)$$

where $\tilde{\mathbf{H}}$ is a $N_r \times N_t$ channel matrix. $\tilde{\mathbf{x}}$ is $N_r \times 1$ transmitted symbol vector. The users are assumed to be synchronized and the channel is assumed to be flat. Each element of $\tilde{\mathbf{H}}$ is assumed to be independent and identically distributed (i.i.d) Gaussian random variable having unit variance and zero mean ($\sim \mathcal{CN}(0, 1)$). Each element of noise vector $\tilde{\mathbf{n}}$ is also i.i.d Gaussian with zero mean and variance σ^2 ($\sim \mathcal{CN}(0, \sigma^2)$). Without loss of generality, the complex valued system model in (1) is transferred to a real-valued system as [15]

$$\mathbf{y} = \mathbf{H}\mathbf{x} + \mathbf{n}, \quad (2)$$

$\mathbf{x} = \left[\Re(\tilde{\mathbf{x}}), \Im(\tilde{\mathbf{x}})\right]^T_{2N_t \times 1}$, $\mathbf{y} = \left[\Re(\tilde{\mathbf{y}}), \Im(\tilde{\mathbf{y}})\right]^T_{2N_r \times 1}$, $\mathbf{n} = \left[\Re(\tilde{\mathbf{n}}), \Im(\tilde{\mathbf{n}})\right]^T_{2N_r \times 1}$ and $\mathbf{H} = \begin{bmatrix} \Re(\tilde{\mathbf{H}}) & -\Im(\tilde{\mathbf{H}}) \\ \Im(\tilde{\mathbf{H}}) & \Re(\tilde{\mathbf{H}}) \end{bmatrix}_{2N_r \times 2N_t}$. $\Re(.)$ and $\Im(.)$ denote real and imaginary parts of $(.)$ respectively.

In practical scenarios, there may be some channel estimation information (CSI) error at the BS. Hence, under CSI mismatch scenarios, the channel matrix $\mathbf{H}$ can be represented as

$$\hat{\mathbf{H}} = \mathbf{H} + e\mathbf{F}, \quad (3)$$

where $\mathbf{H}$ is the actual channel gain matrix and $e\mathbf{F}$ is the channel estimation error. Without loss of generality, the elements of $\mathbf{F}$ are assumed to be i.i.d Gaussian random variables with unit variance and zero mean ($\sim \mathcal{CN}(0, 1)$). e is the accuracy in channel estimation. $(.)^T$ refers to matrix transpose. $\mathbf{H}$ and $\mathbf{F}$ are uncorrelated.

B. ML Detection

ML detection technique, which is a special case of maximum a posteriori probability (MAP) based estimation, is a method in which defining parameters of a model are estimated by maximizing the likelihood function, in such a manner that the observed data has highest probability under the assumed model. MAP estimate is equivalent to ML estimate when the symbol vectors are equiprobable. The ML detection in uplink massive MIMO can be formulated as

$$\hat{\mathbf{x}} = \underset{\mathbf{x} \in \mathcal{A}^{2N_t}}{\arg\max}\ \mathbb{P}(\mathbf{x}|\mathbf{y}, \mathbf{H}) = \underset{\mathbf{x} \in \mathcal{A}^{2N_t}}{\arg\min}\ ||\ \mathbf{y} - \mathbf{H}\mathbf{x}\ ||_2^2, \quad (4)$$

where $\mathcal{A}$ is real valued constellation set of M-QAM modulation. As ML detection performs exhaustive search, it is not preferable for low complexity symbol detection in massive MIMO system.

C. MMSE Detection

The symbol $\hat{\mathbf{x}}$ estimated through MMSE detection technique for massive MIMO system is described as

$$\hat{\mathbf{x}} = \mathbf{A}^{-1}\mathbf{b}, \quad (5)$$

where $\mathbf{A} = \mathbf{G} + \frac{\sigma^2}{E_{\mathbf{x}}}\mathbf{I}_{2N_t}$ is the MMSE filter matrix. $\mathbf{I}_{2N_t}$ is $N_t \times N_t$ identity matrix. $E_x = \frac{2}{3}(M-2)$ denotes the average energy per symbol. $\mathbf{G} = \mathbf{H}^T\mathbf{H}$ is called the Gram matrix and $\mathbf{b} = \mathbf{H}^T\mathbf{y}$. The Gram matrix becomes diagonally dominant [16] when the system loading factor $\alpha = \frac{N_r}{N_t}$ increases. The MMSE detection technique yields near optimal BER performance for $\alpha = \frac{N_r}{N_t} \geq 10$[17].

III. Proposed Detection Technique

In this section, the proposed detection technique is explained in detail.

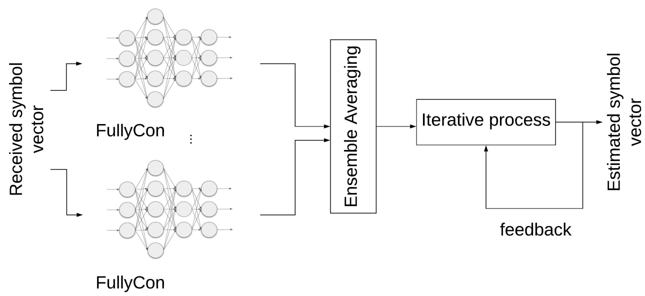

Fig. 1. Proposed detection model

In proposed detection technique, B FullyCon networks with L number of layers is considered as the basic block for collaborative learning. Each network have $2N_r$ neurons in the input layer and $2N_t$ neurons in the output layer. The output of each layer serves as input to the succeeding layer, which can be represented by the following equation

$$\mathbf{v}_{(k+1)} = \delta\Big(\mathbf{\Omega}_{(k)}\mathbf{v}_{(k)} + \mathbf{d}_{(k)}\Big), \tag{6}$$

where $\mathbf{v}_{(1)} = \mathbf{y}$. $\mathbf{v}_{(L)} = \hat{\mathbf{x}}$. $\delta(.)$ is the activation function of the layer. $\mathbf{\Omega}_{(k)}$ and $\mathbf{d}_{(k)}$ are respectively weight matrix and bias vector associated with the k^{th} layer. The activation function $\delta(.)$ used in the output layer is hard hyperbolic tangent (Hard Tanh), which is defined as

$$\delta(.) = \max\Big(\mu, \min(\nu, .)\Big), \tag{7}$$

where μ is the maximum boundary value and ν is the minimum boundary value. The parameters θs those are trained and optimized in our models are

$$\theta = \{\mathbf{\Omega}_k, \mathbf{d}_k\}_{k=1}^{L} \tag{8}$$

In learning phase, the error is minimized in normalized mean square sense and the loss function is

$$\lambda(\mathbf{x}, \hat{\mathbf{x}}) = {N_t}^{-1} \mid\mid \mathbf{x} - \hat{\mathbf{x}} \mid\mid_2^2, \tag{9}$$

where $\hat{\mathbf{x}}$ is the estimated value of actual vector $\mathbf{x}$. During the trained phase, B FullyCon networks are trained on B different data sets. All the datasets are prepared based on estimated transmitted symbol vector $\mathbf{x}$ as output label and received symbol vector $\mathbf{y}$ as input feature. The parameters for training and testing each FullyCon are chosen as Table I.

At detection phase, the output of trained FullyCons are ensembled as

$$\hat{\mathbf{x}} = \sum_{i=1}^{B} \frac{\alpha_i \hat{\mathbf{x}}_{FCN_i}}{\sum_{i=1}^{B}\alpha_i} \tag{10}$$

The proposed collaborative learning based detection technique hereafter named as ELD.

TABLE I
Training /testing parameters

Weight and bias initialization	random
learning rate	0.001
Optimizer	Adam
Total samples	20000
Batch size	64
No of hidden layers	2
training and testing data ratio	9:1

To further boost the BER performance of the proposed detection technique, the ensembled estimate $\hat{\mathbf{x}}$ is passed through an iterative detector as follows.

$$\mathbf{x}^{(k+1)} = \mathbf{x}^{(k)} + \mathbf{D}^{-1}\Big(\mathbf{b} - \mathbf{G}\mathbf{x}^{(k)}\Big), \tag{11}$$

where is $\mathbf{D}$ is the diagonal matrix obtained from $\mathbf{G}$. In order to limit the computational cost associated with the iterative process low, only single iteration is performed. ELD with iterative process is named as ELRID. The block diagram of the proposed detection technique is shown in Fig. 1.

IV. Simulation Results and Discussion

This section compares the computational complexity and simulation results of ELD and ELRID with stair matrix based detection (SMD), low complexity message passing based detection (LCMPD), message passing based detection (MPD), JSDJI, ISD and MMSE detection for uplink massive MIMO detection. For brevity, we have considered $B = 2$ in all training, validation and BER simulations, with data sets generated from ISD and MMSE.

A. Computational Complexity

The computational complexity of contending detection techniques are listed in Table II in terms of the number of real valued multiplications. For fair comparisons, the asymptotic upper bounds on computational complexity are also mentioned.

As shown in Table II, single iteration ELD is computationally less expensive as compared to other contending detection techniques. Hence, the proposed detection techniques are computationally more viable as compared to several state-of-art uplink massive MIMO detection technique. It concludes that the proposed ELD and ELRID are computationally promising candidates for symbol detection in uplink massive MIMO system for 5G and beyond wireless communication.

B. BER Performance

Fig. 2 compares the BER performance of ELD with other contending detection techniques for 256×50 massive MIMO systems. As depicted in Fig. 2, single iteration of proposed ELD outperforms MMSE and multiple iterations of JSDJI, SMD, LCMPD and MPD. An SNR gain of approx. 3.7 dB is achieved in ELD as compared to MMSE for a targeted BER of 10^{-3}.

In Fig. 3, the BER performance of ELD is compared with other detection techniques for large number of users $N_t = 64$.

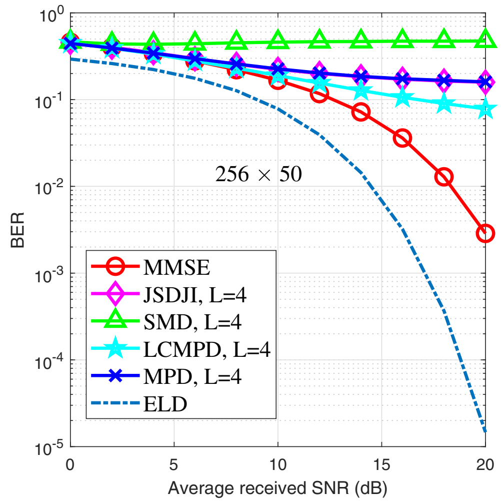

Fig. 2. BER performance comparison of ELD with conventional detection techniques for 256 × 50 massive MIMO system with 64-QAM modulation.

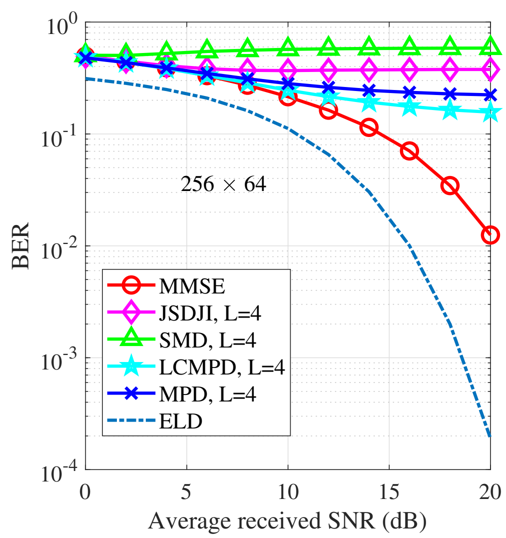

Fig. 3. BER performance comparison of ELD with conventional detection techniques for 256 × 64 massive MIMO system with 64-QAM modulation.

It is observed from Fig. 3 that MMSE, SMD, LCMPD, MPD and JSDJI show far inferior BER performance as compared to ELD. This proves the viability of proposed ELD for uplink massive MIMO detection when the number of users scaled up in the system.

BER performance of the proposed ELRID technique is compared with other state-of-art detection techniques in Fig. 4-5. As shown in Fig. 4, ELRID ouperforms ELD and acheives SNR gain of approx. 1.6 dB as compared to ISD with L=2. Moreover, Fig. 5 corroborates the superior BER performance of proposed ELRID over ELD, ISD and MMSE. This proves that the proposed ELD and ELRID are two promising detection techniques for uplink symbol detection in massive MIMO.

The robustness of the proposed ELD is validated through simulations in Fig. 6 under CSI error scenario at the BS. Fig.

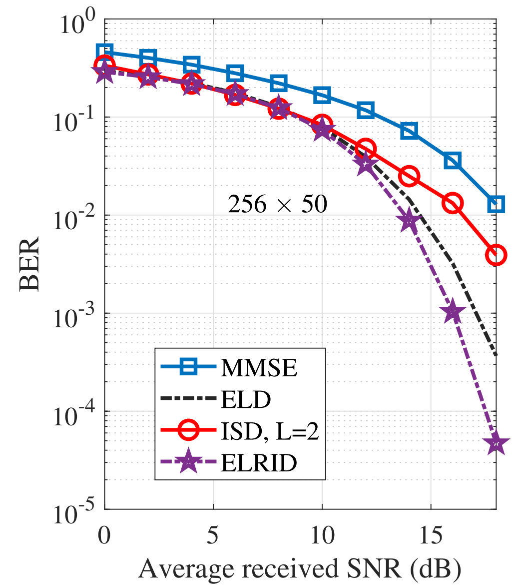

Fig. 4. BER performance comparison of ELRID and ELD with conventional detection techniques for 256 × 50 massive MIMO system with 64-QAM modulation,.

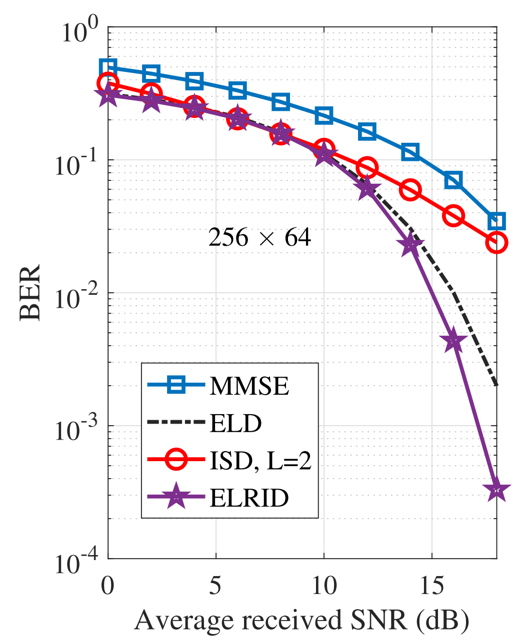

Fig. 5. BER performance comparison of ELRID and ELD with conventional detection techniques for 256 × 64 massive MIMO system with 64-QAM modulation.

6 reveals that ELD outperforms several conventional detection techniques even under $e = 7\%$ BER mismatch conditions.

V. Conclusion

In this article, a low complexity symbol detection technique based on iterative meta-predictor aided collaborative learning is proposed for symbol detection in massive MIMO with large number of users. The proposed detection technique stacks

TABLE II
COMPUTATIONAL COMPLEXITY

Detection techniques	**No of real valued multiplications**	**Asymptotic upper bound**
MMSE [6]	$4N_t^3+8N_t^2+4(N_t^2+N_t)N_r$	$\mathbb{O}\Big(N_t^3+N_rN_t^2\Big)$
SMD [18]	$2((N_r+2L)N_t^2)+2(2N_r+5-L)N_t-7$	$\mathbb{O}\Big((N_r+2L)N_t^2\Big)$
LCMPD [19]	$2(N_r+2L-2)N_t^2+2(2N_r+2T_{\mathcal{A}}L-L+1)N_t$	$\mathbb{O}\Big((N_r+2L)N_t^2+2T_{\mathcal{A}}LN_t\Big)$
MPD [19]	$4(2N_r+T_{\mathcal{A}}(2L-1)+3L-2)N_t^2+2(N_r+T_{\mathcal{A}}(L+1)-3L+2)N_t$	$\mathbb{O}\Big(4(N_r+T_{\mathcal{A}}L)N_t^2+(N_r+T_{\mathcal{A}}L)N_t\Big)$
JSDJI [8]	$2(2(L+1)+N_r)N_t^2+2((L+4)+2N_r+1)N_t$	$\mathbb{O}\Big((N_r+2L)N_t^2\Big)$
ISD [9]	$8N_rN_t^2+4N_rN_t+2(2L+1)N_t+4LN_t^2$	$\mathbb{O}\Big((2N_rN_t+N_r+LN_t)N_t\Big)$
ELD	$4N_t^2+8N_rN_t^2+4N_rN_t$	$\mathbb{O}\Big((2N_rN_t+N_t)N_t\Big)$
ELRID	$8N_t^2+8N_rN_t^2+4N_rN_t+2N_t$	$\mathbb{O}\Big((N_rN_t+N_t)N_t\Big)$

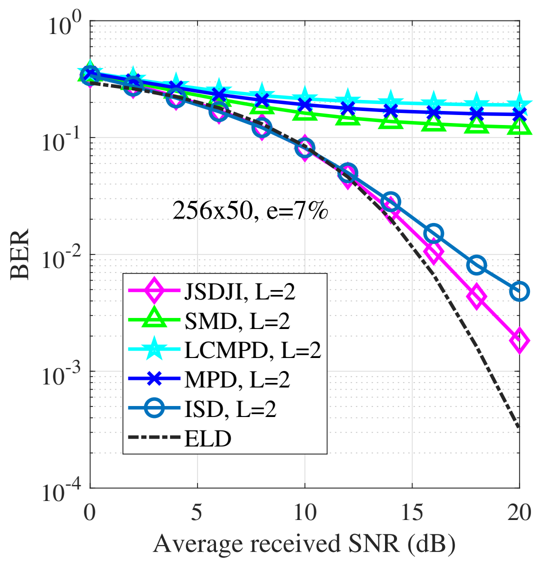

Fig. 6. BER performance comparison of ELD with conventional detection techniques for 256×50 massive MIMO system with 64-QAM modulation under CSI mismatch at the receiver.

multiple FullyCons utilizing an iterative predictor. Simulation results reveal that the proposed detection technique outperforms JSDJI, SMD, LCMPD, MPD, ISD and MMSE for uplink massive MIMO detection. The robustness of the proposed detection technique is also validated through simulations under CSI mismatch scenarios at the BS. Hence, it concludes that the proposed detection technique is a viable candidate for low complexity symbol detection in uplink massive MIMO when the number of users scales up in the system, in terms of both BER performance as well as computational complexity.

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