An Optimal Approximation message passing technique in Large-Scale MIMO Detection

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Abstract

In modern wireless communication standards, a Multiple-Input Multiple Output (MIMO) detection has a major role in detection and decoding aspects. The general problem raised in the communication process is to replicate the message at one point approximately a message selected at another point. Conventional standards like Markov chain Monte Carlo (MCMC) algorithm results in better performance expect bit error rate and complexity. Hence, recent researchers focused on applying the new optimal concept applying on various detection units for performance improvement and implementation. Similarly, the lattice reduction methodologies are limited with its performance. To improve such things, we proposed an Optimal Approximation message passing technique in Large-Scale MIMO Detection. This method operated with two constraints namely, noise variance and modulation noise variance. It is concentrated on minimizing the Symbol Error Rate (SER) by testing the proposed detection system with the traditional Quadrature Phase Shift Keying (QPSK) Modulation and Quadrature Amplitude Modulation (QAM). The proposed method is fully designed and tested with the MATLAB simulation tool. It is tested with *m*n* process with a transmitter (m) and receiver (n) antenna with various iterations. The performance evaluation were carried out with Signal to Noise Ratio (SNR)and SER attributes. From analysis, we concluded that the proposed method has the best optimal value when it is implemented with the Quadrature Phase Shift Keying (QPSK). Further, we observed that the complexity of detection unit is minimized.

Keywords: Multiple-Input Multiple-Output (MIMO), Markov chain Monte Carlo, Symbol Error Rate, Quadrature Phase Shift Keying.

I. Introduction

Due to the rapid development of wireless communication, multiple-input multiple output (MIMO) systems is essential for higher spectral efficiency is needed to meet the capacity requirements of modern wireless networks. The wireless communication systems with multiple antennas at both the transmitter and receiver are able to transmit several data streams and for efficient data rate. Modern MIMO are more moderately sized spatial-multiplexing with potential benefits of high throughput in scattering environments, small scale system capabilities appropriate for home use and small cells.

MIMO is an antenna technology for wireless communications in which multiple antennas are used at both at transmitter) and at the receiver. In conventional wireless communication SISO is used but it give rise to multipath propagation and increase in data speed. To overcome this limitations MIMO is widely used in digital communications. MIMO is an essential element of wireless communication standards, including IEEE 802.11 (Wi-Fi), WiMAx (4G), metropolitan area networks (MANs) and mobile communications. The MIMO detector generates soft information of the transmitted coded bits plays a key role to achieve near-capacity performance for the MIMO system.

Catreux et al., (2001) suggested that it is possible to increase the capacity by means of folding the antenna to de-correlation of the complex path gains. The array elements are activated with the respective array elements. In some cases, the adaptive modulation has the transmission parameters such as power, constellation size are adapted to exploit prevailing channel conditions, also yields significant increases in capacity.Some other traditional methods are mentioned without its external interference.

a) Background and Motivation

The MIMO technique is rarely utilized with the adaptive modulation rate to avoid some interference and improve the performance. It is framed with the metrics known as constraints and system design units to manage the process of channel conditions. The motivation behind this research work must follows the basic concepts. The large real time systems must increases the spectral efficiencies for wireless Systems, optimize data speed, it must have increased reliability, minimize errors, provide maximum power efficiency through the exploitation of large spatial dimensions. The designing unit support efficient spatial multiplexing and diversity gains.

b) Research objectives

In this research, we have framed a MIMO system with a Quadrature Phase Shift Keying (QPSK) Modulation and Quadrature Amplitude Modulation technique with the antenna iterations as 2 and 4. It is based on the antenna properties with respect to channel. It helps to maintain the properties of the channel matrix of a proposed system. The main objective is to develop a low complexity large scale MIMO. MIMO detection is analysed by testing it with the Markov chain Monte Carlo (MCMC) algorithm based block-wise sampling. Further, it is proposed with an efficient balanced trade-off between computational complexity and the performance in terms of Symbol Error Rate.

c) Markov Chain Monte Carlo (MCMC)

Markov Chains are Markov processes whose time-dependent random variables (the state of the Markov chain) can assume values in a discrete set (the state space), either finite or countable infinite. The Markov property is essentially a conditional independence of the future evolution on the past (the whole history of the process being summarized in the current state). Basically, the chain can be seen as modeling the position of an object in a discrete set of possible locations over time, the next location being chosen at random from a distribution that depends only on the current oneRandom sampling algorithm. The following advantages areachieved in case of modifying the detector module.

- Estimates model parameters and their uncertainty
- Only samples regions of high probability rather than uniform sampling
- Faster and more efficient.
- MCMC technique for signal detection on the uplink in large scale multiuser multiple input multiple output (MIMO) systems with tens to hundreds of antennas at the base station (BS) and similar number of uplink users
- Markov Chain Monte Carlo (MCMC) detectors is selected which provide the optimal solution.
- MCMC detector can be adapted to take channel estimation errors into account with only a moderate increase in computational complexity.
- Gibbs sampling is one of the MCMC method, which is used for sampling from distributions of multiple dimensions

d) Key problems in MIMO detection

MIMO- Bit-Interleaved Coded Modulation (BICM) system in which coded information sequence can be transmitted through multiple antennas. At the receiver, an iterative detection and decoding (IDD) receiver with maximum a posteriori probability (MAP) to provide a near optimal performance.Lattice Reduction (LR) are employed in MIMO-IDD systems using Markov chain Monte Carlo MCMC to provide near-optimal performances with a relatively low complexity.MCMC algorithm with Gibbs sampling is employed for efficient convergence rate in Markov chain.For the MIMO detection in IDD receivers, MAP approach can be employed to provide the optimal performance, but the complexity grows exponentially with the number of transmit antennas.If the SNR increases, then the transition probability from a state to another decreases exponentially which will result in a low convergence rate of the Markov chain. Then the Gibbs sampler gets stuck at a local minimum it may require a long time to move to another state.

The rest of this paper is organized as follows. Section II presents the detail survey on MIMO methods with various modulation schemes. Section III presents the MIMO detection models with the QAM and QPSK modulation schemes. Section IV presents the experimental comparison of previous and present MIMO modules with the Symbol Error Rate (SER). The complexity analysis is determined with the final conclusion at section V.

II. Literature survey

In this section, the background and the preliminaries of the current work are discussed. Starting with the description of conventional MIMO, the section moves on discussing the large-MIMO systems in depth, which is the focus of the current work. The fundamentals along with the propagation aspects of large-MIMO systems are elaborated. Subsequently, the system model for both independent and identically distributed channels and spatially correlated channels are presented. The conventional methods optimal and suboptimal are surveyed and the problems encountered with respect to the large-MIMO systems are analysed. Further the state-of-the-art techniques of large-MIMO systems are reviewed.

Hedstrom et al.,(2017) proposed MCMC-MIMO detector to resolve high SNR stalling problem. The evaluation of MCMC detector achieves a near maximum-a-posteriori (MAP) performance with highly-correlated channels at the maximum MIMO sizes and modulation rates. Its major limitations are slow convergence time leads to unpredictable fixed-length implementations problematic. Bai et al., (2016) presented an underdetermined MIMO model with the MCMC technique. In addition, the block wise sampling is also utilized to enhance the overall performance of the system. In some cases, the iterative detection and decoding methods are added with the MIMO standards.

Datta et al., (2013) proposed MIMO Detection Using Randomized MCMC and Randomized Search Algorithms. Randomized MCMC is proposed to alleviates the stalling problem and random selection algorithm is to select the candidate vectors to be tested in a local neighbourhood search to achieve near-optimal performance for large number of antennas with 4-QAM.The major drawbacks are identified as Markov chain that can occur with very low probability and less attractive for large scale MIMO. Senst and Ascheid (2010) developed a Markov Chain Monte Carlo MIMO Detection with Imperfect Channel State Information for imperfect channel knowledge systems. This system is adapted to performance gain over mismatched detection and to solve the channel estimation errors with only a moderate increase in computational complexity. The limitations noticed here is computation of the transition probabilities and complexity reduction when compared to other methods.

Liu et al., (2015) developed a near-optimal fast multiple-input multiple-output (MIMO) detector by hybrid approach as QRD-MCMC to reduce the detection delay and error probability performance. The performance results are evaluated in terms of average processing delay and the Bit Error Rate (BER) in which proposed method shows obtain efficient results.The major limitations of QRD-MCMC has high delay constraints that may cause performance degradation in terms of throughput or data rate.Chen et al., (2014)proposed a Stochastic MIMO Detector based MCMC algorithm for arithmetic operations are employed by simple logic structure. sliding window generator (SWG) are utilized increase the transition probability of the MCMC detector and a log-likelihood ratio based updating method (LUM), to reduces the hardware cost. The performance results achieves a throughput of 1.5 Gbps with only a 0.2 dB performance loss. The major limitations are identified with the SWG has more cost and power consumption is also high. It faces a polynomial complexity for multidimensional systems.

Wu et al., (2014) performed some ASIC implementations related with the MIMO techniques. It achieves in first and second ASIC as the maximum throughput of 73 Mbps and 170Mbps with the same SNR ratio as 20db. It is designed mainly for high throughput and low complexity. Srinidhi et al., (2011) carried the MIMO detection with two fold units. Initially, the layered low-complexity local neighbourhood search based algorithm is presented then a Maximum-Likelihood (ML) bit error performance is calculated. The major merits identified in the system is because of low complexity of the search algorithm. The bit error performance of the detection topologies are carried out with the local neighbourhood search. Goldberger and Leshem (2011) deployed a high order QAM constellations in MIMO systems. The Belief Propagation (BP) algorithm is considered as a traditional algorithm with poor results. Hence, optimal tree is considered as the unconstrained linear system. Hence, the performance and complexity are the two different parameters are to be considered in future implementations.

Gestner et al., (2011) considered a recent objective as symbol detection and identifying the complex interaction between the algorithm and hardware unit. It assumes the complex Lenstra-Lenstra-Lov´asz (CLLL) LR algorithm in terms of hardware module. It also merges the LR-aided MIMO symbol detection with the real-time wireless systems.Yang and Hanzo (2015) reviewed the fifty years of MIMO Detection. It identifies some problem and indicated some suggestions in tabulation. The medium and small MIMO units are replaced with the traditional concepts.

Yin et al., (2015) developed a VLSI architecture for the Conjugate Gradient (CG) based soft-output data-detection algorithm proposed by Yin et al., (2014). In particular, an architecture consisting of a reconfigurable array of Processing Elements (PEs) is to compute the CGLS algorithm, as well as the necessary post-equalization signal-to-interference-and-noise-ratio (SINR) information that is crucial for soft-output detection.

In the case of multiuser scenario, it is most likely that the channel tends to be correlated due to one or more of the reasons as reported in Payami and Tufvesson (2012). This results in the channel vectors to become correlated. This further worsens the situation when the correlation makes the channel matrix poor conditioned and in certain cases rank deficient. The impact of spatial correlation is of interest mainly due to the reason that, it complicates the detector algorithm, and degrades the bit error performance too. Spatial correlation leads to loss of orthogonality in the channels and sometimes even makes the channel rank deficient. On account of this, the order of detection diversity reduces leading to degraded BER performance. However, most of the works on detection available in the literature has to be noticed.

The lattice-reduction (LR) aided MIMO detection algorithms is build upon the idea of converting an ill-conditioned problem into an equivalent well-conditioned problem. This is done via a linear transformation T, which is a unimodular matrix. Once the problem is converted to a well-conditioned one, the conventionally available sub-optimal detectors can be employed. Hence, lattice reduction can be seen as a pre-processing method that is applied on the channel matrix before proceeding with the detection methods. Lattice reduction aided detection (LRAD) works with reduced near orthogonal basis with reduced orthogonality defect and can achieve full detection diversity in MIMO detection as well Windpassinger et al. (2006). The performance is found to improve in conjunction with the successive interference cancelation (SIC), and list based detection Choi and Nguyen (2009).

Senning et al., (2014) concentrated on a VLSI implementation of a complete MIMO channel equalization ASIC based on lattice reduction-aided linear detection is presented. The architecture performs preprocessing steps at channel rate and low-complexity linear data detection at symbol rate. Preprocessing is based on Seysen’s algorithm for lattice reduction. It discussed about the algorithmic improvements of the lattice reduction preprocessing in terms of area and throughput of the VLSI implementation with minor impact on the error-rate. Due to the low-complexity implementation of the lattice reduction-aided data detection stage, our architecture is able to achieve very low power in typical packet-based MIMO wireless data transmission scenarios. The final 90 nm CMOS ASIC achieves an energy efficiency for the detection of 24 pJ/bit at a throughput of 720 Mbps with near-optimal error-rate performance.However, enormous research has gone into this topic and plethora of methods are available in the literature. A good survey of lattice reduction techniques is available in Wubben et al. (2011) which provides a good insight on the lattice reduction aided detection.

Tang and Bian (2018) proposed a new low complexity lattice reduction algorithm, namely, the sorted integer Gauss transformation (SIGT). The SIGT algorithm can be interpreted as minimizing the longest basis vector first and assure that there was no integer projection between any two basis vectors. By applying simulation over Rayleigh fading channels, it was demonstrated that the proposed SIGT algorithm can have almost the same bit error rate (BER) performance as the LLL algorithm, while the SIGT algorithm requires only about half iteration as the Lenstra–Lenstra–Lovász lattice basis reduction (LLL) algorithm and the running time of each iteration for both algorithms were similar to each other. It is concluded that the SIGT algorithm can achieve almost the bit error rate (BER) performance, while the SIGT requires fewer iterations than the LLL.

Mussi et al., (2017) analysed the performance of efficient multiple-input-multiple-output (MIMO) detectors under correlated channels and imperfect coefficients channel estimation. A number of signal detection principles and techniques, including the minimum mean squared error detector with and without ordered successive interference cancellation; the sphere decoding MIMO detection, as well as promising near-orthogonal transformation techniques combined with these detectors, namely the lattice reduction and the QR decomposition are analysed under the perspective of complexity-performance tradeoff. While in most of available works perfect channel state information and uncorrelated channels have been considered, herein the complexity-performance tradeoff has been analysed and compared with the maximum likelihood (ML) limit under specific but practical scenarios of interest, namely: high spectral efficiency scenario; channel error estimates; channel/antenna correlation; combined channel errors and correlated channels. Under performance-complexity perspective, the optimum ML–MIMO detector is deployed as reference aiming to evaluate the efficiency and performance degradation of those sub-optimal MIMO detectors operating under hostile channel conditions.

From the literature, it is identified some major limitations like Lattice Reduction (LR) operation is not applicable for low-correlated channel condition with high convergence speed, LR method produce high computational complexity. If the antenna dimension is large and it may not applied in underdetermined MIMO systems. Hence, there is a need for some new technique that adapt all constraints and achieve good performance over other.

III. Proposed research methodology

To overcome the limitations of LR detection, the block wise is employed in large scale MIMO for MCMC system.Based on the MCMC algorithm, the large-scale MIMO system can be divided into several sub-systems and processed block by block.In MCMC algorithm, the detector is carried out by AMP is applied within the successive interference cancellation (SIC) detection to satisfy the sampling distribution of the Gibbs method in each block..It shows that thecomplexity analysis of large scale MIMO detector provide a balanced trade-off between computational complexity and performance in both large-scale and underdetermined MIMO systems.

Vila and Schniter (2013) presented the AMP utilization in Expectation-maximization Gaussian-mixture approximate message passing. Som and Schniter(2012) implemented the AMP in imaging. Hence, it is applied in complex algorithms to solve the complex problems. In this exposition, we want to emphasize the approximate message passing (AMP) has superior complexity when serving Massive MIMO uplink detection problems, although AMP was initially proposed for solving bit error rate.

a) Approximate message passing

The Massive MIMO architecture is to serve tens of users by employing hundreds of antennas,

$$y=Hx+w$$

where the channel $H\in C^{m\times n}$ has its elements sampled from $N_C(0,1/m)N_C(0,1/m)$, $m\gg n$, $y\in C^m$ is the received signal, AWGN noise components w_i are i.i.d with $N_C(0,\sigma^2)$; regarding the transmitted x, we only assume that it's zero mean and finite variance σ^2s.Before incorporating the AMP algorithm, we should be well aware of two facts: directly using maximum a priori (MAP) argmaxp(x|y)or MMSE estimation $E_{p(x|y)}(X)$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. 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.

So we use a proxy prior for detecting x, i.e., assuming that $xi\sim N_C(0,\sigma^2s)$, even though it may be inexact. In this occurrence, we have the signal power $\sigma^2s=2$ in QPSK, $\sigma^2s=10$ in 16QAM, etc. So the target function becomes.

$$\min \|\mathbf{y}-\mathbf{H}\mathbf{x}\|^2, s.t.\, x_i \sim \mathcal{N}_{\mathbb{C}}(0,\sigma_s^2) \quad (1)$$

$$\mathbf{r}^t = \mathbf{y} - \mathbf{H}\mathbf{x}^{t-1} + \frac{n}{m}\frac{\sigma_s^2}{\sigma_s^2+\alpha^{t-1}}\mathbf{r}^{t-1} \quad (2)$$

$$\alpha^t = \sigma^2 + \frac{n}{m}\frac{\alpha^{t-1}\sigma_s^2}{\sigma_s^2+\alpha^{t-1}} \quad (3)$$

$$\mathbf{x}^t = \frac{\sigma_s^2}{\sigma_s^2 + \alpha^t}(\mathbf{H}^* \mathbf{r}^t + \mathbf{x}^{t-1}) \quad (4)$$

where the initialization is to let $r^0=0$, $x^0=0$, $\alpha^0=\sigma^2 s$. In terms of complexity, it only costs 2mn×(#Iteration). Also, according to the equation (2) of the algorithm, it is converging extremely fast. On the contrary, MMSE has complexity $O(mn^2)$. It is noteworthy that known approximation methods to MMSE, such as Richardson's method or Newman series approximation, both fall behind the complexity-performance trade-off of AMP according to our simulations.

b) Algorithmic steps for detection

Step 1: Initialize the transmitter and receiver antennas

Step 2: Calculate the SNR ratio

Step 3: Calculate the signal variance in QPSK

Step 4: Declare the iterations of AMP

Step 5: Channel estimation using LS and MMSE estimators

Step 6: Write the values for AMP detector and perform the SNR comparison.

Step 7: Provide AMP iteration with the bit error representation.

Step 8: Repeat the process until the iteration gets completed.

c) Pseudo code for AMP detector in Large scale MIMO

```
Initialized m, n
    for s=SNRrange
            SNRdb=s;
for monte=1:1000
        Assign signal variance in QAM
        Signal variance in QPSK
Declare channel matrix
Noise variance in control by SNR in DB
Channel model
Iterations in AMP
  iterAMP1=2;
  load xes;
end
  count=count+1;
end
Plot the SER
```

In the case of the MIMO frequency selective channel (convolutive model), the system can be reduced to the model in tanks to the linear prediction method presented. Afterwards, AMP methods can be applied. The following assumptions are considered:

(1) H has full column rank M,

(2) The noise is additive white Gaussian independent from the source signals,

(3) The source signals are independent and identically distributed (i.i.d), mutually independent.

IV. Simulation Results

In this section, we present the simulation results with respect to the complexity and the Symbol error rate (BER) to illustrate the performances of the proposed method. For comparisons, the following detectors are considered.

- MIMO detector with QPSK
- MIMO detector with QAM

For the detection of underdetermined MIMO systems, the system is usually divided into a symmetric sub-system and an underdetermined or symmetric one. In general, an exhaustive search is often used to provide a near-optimal performance in the underdetermined sub-system. However, the computational complexity will become prohibitively high for a large number of transmit antennas. The approximate message passing is done with the help of 16 transmitter antennas and 4 receiver Antenna.

a) SER Performances of MIMO Systems

In this subsection, we show the SER performance improvement of the proposed block-wise detector compared with the conventional method with 16 × 4 MIMO-QPSK systems and MIMO-QAM systems.From Fig. 1 with ρ = 0, we can observe the similar phenomenon which can be explained as follows. In the*i* -th sub-system, the LR method can be used to find a closer $\hat{\mathbf{s}}i$ which results in $(\mathbf{r}_i - \mathbf{H}i\ \hat{\mathbf{s}}i) \approx 0$. Unfortunately, under low-correlated channel environment, this improved decoding performance could result in the stalling problem where the sampler is locked in a local minimum easily.

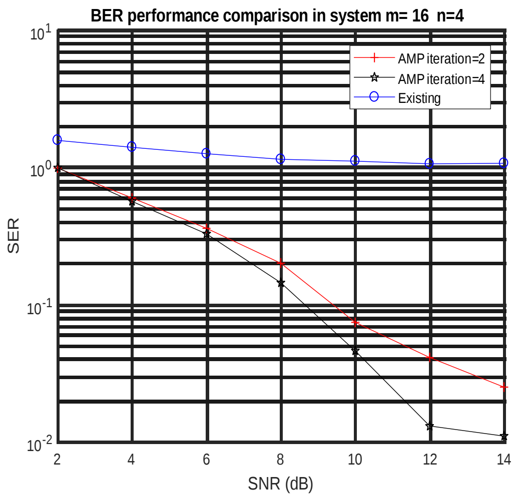

Figure1:BER performances of the 16 × 4 MIMO system with QPSK.

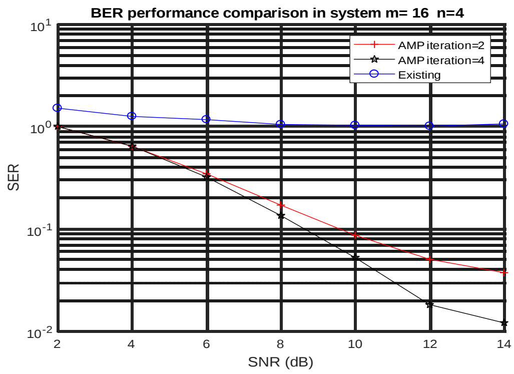

Figure 2: BER performances of the 16 × 4 MIMO system with QAM.

It is observed from figure 2 that the computational consuming can be reduced by the block-wise processing. Moreover, comparing the standard with MIMO module with QPSK and MIMO module with QAM methods, we can find that the complexity is reduced in reduced. It is significantly reduced by the block-wise sampling. Consequently, the proposed method can enjoy a trade-off between the performances.

V. Conclusion

In this research, a modulation wise sampling method using MCMC approach with QAM and QPSK was studied for the detection of large-scale (underdetermined) MIMO. Lower-complexity suboptimal algorithm is introduced. By using the Approximate Message Passing (AMP) algorithm, the MCMC detector can be carried out in a block-wise manner. Through complexity analysis and various simulation results, we verified that the proposed detector can provide a balanced trade-off between computational complexity and performance in both large-scale and underdetermined MIMO systems. In addition, it was illustrated that the 16*4iteration cannot improve the performance of the proposed approach in QAM channel since the AMP algorithm MCMC algorithm is employed.In future, all the issues in MIMO-QPSK/QAM systems including allocation of resources, channel estimation, modelling/ channel measurements, multi user detection and a host of others has to be discussed.

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