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Efficient and Low Complex Uplink Detection for 5G Massive MIMO Systems

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***Abstract*—Massive Multiple Input Multiple Output is most promising technology that has been proposed in recent years, and it has been considered a technology to fulfill the requirement of fifth generation network. Even though this technology has many advantages, it must surpass certain challenges as well, and one of the major challenge is signal detection at the base station which becomes more complex with an increased number of antennas. Conventional methods that are used in MIMO detection are computationally very complex and inefficient to use in Massive MIMO system. So, there is a need for suitable detection method for these systems to have good bit error rate performance with lower complexity. In this paper, we propose a more efficient and computationally less complex algorithm for detection of Massive MIMO systems. Results through MATLAB simulations show that our proposed method provides a good tradeoff between computational complexity and BER performance and it is efficient for detection of Massive MIMO systems.**

Keywords*—*Massive MIMO, 5G, signal detection, bit error rate, computational complexity

I. INTRODUCTION

After the introduction of smartphones, tablets, and laptops, mobile data traffic has observed an exponential growth during the past few years, and this growth is expected in next few years as well. With the increase in the number of mobile users, not only the mobile traffic has increased but every user wants higher data rate with more accuracy and reliability. This considerable amount of mobile data traffic is challenging to manage with current technologies. Future generation network called fifth generation (5G) must accommodate this huge traffic and address the current limitation of data rates reliability, and efficiency. Currently, many technologies are trying to answer all these problems in mobile communication, but none have found an optimal solution. On the top of that, these technologies must take complexity, energy efficiency, reliability into account while designing the new system. Recently, a technology called massive MIMO has been proposed, which uses hundreds or even thousands of antennas at the base station, and it can serve tens of user simultaneously [1]. These thousands of antennas focus the transmission and reception of signal onto smaller region and help the system to achieve high diversity and multiplexing gains to improve reliability and increase data rate [2]. In massive MIMO systems, a user sends pilot towards the base station and based on these pilot signals base station estimates the channel between it and the user. The base station should have knowledge of channel during both uplink and downlink as massive MIMO is a technology that is dependent upon spatial multiplexing [3].

There are several advantages of using these systems such as high spectral efficiency, antenna array gain, high reliability, robustness to internal jamming and interference and energy efficiency. Along with these advantages, Massive MIMO comes up with certain challenges as well, and one of the major challenges that massive MIMO is facing is high computational complexity and poor bit error rate (BER) performance during received signal detection at the base station which due to the higher number of antennas at the base station and more number of users. In Massive MIMO, all the signal transmitted by the user terminals superimpose at the base station and thus interfere with each other. There are several algorithms or methods for Massive MIMO detection and non- linear detectors like sphere detector, and successive interference cancellation detector are computationally very complex. Therefore, these methods are not recommended. Linear detectors are computationally less complex than non-linear detector, but the performance is much degraded. All the conventional detection methods like Maximum Likelihood detection(ML), Minimum mean square error detection (MMSE), Zero-forcing detection (ZF) are not very efficient in terms of performance and complexity. During detection, these linear methods include inversion of high dimensional matrices which drastically increases the complexity of the system and this complexity increases exponentially with more number of antennas. [4]. In this paper, we present a low complex and efficient algorithm for detection of Massive MIMO systems which is based upon modified Approximate Message Passing(AMP) algorithm. The rest of the paper is organised as follows: In section II, we will discuss related works, section III will present description of used system model, in section IV, we will describe different uplink detection methods, proposed algorithm is described in section V, numerical results are presented in section VI, and section VII concludes the paper.

II. RELATED WORKS

A significant amount of research has been done on various detection methods for Massive MIMO system to reduce computational complexity and maximize performance. The non-linear detector like Sphere decoder, Maximum likelihood decoder are computationally not feasible to use in massive MIMO system and is described in [5]. Many linear approaches for massive MIMO detection are based on matrix inversion [6-10] which are also computationally complex to implement in real time. Gaussian message passing iterative detection is described in [11] [12], Jacobi iteration detection method is based on [13], and Richardson method is described in [14]. Performance of these algorithms degrades when the number of users increases and they require more iterations for achieving satisfactory performance, and thus more iterations increase the complexity of the system [2]. Our Massive MIMO detection method is primarily based upon Approximate Message Passing Algorithm [15-16] which was initially designed for recovery of sparse signals. Recently, many algorithms have been proposed for detection of Massive MIMO systems based on AMP, but most of them lack in performance [17-19].

III. SYSTEM MODEL

We consider a Massive MIMO system with BS (base station) equipped with a substantial number of antennas (M=64,128,256). The BS communicate with N (N=12) number of users having a single antenna. These users may have more than one antenna, but for simplicity, we have assumed that these users have a single antenna. Perfect channel state information is assumed between the user and base station. We have used Time division duplex protocol because this protocol removes the requirement of downlink signaling. The received signal at the base station is given by:

$$\boldsymbol{y} = \boldsymbol{H} * \boldsymbol{X} + \boldsymbol{w} \tag{1}$$

Where, $\boldsymbol{y} \in \mathbb{C}^{\mathbf{M}}$ is the received signal vector at the base station, $\boldsymbol{H} \in \mathbb{C}^{M\times N}$ is the channel matrix whose elements are independent and identically distributed (i.i.d), i.e. $\boldsymbol{H} \sim \mathrm{CN}\ (0,1)$, $\boldsymbol{X} \in \mathbb{C}^{N}$ is the uncoded signal transmitted by the user. $\boldsymbol{w} \in \mathbb{C}^{N}$ is the AWGN (additive white gaussian noise) and its each component w_i are i.i.d with zero mean and finite variance σ^2, i.e. $\boldsymbol{w} \sim \mathrm{CN}\ (0, \sigma^2\boldsymbol{I})$.

IV. UPLINK DETECTION METHODS

In Massive MIMO systems, detection is required at the base station to separate signal transmitted by each user from the received signal. There are several methods to detect received signal, but we need an efficient detector with feasible computational complexity to get better performance. Although non-linear detectors are easy to implement they are not used because of their computational complexity. Optimal detectors like ML detector also has a high complexity which increases exponentially with a number of antennas. The linear detector has satisfactory performance, but they are difficult to implement in real-time with thousands of antennas.

A. Zero-Forcing Detector

This a simple linear detector which uses matrix inversion and eliminates interference. Sometimes, noise gets amplified at frequencies where channel spectrum has the highest attenuation. Therefore, ZF suffers from noise enhancement. This detection method has poor bit error rate performance as well. Interference is suppressed by multiplying the received signal with the pseudoinverse of the channel matrix, A_{ZF}, which is defined as:

$$A_{ZF} = (H^H H)^{-1} H^H \tag{2}$$

Where $(.)^H$ is Hermitian transpose operation. From the above expression, each calculated value is mapped to the nearest symbol [20].

$$X = A_{ZF} * y$$

$$X_{ZF} = X + (H^H H)^{-1} H^H * w \tag{3}$$

B. MMSE Detector

MMSE is also linear detector which reduces both noise and interference. The estimated signal matrix for MMSE is defined as:

$$A_{MMSE} = (H^H H + \frac{\sigma_w^2}{\sigma_X^2})^{-1} H^H \tag{4}$$

Where, σ_w^2 is the noise variance and, σ_X^2 is the signal variance which is controlled by signal to noise ratio(SNR).

C. AMP Detector

This AMP algorithm was initially designed for solving least absolute double shrinkage and selection problem in compressed sensing, and it was initially proposed by Donoho in [15]. This algorithm uses iterative thresholding to approximate the signal transmitted by the user from the signal received by the base station. In each step, this algorithm calculates the residual error and tries to minimize this error in each successive iteration. This algorithm was used in Massive MIMO detection by various researchers because of its low complexity when compared to contemporary MIMO detection methods such as ML, ZF, and MMSE. Although AMP algorithm is computationally less complex, its error performance is not very good. We are proposing an algorithm which improves the error performance of the massive MIMO detector with less computational complexity.

V. PROPOSED ALGORITHM

In this section, we will describe our proposed algorithm for uplink detection is Massive MIMO systems. This proposed algorithm is compared with AMP algorithm, Zero-Forcing algorithm and Minimum mean square error algorithm used for uplink detection in massive MIMO systems. The Pseudo-code for the proposed algorithm is given in algorithm 1. Initially, the residual value is initialized as the received signal at the base station y, and the output signal X is initialized as zero vector with dimension N×1. We calculate α as the sum of transmitted signal with the product of transposed channel matrix and residual value. Threshold value θ is taken as absolute positive value of the α calculated in step four, and complexity wise this term is very easy to compute. We then perform soft thresholding to get the updated value of transmitted signal by the users. This thresholding function is defined in (5).

Algorithm 1 Proposed Algorithm for Uplink Detection of Massive MIMO Systems

```
1:  Initialization: r^0 = y
2:  Initialization: X^0 = 0_{N×1}
3:  for j = 1 to j_maximum do
4:      α = X^{j-1} + H^T * r^{j-1}
5:      θ = |real(min(α))|
6:      X^j = S(α, θ)
7:      b = (1/M) * ||X||_2 / ||X||_1
8:      r^j = y − H * X^j + b * r^{j-1}
9:  end
10: return X^{j_maximum}
```

$$S(\alpha,\theta) = sgn(\alpha)(|\alpha| - \theta)_+ = \begin{cases} \alpha - \theta & \text{if } \alpha > \theta \\ 0 & \text{if } |\alpha| \le \theta \\ a + \theta & \text{if } \alpha < -\theta \end{cases} \tag{5}$$

The proportionality factor is then calculated, and here sparsity is measured from the ratio of l_2 -norm and l_1-norm. Although l_0-norm has been widely used for compressed sensing, it is not very suitable for this application. The reason that we do not use l_0-norm for calculating sparsity measure is that its derivative contains no information of the signal, and performance of l_0-norm is very poor in the presence of noise [21]. l_0-norm is highly unstable, and if the signal is not equal to zero, then the output of the l_0-norm does not give a useful description of the effective number of coordinates [22]. The ratio of l_2 -norm and l_1-norm follows attributes such as Robin Hood, Scaling and Bill Gates which are described in [21]. Hence, using l_2 -norm and l_1-norm ratio instead of l_0-norm is very useful in the detection of Massive MIMO systems. Norm is the total size of all the vectors in vector space or matrix, and l_1-norm of X is defined as:

$$\|X\|_1 = \Sigma_i |X_i| \tag{6}$$

And, l_2-norm of x is defined as:

$$\|X\|_2 = \sqrt{\Sigma_i X_i^2} \tag{7}$$

Residual value is then calculated, and during each iteration, we try to minimize the residual error until a maximum number of iteration is reached.

VI. NUMERICAL RESULTS

Table I shows the simulation parameters used for conducting the simulation. All the simulations are done in MATLAB, and we have used the system model defined in section III. With these defined simulation parameters and system model, we will compare BER performance and computational complexity of proposed algorithm with other Massive MIMO detection algorithms.

TABLE I. SIMULATION PARAMETERS

Parameter	Value
System Bandwidth	5 MHz
Subcarriers	25
Coherence Interval	200 symbols
Coherence Bandwidth	200 kHz
Number of Users	12
Signal Variance	2
Number of Receive Antennas	64 or 128 or 256 or 512
Signal to Noise Ratio	1 to 10 dB
Noise Variance	Controlled by SNR
Channel Model	Uncorrelated Rayleigh Fading

A. BER Performance

In this section, we access the BER performance of the proposed algorithm by comparing it with other detection algorithms such as MMSE, ZF, and AMP. In, Fig. 1, Fig. 2 and Fig.3 we present the BER performance against the received signal to noise ratio (SNR) for M=64, M= 128 and M=256. We compare their performance with MMSE, ZF, and AMP detection methods. We did 10,00,000 Monte-Carlo simulations for all these methods and several rounds of iterations for the proposed and AMP algorithm. For M=64 the BER performance of proposed algorithm is like that of MMSE and ZF for the lower value of SNR, but for the higher value of SNR, the performance of proposed algorithm is better than AMP, and when compared to ZF and MMSE, BER performance is slightly degraded. For M= 128 there is a huge improvement in BER performance. All the detection methods have improved the BER performance with the higher number of receive antennas. The proposed algorithm has better BER performance than the AMP algorithm, and it has almost similar performance when compared with ZF and MMSE. For M= 256, BER performance improves for all the methods, and almost all the methods have similar BER performance. Fig4. shows the performance of proposed detection method with a different number of iterations. We can see that BER performance of Massive MIMO detection will increase with an increase in a number of iterations, but the performance will saturate after we reach a certain number of iterations.

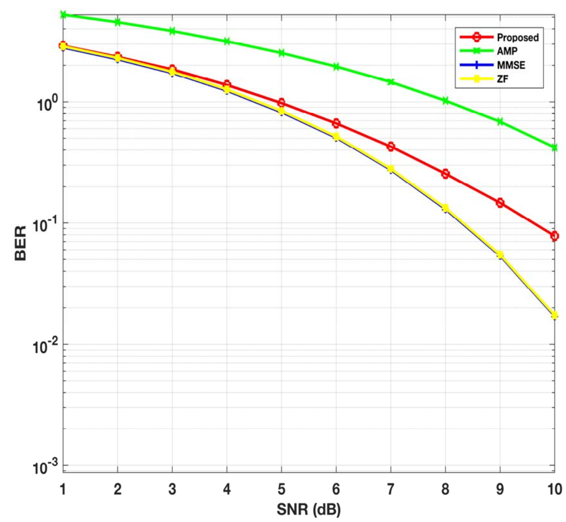

Fig.1. BER vs. SNR performance of the proposed algorithm with M=64

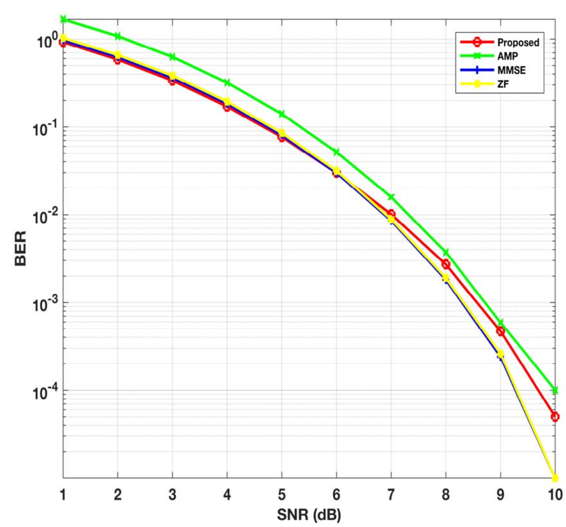

Fig.2. BER vs. SNR performance of the proposed algorithm with M=128

B. Complexity Comparison

The complexity of the proposed algorithm is measured and compared with different Massive MIMO detection algorithms. If M is the number of receive antennas and N is the number of users then, the complexity of ZF and MMSE detection algorithm is in order of $O(MN^2)$, and these algorithms require matrix inversion which increases their complexity. AMP and the Proposed algorithm do not require matrix inversion, and their complexity is in order of O(MNj), where, j is the number of iterations. The complexity of Proposed and AMP detection method also depends upon the number of iterations. The detection method, ZF, and MMSE contain a term which is in order of $N^{2,}$ and therefore they fall behind complexity trade-off of proposed and AMP detection method. Each algorithm was run for hundred thousand Monte Carlo simulations with 128 receive antennas and 12 users. For different algorithms, we measured time to complete one Monte Carlo run, and we averaged it for hundred thousand Monte Carlo runs. The code was run on MATLAB R2017b under Mac OS, with 3.4 GHz Intel Core i7 processor and 10 GB of RAM. Results of the simulation are shown in Fig. 5 which shows the time taken to complete one run by a different algorithm with a different number of receive antennas and we can see that MMSE and ZF are very complex when compared to AMP and proposed algorithm. With more number of receive antennas, complexity increases drastically for ZF and MMSE and for proposed and AMP complexity is increased slightly. The proposed algorithm has time complexity almost like that of AMP, but it is far better than ZF and MMSE detection algorithm.

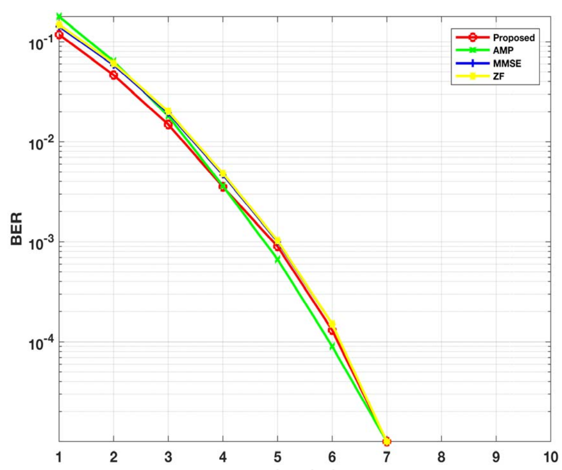

Fig.3. BER vs. SNR performance of the proposed algorithm with M=256

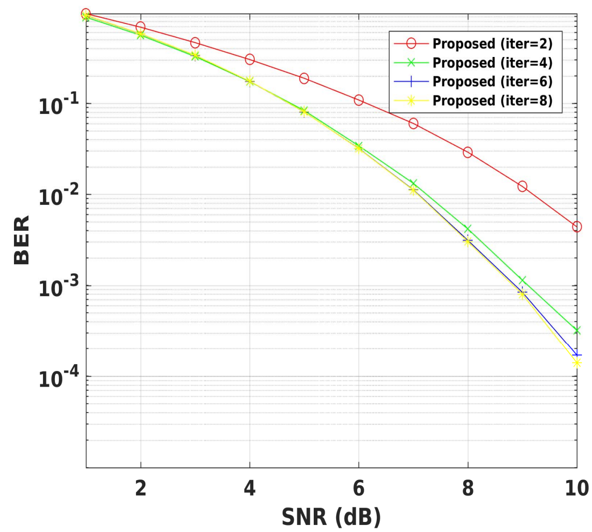

Fig.4. BER vs. SNR of proposed detection method with different iterations

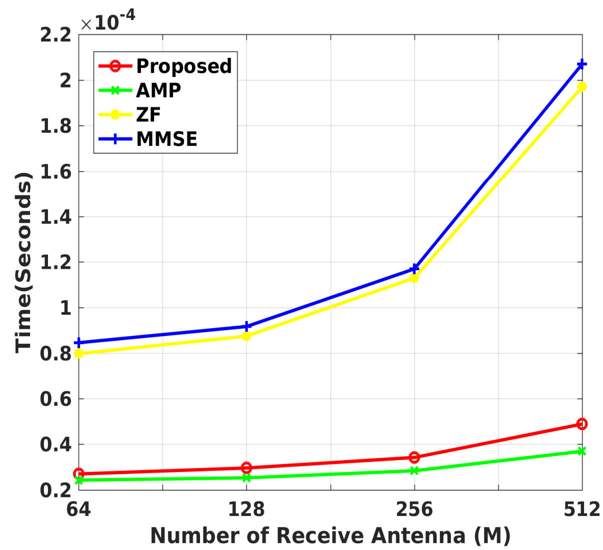

Fig.5. Average time to complete one run vs. Number of received antenna

VII. CONCLUSION

In this paper, we proposed an algorithm for detection of Massive MIMO system which is based upon Approximate Message passing algorithm. Simulation results through MATLAB show that the proposed algorithm can achieve BER performance same as ZF and MMSE and outperforms original AMP detection algorithm. The proposed algorithm has complexity less than that of ZF and MMSE, and it has almost similar complexity as AMP algorithm. This proposed algorithm provides a good tradeoff between complexity and performance, and it is efficient for detection of Massive MIMO system. Future work for this research would be to test this simulation by integrating several network parameters. It would be interesting to test this experiment for large Massive MIMO systems with thousands of antennas and more number of user and investigate the BER performance and complexity.

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