Monte-Carlo Based MGS-MR Detection

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Abstract

In this project we implemented and evaluated the algorithm proposed in paper "A Novel Monte-Carlo-Sampling-Based Receiver for Large-Scale Uplink Multiuser MIMO Systems" by Tanumay Datta et.al. We have implemented the algorithm proposed and compared our simulation results with the one claimed in paper. We were able to reproduce the results published in paper to a fair extent and therefore agree with authors claim of providing near ML performance with lower complexity than Sphere decoder in Large Scale Uplink MIMO.

Introduction

This paper proposes a low-complexity algorithms based on Markov Chain Monte Carlo(MCMC) sampling for signal detection on the uplink in large-scale multiuser multiple-input–multiple-output (MIMO) systems with tens to hun- dreds of antennas at the base station (BS) and a similar number of uplink users. A novel mixed sampling technique (which makes a probabilistic choice between Gibbs sam- pling and random uniform sampling in each coordinate update) for detection is proposed. The algorithm proposed for detection alleviates the stalling problem encountered at high signal-to-noise ratios (SNRs) in conventional Gibbs-sampling-based detection and achieves near-optimal performance in large systems with M -ary quadrature amplitude modulation (M -QAM). A novel ingredi- ent in the detection algorithm that is responsible for achieving near-optimal performance at low complexity is the joint use of a mixed Gibbs sampling (MGS) strategy coupled with a multiple restart (MR) strategy with an efficient restart criterion.

Background

Markov Chain Monte-Carlo(MCMC) techniques is a way to sample from a probability distribution. The probability distribution to be sampled is modeled as the stationary distribution of underlying Markov Chain. Gibbs Sampling is one way most popular way of implementing MCMC.

$$
\begin{aligned}
x_1^{(t+1)} &\sim p\left(x_1 \,\middle|\, x_2^{(t)}, x_3^{(t)}, \ldots, x_{2K}^{(t)}, \mathbf{y}, \mathbf{H}\right) \\
x_2^{(t+1)} &\sim p\left(x_2 \,\middle|\, x_1^{(t+1)}, x_3^{(t)}, \ldots, x_{2K}^{(t)}, \mathbf{y}, \mathbf{H}\right) \\
x_3^{(t+1)} &\sim p\left(x_3 \,\middle|\, x_1^{(t+1)}, x_2^{(t+1)}, x_4^{(t)}, \ldots, x_{2K}^{(t)}, \mathbf{y}, \mathbf{H}\right) \\
&\vdots \\
x_{2K}^{(t+1)} &\sim p\left(x_{2K} \,\middle|\, x_1^{(t+1)}, x_2^{(t+1)}, \ldots, x_{2K-1}^{(t+1)}, \mathbf{y}, \mathbf{H}\right).
\end{aligned}
$$

Figure 1: Gibbs Sampler Updates

Conventional Gibbs Sampling starts with random initial vector and element wise update is done. Updates are done by sampling the distribution as shown in Figure 1. Symbol vector is updated iteratively and it is guaranteed to converge but can take infinite many iterations. In practical scenarios we generally stop after a fixed number of iterations and hope that chain has mixed(converge). However, there can be cases where chain gets trapped in some low transition probability state and takes many iteration to come out. Such cases cause Stalling Problem which degrades Conventional Gibbs sampler performance at high SNR. Figure 2 below shows this problem.

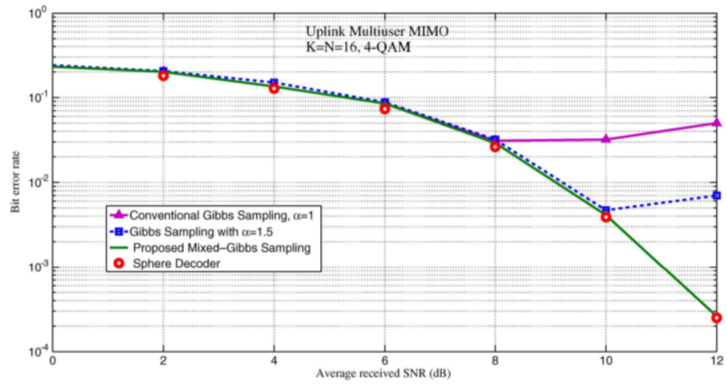


Figure 2: Stalling Problem

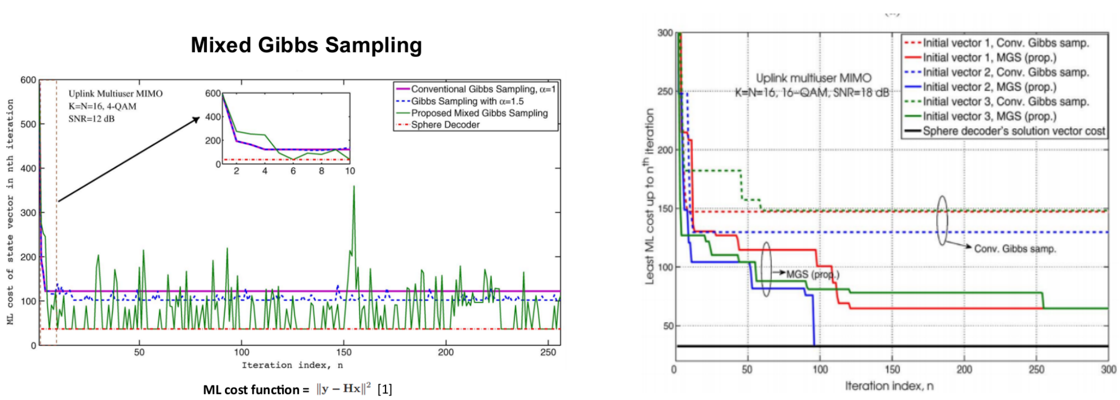
Algorithm

Mixed Gibbs Sampling

At each co-ordinate update, instead of updating x_i with probability 1 as done in conventional Gibbs sampling, update with probability $1-q$ and use different update rule with probability q. The mixed distribution is -

$$p(x_1, ..., x_{2K}|\mathbf{y}, \mathbf{H}) \propto (1-q)\psi(\alpha_1) + q\psi(\alpha_2)$$
$$\psi(\alpha) = exp(-||\mathbf{y} - \mathbf{Hx}||^2/\alpha^2\sigma^2)$$

α_1 and α_2 are chosen as 1 and ∞ respectively.



(a) MGS

(b) MGS-MR

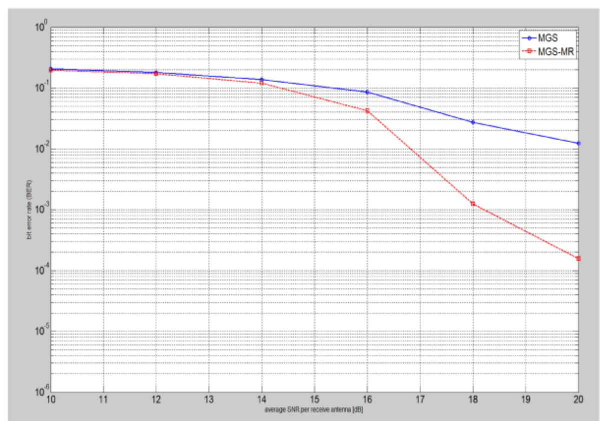
Figure 3

Figure 3a shows how Mixed Gibbs Sampling can reach ML cost in many intermediate iterations but conventional Gibbs Sampling remain stalled at some high loss state. Therefore MGS can achieve near

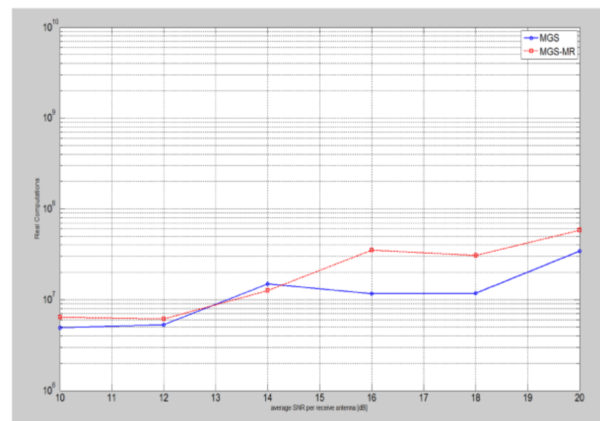
optimal performance.
But BER degrades as the QAM size increases and MGS is far from optimal performance for 16-QAM and 64-QAM. This happens because search space increases exponentially with constellation size and therefore probability to converge to right solution is low.

Mixed Gibbs Sampling-Multiple Restart

To get around the above mentioned problem, mutliple restarts are used. Multiple Restarts is equivalent to running multiple Gibbs Sampler parallely with different initial vector. Figure 3b shows that if we run multiple gibbs sampler with different initial vector the probability that one of them will converge is fairly high.
Figure 4 compares the performance of MGS and MGS-MR for 16-QAM. As can be seen that MGS-MR alleviates the problem faced by MGS for higher QAM.



(a) MGS vs MGS-MR for 16-QAM



(b) MGS-MR

Figure 4

Results

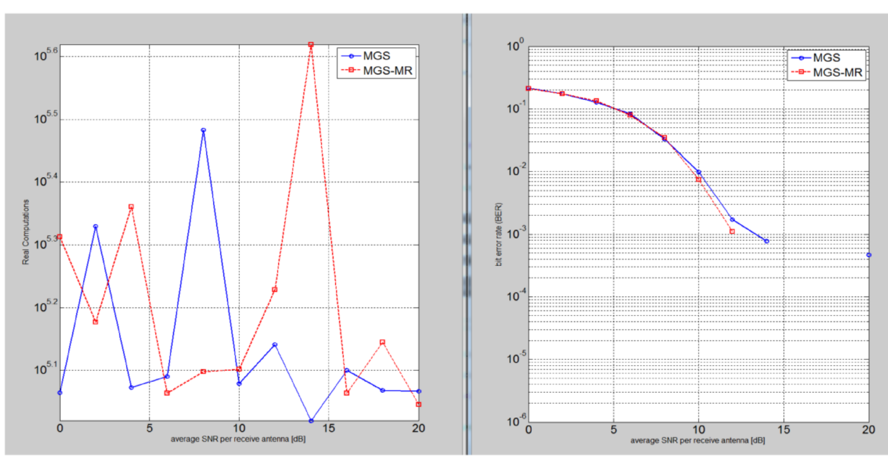


Figure 5: MT=8,MR=8 - QPSK

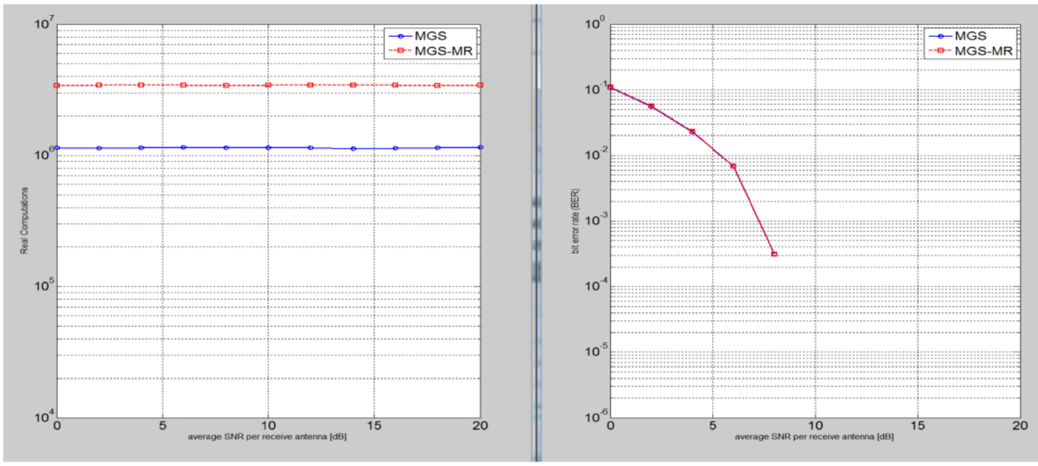


Figure 6: MT=8,MR=16 - QPSK

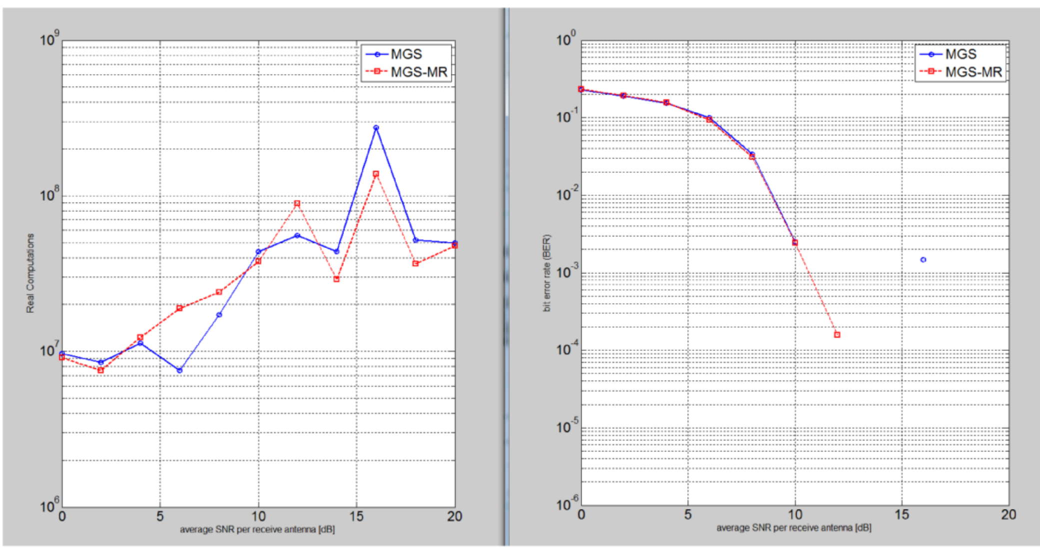


Figure 7: MT=32,MR=32 - QPSK

Conclusion

We implemented the algorithm proposed successfully and demonstrated its performance under various combination of Transmit and Recieve Antennae. We also estimated the complexity of the algorithm and it is seen that the complexity is of the order 10^7 We also studied the problem encountered by MGS algorithm for higher QAMs and implemented MGS-MR to see if it improves the performance as claimed by author.

References

[1] Tanumay Datta et al., A Novel Monte-Carlo-Sampling-Based Receiver for Large-Scale Uplink Multiuser MIMO Systems