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Approximate Message Passing (AMP) Algorithm for Optimal Data Detection in Massive MIMO

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ABSTRACT -Massive multiple-input multiple-output (M-MIMO) system is a possible solution for improving 5G cellular telecommunication networks' spectral efficiency. It is a critical technology for meeting user demands for service performance and quality (QoS).The complexity of the symbol detectors in an M-MIMO uplink receiver developed significantly due to the huge number of antennas and radio frequency (RF) chains. The task is to separate the constituent signals from the composite signal while maintaining a high system limit.The optimum detector gets unreasonably complicated. As a result, low-complexity detection methods with near-optimal performance are required. Because of its low complexity and large system limit, the approximate message passing (AMP) algorithm, which was intended for compressed sensing, has received attention as a solution to this problem. As a result, in M-MIMO systems, the AMP algorithm has been used for detection.

Keywords: 5G, Spectral Efficiency, Massive MIMO, AMP Algorithm

INTRODUCTION

As the number of antennas in M-MIMO systems increases, so does the difficulty of detection. M-MIMO detectors are difficult to implement because to their increased complexity. In compressed sensing(CS), an algorithm called AMP was developed for signal reconstruction.The amount of propagated messages within the factor graph is decreased from $2M \times N$ to $M + N$ by taking advantage of the huge system limit.The algorithm's implementation becomes less complex and feasible as the number of propagated messages decreases. The AMP algorithm does not always converge for a finite size system, hence a strategy to help the algorithm converge is required. The AMP algorithm's behaviour with a large system limit makes it appealing for M-MIMO detection. The AMP algorithm was used to detect M-MIMO in this work. Because the AMP method's convergence is not guaranteed,

the damping principle is used to slow down estimates in order to promote convergence and also to slow down some computational parameter adjustments, although this comes at the cost of more iterations of the process.The AMP method decouples the M-MIMO system into parallel and independent AWGN channels with equal noise variance when the system limit is exceeded. Using estimation functions, the technique approximates the mean and variance of the transmitted data.As most parts of the AMP algorithm can be performed using matrix

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vector multiplication, the AMP algorithm is easy to implement. However, because each mean and variance are calculated independently utilizing all of the symbols in the constellation in the mean and variance estimation functions, the algorithm's "vector" behaviour is distorted.

The estimates provided by AMP in the large-system limit correspond to the actual signal affected by i.i.d. Gaussian noise. Furthermore, the state evolution (SE) framework may track the variance of the Gaussian random variables in each AMP iteration, allowing for precise performance analysis. The Bayesian AMP framework has been used to generalize AMP to i.i.d. signal priors and sparse recovery in complex-valued systems.AMP and the SE framework have recently been expanded to include more general observation models. AMP has been effectively used in a range of applications in recent years, including signal restoration, imaging, phase recovery, and de-noising. Many different communication systems have used AMP-related algorithms for data detection. While these findings demonstrate AMP's potential for data detection in wireless networks, they need a thorough performance evaluation.

Massive MIMO (M-MIMO) Technology

MIMO is a key technique that has been utilized to improve the performance of wireless transceivers since the third generation (3G) wireless networks. The objective is to maximize spectral efficiency, range, and/or connection reliability by using multiple antennas in the transmitter and receiver. Because many interfering signals are sent from various antennas, the MIMO receiver is intended to use a detection system to identify the symbols that have been distorted by interference and noise. During the last 50 years, the MIMO detector has captivated people's interest. M-MIMO is a larger-scale variation of traditional small-scale MIMO systems.M-MIMO is a multiuser communications solution that uses a large number of antenna elements (practically dozens or hundreds, theoretically thousands) to serve several users at the same time, with the freedom to choose which users to receive at any given time. With a single or several antennas in the same frequency band, the M-MIMO BS can service a large number of user terminals. The number of BS antennas is clearly bigger than the total number of antennas in the user equipment within the cell or service area in the classic M-MIMO system operating below 6 GHz carrier frequency.As a result, multiuser interference averages out to appear as increased additive noise, causing channel estimation issues owing to pilot contamination.

For fifth-generation (5G) communication systems operating below 6 GHz, where radio channels have a lot of scattering and multipath propagation, the traditional M-MIMO technology has been used. As a result of the interference averaging caused by the huge number of antenna elements, conventional matched filter (MF) based receivers are frequently close to optimum.At higher carrier frequencies, such as the µmWave or mm Wave bands, and beyond toward the THz band, very large antenna arrays are also required. However, propagation pathways are far more directed, resulting in quite different interference circumstances. Because antennas are smaller, large arrays are easier to construct and pack in higher frequencies. As a result, although the propagation characteristics of the channels make

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the multiuser interference scenario relatively different, M-MIMO detection approaches may play a role in µm Wave or mm Wave systems.

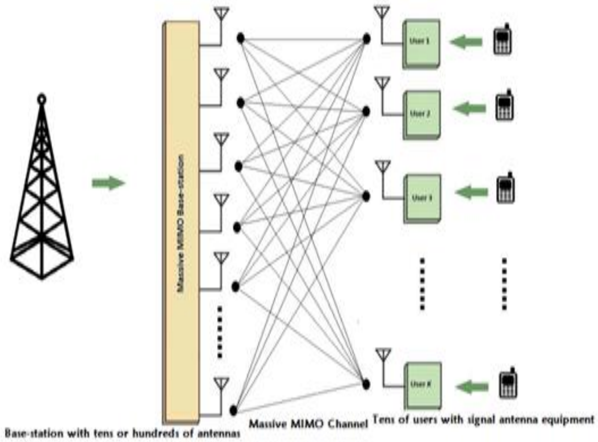

Figure 1: Massive MIMO Architecture

Notations:

Notations – We employed the standard notations that have been used in other papers in this work. The upper case letters R_j^t and R_j^{t+1} represents the j^{th} element of a vector at the t^{th} and $t^{th}+1$ iterations, respectively. Similarly the lower case v_i^t and v_i^{t+1} stand for the i^{th} element of a vector at the t^{th} and $t^{th}+1$ iterations. The notations $H_{j,i}$ and $\left|H_{j,1}\right|^2$ represent the entry at j^{th} row and i^{th} column of a matrix and its absolute squared, respectively. Lastly the notation $\hat{x}_i^t$ represents the i^{th} element of an estimate vector at the t^{th} iteration. In addition, the symbols x, H and y represent a vector, a matrix and a vector, respectively.

SYSTEM MODEL

A multiuser MIMO system with n users is one in which each user's equipment has a single antenna and the receiver has m antennas.The received signal at the receiver is given by

$$y = Hx + n,$$

where $y \in \mathbb{C}^m$, $H \in \mathbb{C}^{m \times n}$ and $x \in \mathbb{C}^n$ denote the received signal vector, the channel matrix and the transmit vector, respectively. Also, $n \in \mathbb{C}^m$ is additive white Gaussian noise (AWGN).

Before incorporating the AMP algorithm, be well aware of two facts: 1. directly using maximum a priori (MAP) or MMSE estimation to work with the exact prior degrade the necessity of employing AMP, because achieving a full diversity requires an extremely large set of constellation points, in which AMP works slowly while doing the moment matching process, not to mention problems about its inability to converge to the lowest fixed point. 2. In the CDMA multiuser detection theory, their "MMSE" detector does not mean the one working with exact prior, but rather the one assuming a Gaussian prior.

ALGORITHM

1. Initialization
2. Set $\hat{x}^0 = 0, \sum^0 = \sigma_x^2, v^0 = 1$
3. for t = 1, 2, ….., do
4. $V_j^{t+1} = \sum_i \left|H_{j,i}\right|^2 v_i^t$
5. $V = \sigma_n^2 + V_j^t$
6. $D = y_j - w_j^t$
7. $w_j^{t+1} = \sum_{i=1}^{n} H_{j,i}\, \hat{x}_i^t - \frac{D}{V} \sum_i \left|H_{j,i}\right|^2 v_i^t$
8. $D_{new}^{'} = y_j - w_j^{t+1}$
9. $V_{new}^{'} = \sigma_n^2 + V_j^{t+1}$
10. $D_{new}^{t+1} = d_\alpha \left(D, D_{new}^{'}\, \alpha\right)$
11. $V_{new}^{t+1} = d_\alpha \left(V, V_{new}^{'}\, \alpha\right)$

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12. $\sum_i^{t+1} = \left[\sum_j \frac{\left|H_{j,i}\right|^2}{V_{new}^{t+1}} \right]^{-1}$

13. $R_i^{t+1} = \hat{x}_i^t + \frac{\sum_j H_{j,i} * \frac{D_{new}^{t+1}}{V_{new}^{t+1}}}{\sum_j \frac{\left|H_{j,i}\right|^2}{V_{new}^{t+1}}}$

14. $\hat{x}_i^{t+1} = f_a\left(R_i^{t+1}, \sum_i^{t+1}\right)$

15. $v_i^{t+1} = f_c\left(R_i^{t+1}, \sum_i^{t+1}\right)$

16. end for

The function $d_\alpha(.)$ in lines 10 and 11 is a damping function with a damping factor of α, which is used to aid estimate convergence.It is given by

$$d_\alpha(A, A_{new}, \alpha) = \alpha A + (1-\alpha) A_{new}$$

However, in actual situations, the BS antennas may show correlation and inconsistent power profiles, particularly in multi-user environments. To deal with non-zero mean, low-rank channels, a modified GAMP employs the damping technique.

SIMULATION RESULTS

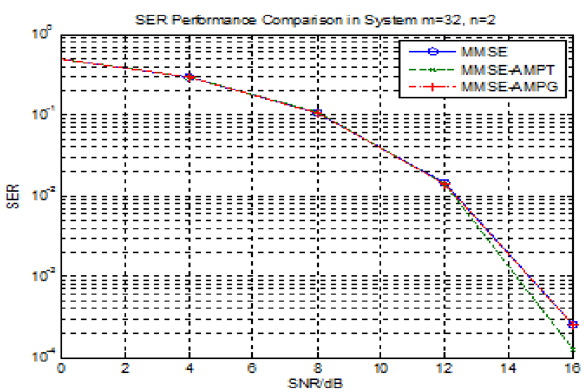

Fig 1: The Symbol Error Rate Performance of the system with m=32 and n=2

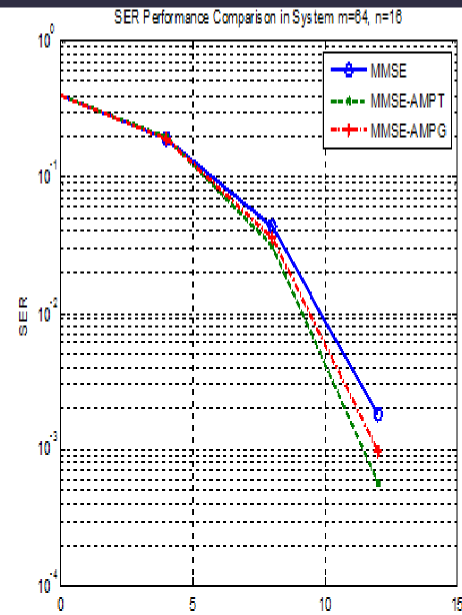

Fig 2: The Symbol Error Rate Performance of the system with m=64 and n=16

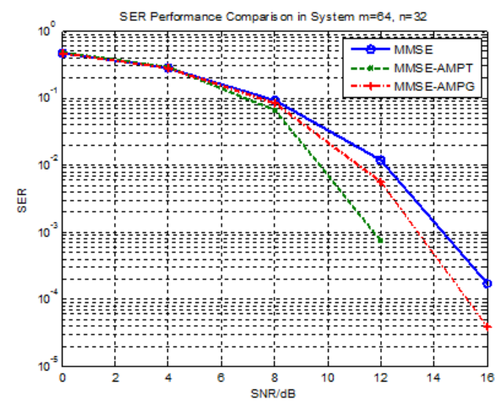

Fig 3: The Symbol Error Rate Performance of the system with m=64 and n=32

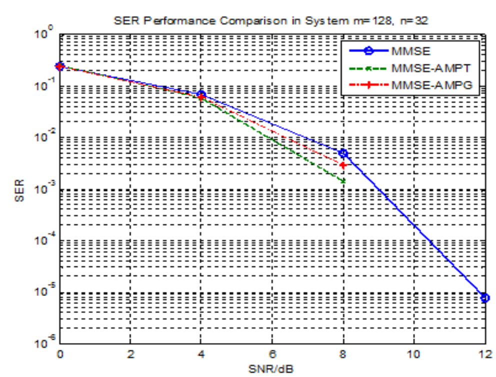

Fig 4: The Symbol Error Rate Performance of the system with m=128 and n=32

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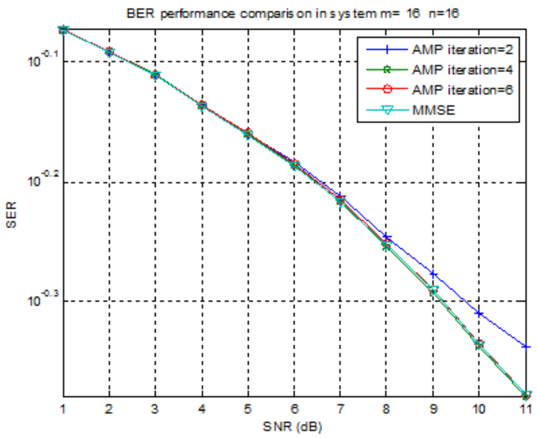

Fig 5: BER performance comparison in System with m=n=16.

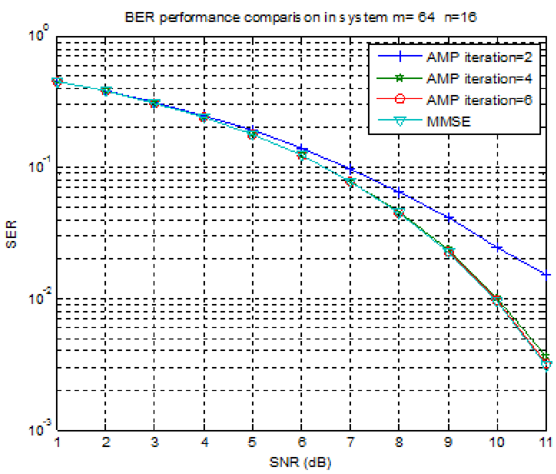

Fig 6: BER performance comparison in System with m=64, n=16.

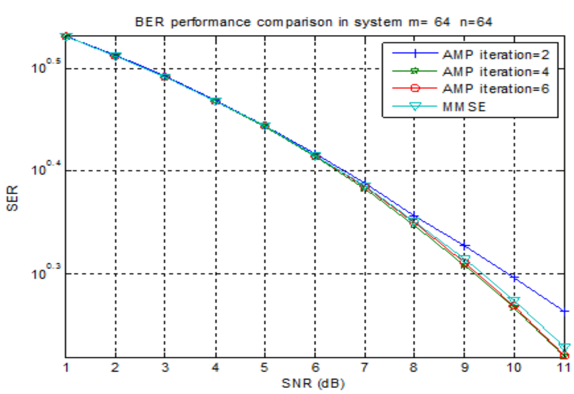

Fig 7: BER performance comparison in System with m=n=64.

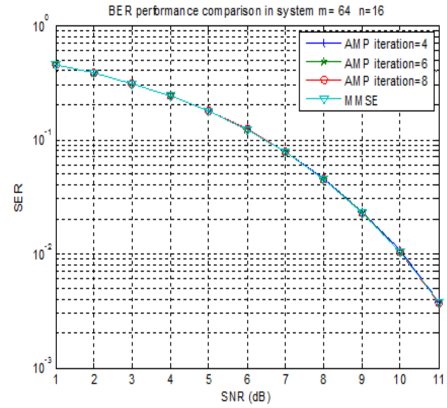

Fig 8: BER performance comparison in System with m=64, n=16 and different iterations

The performance of the MMSE and AMP algorithms for M-MIMO detection is shown in Figures 1 through 4. The results are averaged across 10000 Rayleigh fading MIMO channel matrix realizations. Various situations with increasing dimensions were examined in this work. The Symbol error rate (BER) as a function of SNR is used to illustrate the detector's performance. To begin, we evaluated the performance of the MMSE detector on a small scale configuration. We have created a simpler AMP that can match the performance of the MMSE detector in six iterations. The results also show that as the number of transmitting antennas increases, MMSE becomes ineffective.

Figures 5 through 8 show the MMSE's BER performance utilising various iterative matrix inversion methods at various MIMO sizes. Even when n is big, the performance suffers. The performance profile of detectors based on approximate matrix inversion algorithms clearly converges to that of the MMSE.

At the receiver, we studied a large-scale MIMO system with various M-MIMO sizes (m=n=16; m = n = 64; m=64, n=16 users and antennas). Comparisons are made between the

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AMP and the MMSE algorithms. With 6 iterations, AMP matches the performance of the MMSE algorithm for QPSK transmission, however the latter exceeds them with 3 iterations. Furthermore, the detector that uses the classic AMP technique achieves the goal performance with a higher level of complexity.

CONCLUSION

The use of iterative approaches to efficiently initialize the AMP detector is proposed in this study. It is demonstrated that with the proposed detectors, considerable performance improvements and complexity reductions can be realized. The desired performance was obtained with the least complexity using an initialized AMP detector based on the GS approach and a stair matrix. Recently, there has been a noticeable trend to use the ML technique in the design of M-MIMO detectors.

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