Journal of Information Systems and Telecommunication
Vol.10, No.4, October-December 2022, 249-256
http://jist.acecr.org
ISSN 2322-1437 / EISSN:2345-2773

A Novel Detector based on Compressive Sensing for Uplink Massive MIMO Systems

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Received: 19 Feb 2022/ Revised: 07 Apr 2022/ Accepted: 13 Apr 2022

Abstract
Massive multiple-input multiple-output is a promising technology in future communication networks where a large number of antennas are used. It provides huge advantages to the future communication systems in data rate, the quality of services, energy efficiency, and spectral efficiency. Linear detection algorithms can achieve a near-optimal performance in large-scale MIMO systems, due to the asymptotic orthogonal channel property. But, the performance of linear MIMO detectors degrades when the number of transmit antennas is close to the number of receive antennas (loaded scenario). Therefore, this paper proposes a series of detectors for large MIMO systems, which is capable of achieving promising performance in loaded scenarios. The main idea is to improve the performance of the detector by finding the hidden sparsity in the residual error of the received signal. At the first step, the conventional MIMO model is converted into the sparse model via the symbol error vector obtained from a linear detector. With the aid of the compressive sensing methods, the incorrectly detected symbols are recovered and performance improvement in the detector output is obtained. Different sparse recovery algorithms have been considered to reconstruct the sparse error signal. This study reveals that error recovery by imposing sparse constraint would decrease the bit error rate of the MIMO detector. Simulation results show that the iteratively reweighted least squares method achieves the best performance among other sparse recovery methods.

Keywords: Massive MIMO; MMSE Detector; Error Recovery; Compressive Sensing; Iteratively Reweighted Least Squares (IRLS) Method.

1- Introduction

The number of cellular phones and mobile data traffic are extremely growing each year. Telecommunication companies are asked to provide higher data rates, further spectral efficiency, and larger capacity. The fifth-generation (5G) wireless communication systems are being designed to answer excessive data rate demands. Massive MIMO technology is a good candidate for the next-generation of the wireless communication. The base station (BS) in massive MIMO systems equipped with hundreds of antennas are used to serve tens of users simultaneously [1, 2]. But there are some challenges such as pilot contamination, detection performance, channel estimation and detection complexity [3-5].
The purpose of each detection algorithm is to obtain an estimate of the transmit signal, given knowledge of the received signal and the channel state information (CSI). The maximum a posteriori (MAP) and the maximum likelihood (ML) algorithms provide the optimal detectors but they are not practically feasible for the massive MIMO systems since their computational complexity increase exponentially with the number of antennas. Linear MIMO detectors such as zero forcing (ZF) and minimum mean square error (MMSE) receivers can achieve near optimal performance when the number of users is much lower than the number of the antennas in BS [6]. Many methods have been proposed to achieve the performance of MMSE detector with low complexity such as the optimized coordinate descent (OCD) [7], Gauss-Seidel (GS) method [8], parallelizable Chebyshev iteration (PCI) [9] and alternating minimization method (Alt-Min) [10]. The performance of the linear detectors and also the previously mentioned methods degrade when the number of transmitters is close to the number of receiver antennas [11]. Therefore, new and efficient detectors with a low error rate are highly needed to solve this problem. This paper focuses on developing a detector which achieves favorable performance in loaded scenarios.
Recently, compressive sensing (CS) and sparse signal

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recovery techniques have received much attention in different signal processing applications. Compressive sensing has emerged as a promising approach for use in large MIMO systems [12, 13].

It is noteworthy that the original signals in massive MIMO systems are not intrinsically sparse, but it is expected that the detector output contains an error only for a few number of users. Thus, the error vector resulting from a primary estimator is likely to be sparse, especially in high SNR regime. The motivation of this paper is to improve the performance of the detector by using the sparsity in the residual error of large MIMO systems. In order to exploit the sparsity of the detection errors, the conventional model is converted into a sparse model via the symbol error vector [13, 14]. After that, the error recovery algorithm can be performed to improve the detection performance by recovering the non-zero entries of the error vector.

Sparse signal recovery is basically an optimization problem with l_0-norm and is NP-hard. Therefore, different approaches are proposed to solve this problem. Greedy methods [15-17], l_1-relaxation based optimization [18, 19] and Bayesian methods [20, 21] are the main approaches to estimate the sparse vector. Many different algorithms have been proposed for sparse signal reconstruction. The contribution of this paper is to address the effectiveness of the l_1 -relaxation-based sparse recovery methods in massive MIMO detectors for the first time.

The rest of the paper is organized as follows. Section II introduces the system model of the massive MIMO system. Section III presents the conversion of the conventional MIMO system model into the sparse error domain. Sparse recovery algorithms are introduced in section IV. The simulation results and discussions about the performance of the proposed algorithm are presented in section V and finally the paper is concluded in Section VI.

Notation: Boldface capital letters and lowercase letters represent matrices and vectors, respectively. $\mathbf{I}_K$ denotes the $K \times K$ identity matrix; $(.)^{H}$, $(.)^{-1}$, $(.)^{T}$ denote the conjugate transposition, the inversion and the transposition, respectively. $\mathbb{C}^{m\times n}$ denotes the $m \times n$ complex matrix. The p-norm (also called l_p-norm) of vector $\boldsymbol{v} = (v_1, v_2, \dots, v_n)$ is $\|\boldsymbol{v}\|_p = (\sum_{i=1}^{n} |v_i|^p)^{1/p}$.

2- System Model

Consider a multi-user MIMO model with n_t users and n_r receivers in the BS. The received signal can be described as:

$$\mathbf{y} = \mathbf{H}\mathbf{x} + \mathbf{n} \tag{1}$$

where $\mathbf{H} \in \mathbb{C}^{n_r \times n_t}$ is the channel matrix between the BS and the n_t users whose entries are modeled as independent and identically distributed (iid) complex Gaussian with zero mean and unit variance. $\mathbf{x} \in \mathbb{C}^{n_r \times 1}$, is the complex-valued information vector, and $\mathbf{n}$ is a white Gaussian noise vector with zero mean and correlation matrix $E(\mathbf{n}\mathbf{n}^{H}) = \sigma_n^2 \mathbf{I}_{n_r}$. It is assumed that the channel matrix is known perfectly at the BS but it is unknown at the transmitter side.

2-1- Linear Detection

The maximum likelihood (ML) detector is not suitable for solving large dimensional problems due to the high computational complexity. Therefore, suboptimal detectors such as Minimum Mean Square Error with low complexity are beneficial in operational conditions.

The MMSE detector can be obtained by the solution of the following minimization problem.

$$\min_{G} E[|\mathbf{x} - \hat{\mathbf{x}}|^2] \tag{2}$$

where $\hat{\mathbf{x}} = \mathbf{G}\mathbf{y}$ is the estimation of the user's data.

3- Massive MIMO Detection in Sparse Domain

This section, presents a class of detectors based on error recovery technique for detection of the transmitted symbols in uplink massive MIMO system. This method iteratively achieves near-optimal performance in terms of bit error rate. In the following the error domain sparse model is introduced.

3-1- Sparse Model

At the first step, the conventional system model (1) should be converted into a sparse model via the symbol error vector obtained from a linear detector.

The error vector $\mathbf{x}_e$, is defined as the difference between the original signal and the recovered one. Therefore, the system model in error domain can be formulated as follows:

$$\mathbf{y}_e = \mathbf{y} - \mathbf{H}\hat{\mathbf{x}}_{MMSE} = \mathbf{H}(\mathbf{x} - \hat{\mathbf{x}}_{MMSE}) + \mathbf{n} = \mathbf{H}\mathbf{x}_e + \mathbf{n} \tag{3}$$

where $\mathbf{x}_e = \mathbf{x} - \hat{\mathbf{x}}_{MMSE}$ is the error vector of the primary estimated symbols and its nonzero values correspond to the incorrectly detected symbols.

It is noteworthy that, by recovering the incorrectly detected symbols, the performance of the detector can be improved. Since it is expected that only a few symbols are

incorrectly detected, $\mathbf{x}_e$, is a sparse vector. Therefore, the detection operation is equivalent to recover the sparse error vector, $\mathbf{x}_e$, from the difference signal, $\mathbf{y}_\mathrm{e}$.
Once the sparse error vector is recovered, the estimation of the transmitted signal, $\hat{\mathbf{x}}$, is obtained by adding the error vector to the initial estimate, $\hat{\mathbf{x}}_{\mathrm{MMSE}}$. Thus, the final estimation of the user's data is obtained by

$$\hat{\mathbf{x}} = \hat{\mathbf{x}}_{\mathrm{MMSE}} + \hat{\mathbf{x}}_e \tag{4}$$

3-2- Error Recovery

The problem of sparse representation in the MIMO detection is to find the vector $\mathbf{x}_e$. Therefore, we are looking for the sparsest solution which can be done by solving the following optimization problem:

$$P_0: \qquad min\|\mathbf{x}_e\|_0 \quad s.t.\ \ \mathbf{y}_\mathrm{e} = \mathbf{H}\mathbf{x}_e \tag{5}$$

Where $\|\mathbf{x}_e\|_0$ denotes the l_0-norm of $\mathbf{x}_e$ and gives the total number of non-zero elements in the vector. Since (P_0) is NP-hard, the optimization problem is relaxed with convex l_1-norm. Taking into account the effect of the noise component, the problem (P_0) can be converted to the following optimization problem:

$$P_1: \qquad min\|\mathbf{x}_e\|_1 \quad s.t.\ \| \mathbf{y}_\mathrm{e} - \mathbf{H}\mathbf{x}_e\|_2 \le \varepsilon \tag{6}$$

It is assumed that the noise has bounded entries, i.e. $\| \mathbf{n}\|_2 \le \varepsilon$ for some sufficiently small ε. Additionally, according to the Lagrange multiplier theorem, there exists an appropriate constant λ such that the problem (P_1) is equivalent to the following unconstrained minimization problem.

$$P_2: \qquad min\ \lambda\|\mathbf{x}_e\|_1 + \frac{1}{2}\| \mathbf{y}_\mathrm{e} - \mathbf{H}\mathbf{x}_e\|_2^2 \tag{7}$$

Where the Lagrange multiplier λ depends on $\mathbf{y}_\mathrm{e}$ and ε. Note that the cost function in (P_2) is not differentiable with respect to $\mathbf{x}_e$ and specific optimization algorithms are required to solve (P_2). The following section addresses three well-known sparse coding algorithms to estimate the error vector $\mathbf{x}_e$. The minimization function in (P_2) is composed of two parts. The first term with l_1–norm induces sparsity to the estimated error vector, while the second term, $\frac{1}{2}\| \mathbf{y}_\mathrm{e} - \mathbf{H}\mathbf{x}_e\|_2^2$, makes the estimated vector consistent with $\mathbf{y}_\mathrm{e}$. In order to investigate the effectiveness of the sparsity promoting term in (P_2), the results of the MIMO detection with the following minimization problem are also considered.

$$P_3: \qquad min\ \lambda\|\mathbf{x}_e\|_2 + \frac{1}{2}\| \mathbf{y}_\mathrm{e} - \mathbf{H}\mathbf{x}_e\|_2^2 \tag{8}$$

where the l_1–norm in (P_2) is replaced with the l_2–norm. The closed-form solution of the convex minimization problem (P_3) can be formulated as follows:

$$\hat{\mathbf{x}}_e = (\mathbf{2}\lambda I + \mathbf{H}^\mathrm{H}\mathbf{H})^{-1}\mathbf{H}^\mathrm{H}\mathbf{y}_\mathrm{e} \tag{9}$$

In the simulation result section, the solution to (P_3) is called the regularized least square (RLS) estimation.

4- Sparse Error Reconstruction

The most significant stage in error recovery-based MIMO detection is the sparse error reconstruction. In this study, three algorithms are considered for the sparse coding step. More explicitly, Iterative Re-weighed Least Squares (IRLS), Alternating Direction Method of Multipliers (ADMM), and Iterative Shrinkage-Thresholding Algorithm (ISTA) [22-25] have been applied to reconstruct the error vector. In the following, these three algorithms are introduced briefly.

4-1- IRLS Algorithm

The Iterative Re-weighed Least Squares algorithm is one of the strategies which is able to recover sparse signals. In this algorithm, the l_1-norm in (P_2) is replaced by a weighted l_2-norm [26]:

$$P_3: \qquad min\ \lambda\mathbf{x}_e^T\mathbf{E}^{-1}\mathbf{x}_e + \frac{1}{2}\| \mathbf{y}_\mathrm{e} - \mathbf{H}\mathbf{x}_e\|_2^2 \tag{10}$$

Where $\mathbf{E}$ is a diagonal weight matrix and it is updated from the current iterate $(\mathbf{x}_e)_k$.
The minimization in (P3) is a quadratic optimization problem, soluble using linear algebra. The pseudo-code for the IRLS error recovery-based MIMO detector has been shown in Algorithm 1.

4-2- ADMM Algorithm

The alternating direction method of multipliers is an alternative algorithm for sparse coding. This algorithm uses the augmented Lagrangian to splits the main optimization problem into two quadratic and separable minimization problems.
In this method, the augmented Lagrangian is defined as [27]

$$L_\mu(\mathbf{x}_e, \mathbf{z}, \boldsymbol{\lambda}_a) = \lambda\|\mathbf{x}_e\|_1 + \frac{1}{2}\|\mathbf{z}\|_2^2 - \langle \boldsymbol{\lambda}_a, \mathbf{y}_\mathrm{e} - \mathbf{H}\mathbf{x}_e - \mathbf{z} \rangle + \frac{\mu}{2}\|\mathbf{y}_\mathrm{e} - \mathbf{H}\mathbf{x}_e - \mathbf{z}\|_2^2 \tag{11}$$

Algorithm 1: IRLS error recovery-based detector

Input: $\mathbf{y}$, $\mathbf{H}$, and σ_n^2

Parameters: maximum iteration number (K), threshold (η)

Output: The estimation of the transmitted symbols: $\hat{\mathbf{x}}$

initialization:

1: $\mathbf{A} = \mathbf{H}^{\mathrm{H}}\mathbf{H} + \sigma_n^2\mathbf{I}_{n_t}$, $\mathbf{D}$ = diag ($\mathbf{A}$) **and** $\mathbf{y}_{\mathrm{MF}} = \mathbf{H}^{\mathrm{H}}\mathbf{y}$

2: $\hat{\mathbf{x}}_{\mathrm{MMSE}} = \mathbf{A}^{-1}\boldsymbol{y}_{\boldsymbol{MF}}$ 'Primary Estimation'

3: $\mathbf{y}_{\mathrm{e}} = \mathbf{y} - \mathbf{H}\hat{\mathbf{x}}_{\mathrm{MMSE}}$

4: The initial weight matrix $\boldsymbol{E} = \mathbf{D}$

Iteration: Increase k

5: **Regularized Least-Squares:** approximately solve the linear system

$$(2\lambda\boldsymbol{E}^{-1} + \mathbf{H}^{\mathrm{H}}\mathbf{H})(\mathbf{x}_e)_k = \mathbf{H}^{\mathrm{H}}\mathbf{y}_{\mathrm{e}}$$

6: **Weight Update:** Update the diagonal weight matrix $\boldsymbol{E}$

$$\boldsymbol{E} = \mathrm{diag}(|(\mathbf{x}_e)_k| + \varepsilon)$$

7: **Stopping Rule:** if $\|(\mathbf{x}_e)_k - (\mathbf{x}_e)_{k-1}\| < \eta$ break else go back to step 5

8: **Output:** $(\mathbf{x}_e)_k$.

9: **return** $\hat{\mathbf{x}} = \hat{\mathbf{x}}_{\mathrm{MMSE}} + (\mathbf{x}_e)_k$

where $\boldsymbol{\lambda}_a$ is the Lagrangian multiplier and $\mu > 0$ is a penalty parameter. The pseudo-code of the MIMO detection using the ADMM algorithm has been shown in Algorithm 2.

4-3- ISTA Algorithm

Another algorithm which can be used for solving problem ($P2$) is the iterative shrinkage-thresholding algorithms (ISTA). The solution based on the ISTA algorithm can be written as [23, 28]

$$\boldsymbol{\psi}_k = (\mathbf{x}_e)_{k-1} - 2t\boldsymbol{H}^H(\boldsymbol{H}(\mathbf{x}_e)_{k-1} - \mathbf{y}_{\mathrm{e}}) \quad (12)$$

where t is the step size and the error vector is updated as

$$(\mathbf{x}_e)_k = \boldsymbol{\mathcal{H}}(\boldsymbol{\psi}_k) \quad (13)$$

where $\boldsymbol{\mathcal{H}}()$ is the shrinkage operator and is described by

$$\boldsymbol{\mathcal{H}}(\boldsymbol{\psi}_k) = max(\mathbf{0}, |\boldsymbol{\psi}_k| - \alpha) \circ sgn(\boldsymbol{\psi}_k) \quad (14)$$

where $\circ$ and $sgn(.)$ are the Schur product and the sign function respectively. The parameter $\alpha = \lambda t$ represents the threshold value and λ is the proper scale hyperparameter.

Algorithm 2: ADMM error recovery-based detector

Input: $\mathbf{y}$, $\mathbf{H}$, and σ_n^2

Parameters: maximum iteration number (K), threshold (η), penalty parameter (μ)

Output: The estimation of the transmitted symbols: $\hat{\mathbf{x}}$

initialization:

1: $\mathbf{A} = \mathbf{H}^{\mathrm{H}}\mathbf{H} + \sigma_n^2\mathbf{I}_{n_t}$, $\mathbf{D}$ = diag ($\mathbf{A}$) **and** $\mathbf{y}_{\mathrm{MF}} = \mathbf{H}^{\mathrm{H}}\mathbf{y}$

2: $\hat{\mathbf{x}}_{\mathrm{MMSE}} = \mathbf{A}^{-1}\boldsymbol{y}_{\boldsymbol{MF}}$ 'Primary Estimation'

3: $\mathbf{y}_{\mathrm{e}} = \mathbf{y} - \mathbf{H}\hat{\mathbf{x}}_{\mathrm{MMSE}}$

Iteration: Increase k

4: **Update error vector, $\mathbf{x}_e$:**

$$(2\mathbf{H}^{\mathrm{H}}\mathbf{H} + \mu\mathbf{I})(\mathbf{x}_e)_k = 2\mathbf{H}^{\mathrm{H}}\mathbf{y}_{\mathrm{e}} + \mu\boldsymbol{z}^{k-1} + \boldsymbol{\lambda}_a^{k-1}$$

5: **Update $\boldsymbol{z}^k$:** compute $\boldsymbol{z}^k$ via soft shrinkage

$$\boldsymbol{z}^k = \arg\min_{\boldsymbol{z}} \lambda\|\mathbf{z}\|_1 - <\boldsymbol{\lambda}_a^{k-1}, (\mathbf{x}_e)_k - \mathbf{z} > + \frac{\mu}{2}\|(\mathbf{x}_e)_k - \mathbf{z}\|_F^2$$

6: **Update Lagrangian multiplier, $\boldsymbol{\lambda}_a$:** $\boldsymbol{\lambda}_a^k = \boldsymbol{\lambda}_a^{k-1} - \mu((\mathbf{x}_e)_k - \boldsymbol{z}^k)$

7: **Stopping Rule:** if $\|(\mathbf{x}_e)_k - (\mathbf{x}_e)_{k-1}\| < \eta$ break else go back to step 4

8: **Output:** $(\mathbf{x}_e)_k$.

9: **return** $\hat{\mathbf{x}} = \hat{\mathbf{x}}_{\mathrm{MMSE}} + (\mathbf{x}_e)_k$

The pseudo-code of the MIMO detection using the ISTA algorithm has been shown in Algorithm 3.

5- Simulation Result

In this section, numerical simulation results and complexity of detectors are presented to demonstrate the performance of the proposed methods. The simulations are conducted for $n_r \times n_t$ MIMO system, where n_r and n_t are the number of receive and transmit antennas, respectively. In the simulations, the massive MIMO system with 4-QAM and 16-QAM modulations are considered. Each entry of the channel matrix $\mathbf{H}$ is an i.i.d. circularly symmetric complex Gaussian random variable (i.e., $\mathbf{H} \sim \mathcal{N}(0,1)$) and the channel statistics information is available for the BS and satisfy

$$lim_{n_r \to \infty} \frac{1}{n_r}\boldsymbol{h}_n^H\boldsymbol{h}_n = 1 \quad (15)$$

where $\boldsymbol{h}_n$ is the nth column of the matrix $\mathbf{H}$.

Algorithm 3: ISTA error recovery based detector
Input: $\mathbf{y}$, $\mathbf{H}$, and σ_n^2 **Parameters**: maximum iteration number (K)), threshold (η),   **Output:** The estimation of the transmitted symbols: $\hat{\mathbf{x}}$ **initialization:**   1: $\mathbf{A} = \mathbf{H}^H\mathbf{H} + \sigma_n^2\mathbf{I}_{n_t}$, $\mathbf{D}$ = diag($\mathbf{A}$) **and** $\mathbf{y}_{MF} = \mathbf{H}^H\mathbf{y}$ 2: $\hat{\mathbf{x}}_{MMSE} = \mathbf{A}^{-1}\boldsymbol{y}_{MF}$ 'Primary Estimation'   3: $\mathbf{y}_e = \mathbf{y} - \mathbf{H}\hat{\mathbf{x}}_{MMSE}$ **Iteration:** Increase k 4: **Update $\boldsymbol{\psi}_k$:** $$\boldsymbol{\psi}_k = (\mathbf{x}_e)_{k-1} - 2t\mathbf{H}^H(\boldsymbol{H}(\mathbf{x}_e)_{k-1} - \mathbf{y}_e)$$ 5: **Update error vector, $\mathbf{x}_e$:** $$(\mathbf{x}_e)_k = \boldsymbol{\mathcal{H}}(\boldsymbol{\psi}_k)$$ 6: **Stopping Rule:** if $\lVert(\mathbf{x}_e)_k - (\mathbf{x}_e)_{k-1}\rVert < \eta$ break   else go back to step 4   7: **Output:** $(\mathbf{x}_e)_k$.   8: **return** $\hat{\mathbf{x}} = \hat{\mathbf{x}}_{MMSE} + (\mathbf{x}_e)_k$

All simulations are carried out in Matlab 2015b on a processor Intel(R) Core (TM) i5-6200U CPU at 2.30 GHz and 8GB RAM and all results are averaged over 10000 iterations.

Prior to apply the minimization problems (P_2) or (P_3) for the MIMO detection, the coefficient λ should be adjusted. Fig. 1 shows the BER of the MIMO detectors for ISTA, ADMM, and IRLS algorithms with respect to different values of λ. In this simulation, the SNR has been fixed at 15 dB and the parameter λ varies from 0 to 50. The simulations are conducted with $n_r = n_t = 64$ for 4-QAM modulation. According to this figure, the values of the parameters λ in the following simulations are set to $\lambda_{ADMM} = 30$, $\lambda_{IRLS} = 5$ And $\lambda_{ISTA} = 17$.

Fig .2 (a) shows the error of the primary detector in an uplink massive MIMO system with 16-QAM modulation with $n_r = n_t = 64$. This simulation shows that the error of the estimated user symbols is sparse. Fig. 2 (b), (c) and (d) illustrate the recovered error vector using the ADMM, ISTA, and IRLS respectively. It can be seen that only the error corresponding to the 40^{th} user is not completely recovered. To further investigate the performance of different error recovery methods, various detection scenarios are simulated.

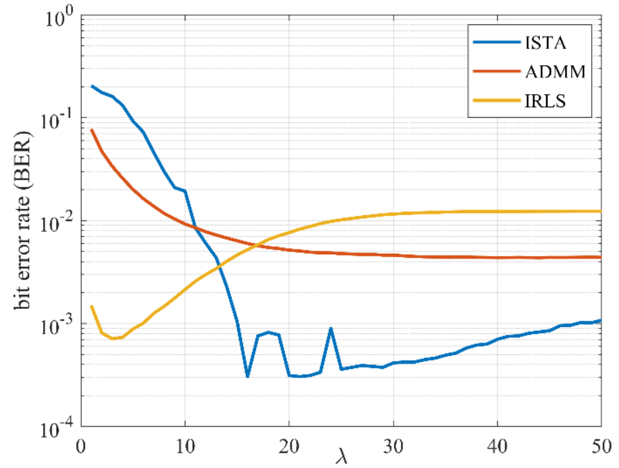

Fig. 1 BER performance versus λ in the uplink massive MIMO for 4-QAM modulation with SNR = 15 dB.

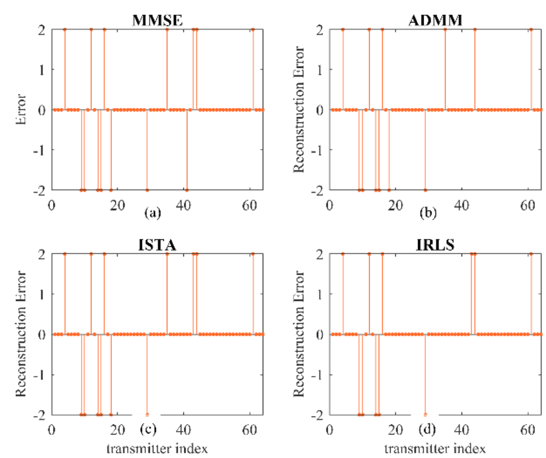

Fig. 2 (a) the error of the primary detector and (b), (c), (d) the recovered error vector using the ADMM, ISTA, and IRLS algorithms in the uplink massive MIMO system for 16-QAM modulation for $n_r = n_t = 64$ with SNR = 15 dB.

Fig.3-Fig .6 shows the bit error rate (BER) of the MIMO detection for $n_r = n_t \in \{32,64\}$ and $\{4,16\}$ -QAM modulations. In Fig. 3 and Fig. 4, 4-QAM constellation with $n_r = n_t = 32$ and $n_r = n_t = 64$ are considered respectively. In comparison to the MMSE detector, performance improvement of the error recovery methods are markedly evident. It can be seen that the IRLS method has the best performance among other error recovery methods. In addition, all sparsity-based error recovery methods lead to lower BER in comparison to the RLS.

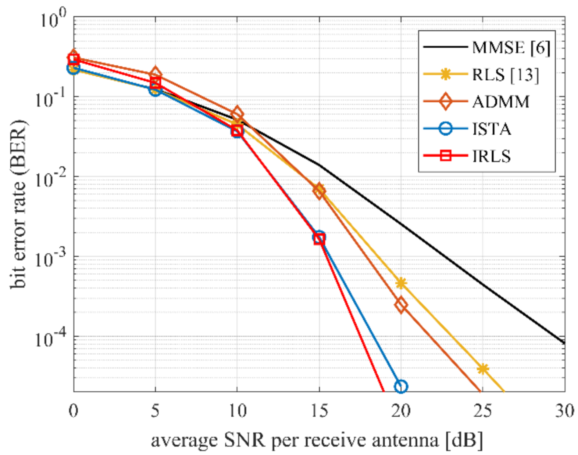

Fig. 3 BER performance comparison of the error recovery algorithms in the uplink massive MIMO for 4-QAM modulation for $n_r = n_t = 32$.

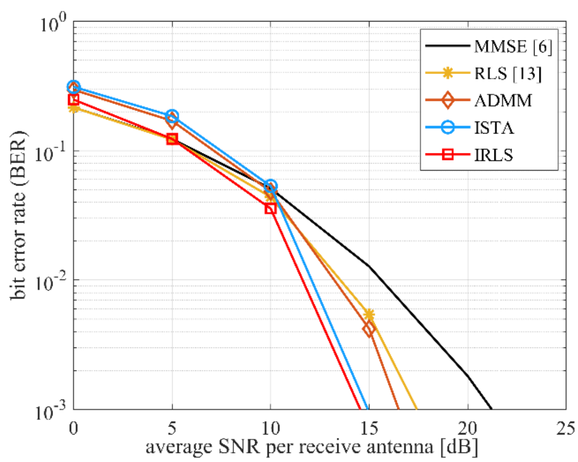

Fig. 4 BER performance comparison of the error recovery algorithms in the uplink massive MIMO for 4-QAM modulation for $n_r = n_t = 64$.

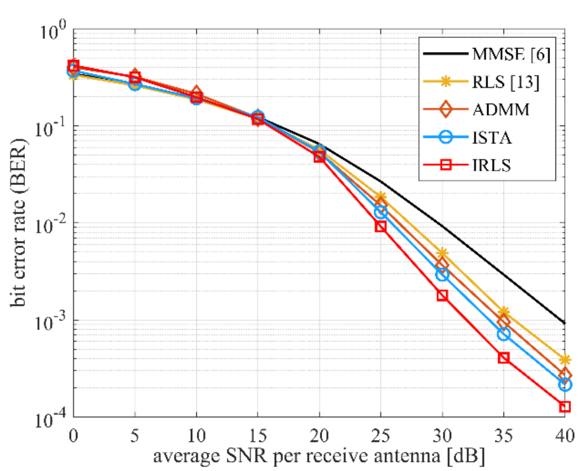

Fig. 5 BER performance comparison of the error recovery algorithms in the uplink massive MIMO for 16-QAM modulation for $n_r = n_t = 32$.

Fig. 5 and Fig. 6 show the detection performance for 16-QAM modulation with $n_r = n_t = 32$ and $n_r = n_t = 64$ respectively. Although the detection improvement is decreased but still all error recovery detectors achieved better performance than the MMSE detector.

Fig.7 compares the run time of the previously mentioned error recovery algorithms for different number of transmitters and $n_r = 64$.

The times are averaged over 10000 iterations. It can be seen that the run time of the all methods increase with the system dimensions. Generally, the run time of the IRLS method is less than that of the ADMM and ISTA algorithms. Since the RLS method has a close form solution, it leads to the least run time.

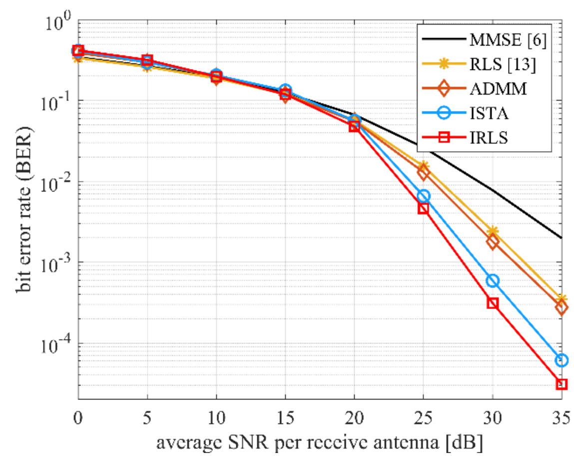

Fig. 6 BER performance comparison of the error recovery algorithms in the uplink massive MIMO for 16-QAM modulation for $n_r = n_t = 64$.

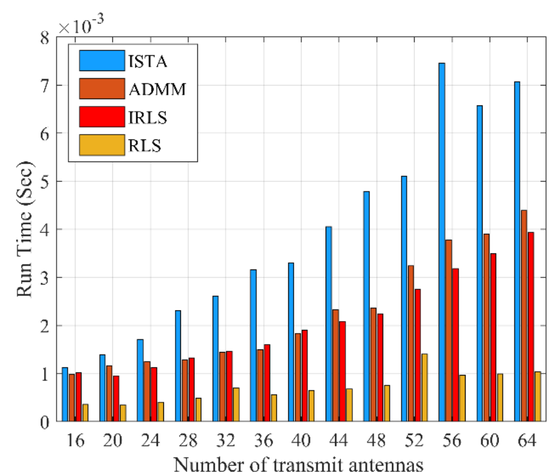

Fig. 7 Run time evaluation for the error recovery algorithms versus number of transmit antennas in the uplink massive MIMO for 64-QAM modulation with $n_r = 64$ and SNR = 10 dB.

The total computational complexity of the methods can be analyzed with respect to the number of multiplications in the Big-O notation. Since in the simulations n_t is close to n_r, it can be easily shown that the computational complexity of all methods is of order $O(n_t^3)$ which is similar to that of the MMSE MIMO detector. In order to summarize the results, it was demonstrated that the IRLS method leads to the best MIMO detection performance. Note that, since the IRLS method is an iterative algorithm and also it requires the matrix inversion operation in each iteration, the run time of the proposed algorithm is more than that of the MMSE detector. Applying the approximation methods in matrix inversion computation such as Gauss-Seidel, Chebyshev, and conjugate gradient methods would decrease the run time of the IRLS sparse recovery method.

The performance of the large-scale MIMO systems depends on the accuracy of the channel state information (CSI). In future works, an algorithm for joint channel estimation and signal detection in sparse error domain would be considered.

6- Conclusions

This paper focused on the problem of detection in massive MIMO systems. The main idea of this algorithm is to improve the performance of the detector by finding the hidden sparsity in the residual error of the received signal. In this paper, three sparse recovery algorithms, i.e. Iterative Re-weighed Least Squares (IRLS), Alternating Direction Method of Multipliers (ADMM), and Iterative Shrinkage-Thresholding Algorithm (ISTA) have been applied to reconstruct the error of the primary detector. It is noteworthy that the iteratively reweighted least-squares (IRLS) method achieved the best performance among other sparse recovery methods. The proposed methods outperform the MMSE detector but it is obvious that the complexity of the sparse error recovery-based MIMO detectors is more than that of the MMSE detector. Consequently, more efforts are needed to decrease the computational burden of the sparse error recovery algorithms.

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