MCMC Sampling based Signal Detection in Multiuser Load Modulated Arrays

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***Abstract*—Load modulated arrays (LMAs) is getting recent research attention as an attractive multiantenna transmission architecture in wireless communications. LMAs use a single power amplifier to drive the entire transmit antenna array and implement the multidimensional signaling constellation in the analog domain. In this paper, we consider LMAs in a multiuser setting on the uplink. In this setting, multiple user terminals, each using an LMA (e.g., with 2 or 4 antenna elements), communicate with a base station (BS) with multiple (tens to hundreds) receive antennas. For this system, we consider the problem of low-complexity signal detection at the BS receiver. Specifically, we propose a Markov Chain Monte Carlo (MCMC) sampling based detection algorithm. We evaluate the bit error rate performance of the algorithm via numerical simulations. Simulation results show that the proposed detection achieves very good performance while scaling well in complexity.**

***Index Terms*—Load modulation, multidimensional hypersphere, LM array, multiuser multiantenna systems, Markov chain Monte Carlo sampling.**

I. Introduction

Continued research and development efforts in multiple-input multiple-output (MIMO) systems will ensure that they are the norm in future wireless networks. The traditional approach in multiantenna transmission has been to typically employ a separate radio frequency (RF) chain for each antenna and use conventional modulation and precoding techniques like QAM and OFDM for transmission. This results in their cost, complexity, and size to increase with the number of antennas. In addition, owing to linearity requirements of the transmit signals, power amplifiers in each of the RF chains suffer from a poor power efficiency. Load modulated arrays (LMA) [1],[2] is emerging as a promising MIMO array architecture that alleviates the aforementioned issues.

Conventional MIMO transmitters employ *voltage modulation* for transmission, i.e., the input voltage to the power amplifier (PA) in each transmit RF chain is modulated according to the transmit signal in that chain. On the other hand, *load modulation* (LM) creates an antenna current by varying the antenna load impedance in accordance with the transmit information signal, while the PA input is maintained at a constant level [2]. In a load modulated MIMO transmitter, a single central power amplifier (CPA) drives the entire transmit antenna array [3]. The CPA is fed by a source with a fixed voltage level and frequency. Information bits directly modulate the antenna load impedances, which has the effect of implementing the signal set in the analog domain. This analog implementation of the signal set eliminates the need for DACs, mixers, and upconverters that constitute the transmit RF chains.

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In the next generation of wireless systems, where communication terminals are desired to be spectrally efficient, power efficient, compact, and cost effective, LMAs present an appealing transmission architecture. While there have been studies on the implementation and RF aspects of LMAs in [4],[5], problems of low-complexity detection and precoding in LMAs are yet to be investigated carefully. In view of this, in this paper, we consider LMAs in multiuser communications on the uplink and investigate LM signal detection at the BS receiver. The use of LMAs on the multiuser uplink has been recently shown to offer excellent bit error rate (BER) performance advantage compared to multiuser MIMO with conventional modulation and spatial modulation [6]. Here, we propose a low-complexity signal detection algorithm using Markov Chain Monte Carlo (MCMC) sampling technique for multiuser uplink systems that use LMAs at the user terminals. MCMC techniques have found application in many areas of science and engineering to efficiently solve problems that are governed by complicated probabilistic laws [7]. In digital communication applications, MCMC methods have been used to design receivers in CDMA and large MIMO systems [8],[9]. Our scheme uses MCMC sampling to perform randomized simulations of multiuser LMA systems in order to arrive at a solution. Numerical results show that the proposed scheme retains the performance advantage of multiuser LMAs, while requiring relatively less computations compared to the graph based detection in [6].

The rest of the paper is organized as follows. A brief introduction to LMAs is presented in Sec. II. LMAs on the multiuser uplink is presented in Sec. III, wherein we introduce the system model, present the proposed detection algorithm for large-scale multiuser LMA systems and numerical simulation results. Conclusions are presented in Sec. IV.

II. Load modulated arrays

Figure 1 shows an LM array with n_t transmit antennas. The load impedance in the lth antenna, denoted by $Z_l(t)$, is chosen to be proportional to the lth transmit signal $s_l(t)$, $l = 1, 2, \cdots, n_t$. The effective admittance seen by the power source is the sum of the admittances of all antenna loads, i.e.,

$$Y(t) = \sum_{l=1}^{n_t} \frac{1}{Z_l(t)}. \tag{1}$$

The single power source becomes equivalent to n_t parallel power sources, each with an average admittance $Y(t)/n_t$. Since $Y(t)$ varies with the information signals, there may be a mismatch between circuit impedance and effective antenna impedance, which can cause power to be reflected back to the

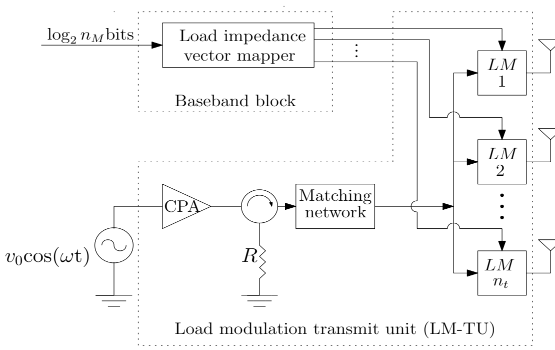

Fig. 1. Load modulated array.

CPA. So a circulator is used to redirect any reflected power to a resistor R.

For large arrays (large n_t), because of the law of large numbers, the average admittance $Y(t)/n_t$ does not vary much even if the individual admittances may vary significantly. This, in turn, results in only a small power being reflected back to the CPA in large arrays. Since a single CPA drives the entire antenna array, its efficiency is determined by the sum power of the transmit signal over all the antenna elements. A measure that characterizes this efficiency is the peak to average sum power ratio (PASPR), which is the peak to average power ratio (PAPR) aggregated over all the antenna elements [3]. With large arrays, operating the CPA at a power equal to the mean power of the transmit signals results in a PASPR that asymptotically tends to one. For small arrays (small n_t as in user terminals), however, the PASPR can be more than one. To obtain a PASPR close to one in small arrays, it is desired that the sum power radiated by the antennas be made constant. This is achieved by choosing the LM signal vectors on the surface of an n_t-dimensional hypersphere. Let $\mathbb{S}_{\text{LM},n_t}$ denote the n_M-ary LM signal set on the surface of an n_t-dimensional hypersphere, where $n_M \triangleq |\mathbb{S}_{\text{LM},n_t}|$. Let

$$\mathbb{S}_{\text{H}}(n_t, P) = \{\mathbf{s} \in \mathbb{C}^{n_t} \mid \|\mathbf{s}\|^2 = P\} \tag{2}$$

denote the n_t-dimensional complex-valued hypersphere of radius $\sqrt{P}$. Then,

$$\mathbb{S}_{\text{LM},n_t} = \{\mathbf{s}_1, \mathbf{s}_2, \cdots, \mathbf{s}_{n_M}\} \subset \mathbb{S}_{\text{H}}(n_t, P). \tag{3}$$

An $n_t \times 1$ signal vector $\mathbf{s}$ from $\mathbb{S}_{\text{LM},n_t}$ chosen based on $\log_2 n_M$ information bits gets transmitted in a channel use by the n_t load modulators.

LM signal detection: Assuming n_r antennas at the receiver, the received signal vector $\mathbf{y}$ can be written as

$$\mathbf{y} = \mathbf{H}\mathbf{s} + \mathbf{n}, \tag{4}$$

where $\mathbf{H}$ denotes the $n_r \times n_t$ matrix of channel gains such that the gain from the jth transmit antenna to the ith receive antenna $h_{ij} \sim \mathcal{CN}(0, 1)$ and $\mathbf{n}$ is the $n_r \times 1$ noise vector with $\mathbf{n} \sim \mathcal{CN}(0, \sigma^2\mathbf{I})$. The maximum likelihood (ML) detection rule is then given by

$$\hat{\mathbf{s}} = \underset{\mathbf{s}\in\mathbb{S}_{\text{LM},n_t}}{\text{argmin}} \|\mathbf{y} - \mathbf{H}\mathbf{s}\|^2. \tag{5}$$

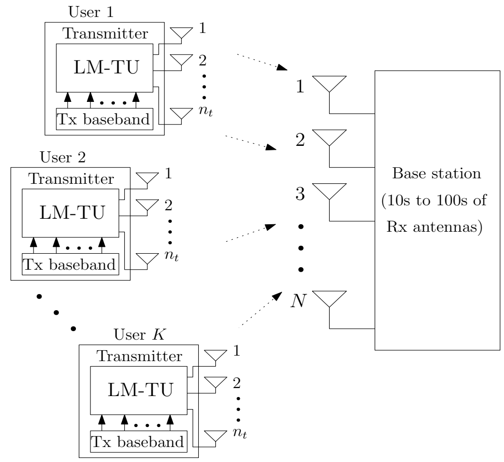

Fig. 2. Multiuser LMAs on the uplink.

III. LMAs on the multiuser uplink

In this section, we consider LMAs on the multiuser uplink and present a MCMC sampling based low-complexity algorithm for the detection of multiuser LM signals at the BS.

A. System model

Consider a multiuser system with K uplink users communicating with a BS having N receive antennas (Fig. 2). Users employ LM for their transmission. Each user has n_t transmit antennas and their associated load modulators. The transmit vector $\mathbf{s}_k \in \mathbb{S}_{\text{LM},n_t}$ for the kth user is chosen based on $\log_2 n_M$ bits. Let $\mathbf{s} \triangleq [\mathbf{s}_1^T \mathbf{s}_2^T \cdots \mathbf{s}_k^T \cdots \mathbf{s}_K^T]^T$ denote the vector comprising of transmit vectors from all the users, where $(\cdot)^T$ denotes transpose operation. Note that $\mathbf{s} \in \mathbb{S}_{\text{LM},n_t}^K$.

Let $\mathbf{H} \in \mathbb{C}^{N\times Kn_t}$ denote the channel gain matrix, where $\mathbf{H}_{i,(k-1)n_t+j}$ denotes the complex channel gain from the jth transmit antenna of the kth user to the ith BS receive antenna. The channel gains are assumed to be independent Gaussian with zero mean and variance σ_k^2, such that $\sum_{k=1}^{Kn_t} \sigma_k^2 = Kn_t$. σ_k^2 models the imbalance in the received power from the kth antenna, $k \in \{1, \cdots, Kn_t\}$, due to path loss etc., and $\sigma_k^2 = 1$ corresponds to the case of perfect power control. Assuming perfect synchronization, the received signal at the ith BS antenna is given by

$$y_i = \sum_{k=1}^{K} \mathbf{h}_{i,[k]}\mathbf{s}_k + n_i, \tag{6}$$

where $\mathbf{h}_{i,[k]}$ is a $1 \times n_t$ vector obtained from the ith row and $(k-1)n_t+1$ to kn_t columns of $\mathbf{H}$, and n_i is the noise modeled as a complex Gaussian random variable with zero mean and variance σ^2. The received signal at the BS antennas can be written in vector form as

$$\mathbf{y} = \mathbf{H}\mathbf{s} + \mathbf{n}, \tag{7}$$

where $\mathbf{y} = [y_1, y_2, \cdots, y_N]^T$ and $\mathbf{n} = [n_1, n_2, \cdots, n_N]^T$. For this system model, the ML detection rule is given by

$$\hat{\mathbf{s}} \;=\; \underset{\mathbf{s}\in\mathbb{S}_{\text{LM},n_t}^K}{\text{argmin}} \|\mathbf{y} - \mathbf{H}\mathbf{s}\|^2. \tag{8}$$

Since $|\mathbb{S}^K_{\text{LM},n_t}| = |\mathbb{S}_{\text{LM},n_t}|^K$, the exact computation of (8) requires exponential complexity in K. In the rest of this section, we refer to the n_t-sized vector $\mathbf{s}_k \in \mathbb{S}_{\text{LM},n_t}, k = 1, \cdots, K$, in a K-user vector $\mathbf{s} = [\mathbf{s}_1^T \mathbf{s}_2^T \cdots \mathbf{s}_k^T \cdots \mathbf{s}_K^T]^T \in \mathbb{S}^K_{\text{LM},n_t}$ as the kth *coordinate* of $\mathbf{s}$. The K-user signal set $\mathbb{S}^K_{\text{LM},n_t}$ is the coordinate space of which $\mathbf{s}_k$ is the kth coordinate. This interpretation would facilitate our discussion of detection schemes for multiuser LM signals.

B. Proposed MCMC sampling based detection

The ML detection problem in (8) can be solved by using MCMC simulations [7]. A conventional MCMC method is Gibbs sampling from the joint distribution of random variables of interest. In the context of detection of multiuser LM signals, the joint probability distribution of interest is

$$p(\mathbf{s}_1, \ldots, \mathbf{s}_K|\mathbf{y}, \mathbf{H}) \propto \exp\Big(-\frac{\|\mathbf{y}-\mathbf{H}\mathbf{s}\|^2}{\sigma^2}\Big). \tag{9}$$

1) Conventional Gibbs sampling: In conventional Gibbs sampling approach, the algorithm starts with an initial solution vector, which is denoted by $\mathbf{s}^{(t=0)}$. The initial vector can be a random vector or an output vector from one of low-complexity linear detectors such as zero-forcing (ZF) and minimum mean square error (MMSE) detectors. Let t denote the iteration index and k denote the coordinate index, $k = 1, 2, \cdots, K$. Each iteration consists of K coordinate updates. In each iteration, K updates are carried out by sampling from the distributions as follows:

$$\begin{aligned}
\mathbf{s}_1^{(t+1)} &\sim p\big(\mathbf{s}_1|\mathbf{s}_2^{(t)}, \mathbf{s}_3^{(t)}, \ldots \mathbf{s}_K^{(t)}, \mathbf{y}, \mathbf{H}\big)\\
\mathbf{s}_2^{(t+1)} &\sim p\big(\mathbf{s}_2|\mathbf{s}_1^{(t+1)}, \mathbf{s}_3^{(t)}, \ldots \mathbf{s}_K^{(t)}, \mathbf{y}, \mathbf{H}\big)\\
\mathbf{s}_3^{(t+1)} &\sim p\big(\mathbf{s}_3|\mathbf{s}_1^{(t+1)}, \mathbf{s}_2^{(t+1)}, \mathbf{s}_4^{(t)}, \ldots \mathbf{s}_K^{(t)}, \mathbf{y}, \mathbf{H}\big)\\
&\vdots\\
\mathbf{s}_K^{(t+1)} &\sim p\big(\mathbf{s}_K|\mathbf{s}_1^{(t+1)}, \mathbf{s}_2^{(t+1)}, \mathbf{s}_3^{(t+1)}, \ldots \mathbf{s}_{K-1}^{(t)}, \mathbf{y}, \mathbf{H}\big).
\end{aligned} \tag{10}$$

The updated vector at the end of each iteration is fed back to the next iteration. The algorithm is run for a certain number of iterations. The output vector is chosen to be that vector that has the least ML cost in all the iterations.

An issue with the conventional Gibbs sampling approach is the stalling problem, which results in degraded BER performance at high SNRs. It has been shown that because of the stalling problem, the BER can in fact increase for increasing SNRs [8],[9]. The is because the algorithm gets trapped in some poor local solutions for a long time (i.e., for many iterations).

2) Proposed sampling from mixed distribution: The stalling problem in conventional Gibbs sampling necessitates better sampling strategies that avoid local traps. Here, we explore sampling from a mixed distribution. That is, in each coordinate update, instead of updating the $\mathbf{s}_k^{(t)}$s as in the update rule in (10) with probability 1, we update them as in (10) with probability $1-q$ and use a different update rule with probability q. The different update rule is as follows. Generate n_M probability values from the uniform distribution as

$$p(\mathbf{s}_k^{(t)} = \mathbf{v}) \sim U[0, 1], \quad \forall \mathbf{v} \in \mathbb{S}_{\text{LM},n_t}, \tag{11}$$

Algorithm 1: MCMC sampling based detection algorithm

Input: $\mathbf{H}$, $\mathbf{y}$, $\mathbf{s}^{(0)}$, *max-iter*
Output: $\hat{\mathbf{s}}$
$t = 0$; $\hat{\mathbf{s}} = \mathbf{s}^{(0)}$;
$\kappa = g(\mathbf{s}^{(0)})$; $g(\cdot)$: ML cost function; $L_c(\cdot)$: Stalling limit count, $f(\alpha) = \exp\Big(-\frac{\|\mathbf{y}-\mathbf{H}\mathbf{s}\|^2}{\alpha^2\sigma^2}\Big)$
while $t <$ *max-iter* **do**
  for $k = 1$ *to* K **do**
    define r.v. $\Lambda \sim U[0, 1]$
    generate pmf $p\big(\mathbf{s}_k^{(t+1)} = \mathbf{v}\big) \sim \Pr(\Lambda > q) f(\alpha_1) + \Pr(\Lambda < q) f(\alpha_2)$, $\forall \mathbf{v} \in \mathbb{S}_{\text{LM},n_t}$
    sample $\mathbf{s}_k^{(t+1)}$ from this pmf
  end
  $\chi = g(\mathbf{s}^{(t+1)})$;
  if $(\chi \le \kappa)$ **then**
    $\hat{\mathbf{s}} = \mathbf{s}^{(t+1)}$; $\kappa = \chi$
  end
  $t = t + 1$;
  $\kappa_o^{(t)} = \kappa$;
  if $(\kappa_o^{(t)} == \kappa_o^{(t-1)})$ **then**
    calculate $L_c(\hat{\mathbf{s}})$;
    if $(L_c < t)$ **then**
      if $(\kappa_o^{(t)} == \kappa_o^{(t-L_c)})$ **then**
        goto step 28
      end
    end
  end
end
Output $\hat{\mathbf{s}}$

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such that $\sum_{\mathbf{v}\in\mathbb{S}_{\text{LM},n_t}} p(\mathbf{s}_k^{(t)} = \mathbf{v}) = 1$, and then sample $\mathbf{s}_k^{(t)}$ from this generated probability mass function. The general procedure for sampling from a mixed distribution is as follows:

- $\mathbf{s} \triangleq [\mathbf{s}_1^{(t+1)^T} \mathbf{s}_2^{(t+1)^T} \cdots \mathbf{s}_{k-1}^{(t+1)^T} \mathbf{v}^T \mathbf{s}_{k+1}^{(t+1)^T} \cdots \mathbf{s}_K^{(t+1)^T}]^T$; $\mathbf{v} \in \mathbb{S}_{\text{LM},n_t}$.
- $f(\alpha) \triangleq \exp\Big(-\frac{\|\mathbf{y}-\mathbf{H}\mathbf{s}\|^2}{\alpha^2\sigma^2}\Big)$.
- $p(\mathbf{s}_k^{(t+1)} = \mathbf{v}) \propto (1-q) f(\alpha_1) + q f(\alpha_2)$.

Different choices for the values of (α_1, α_2) are possible. For the specific update rule discussed above, $\alpha_1 = 1$ and $\alpha_2 = \infty$. With this, the mixed distribution for sampling becomes a weighted combination of the true distribution and uniform distribution with weights $1-q$ and q, respectively.

A listing of the proposed detection algorithm is given in **Algorithm 1**. The ML cost function $g(\cdot)$ which indicates the closeness of the estimated solution to the ML solution is given by

$$g(\hat{\mathbf{s}}) = \frac{\|\mathbf{y}-\mathbf{H}\hat{\mathbf{s}}\|^2 - N\sigma^2}{\sqrt{N}\sigma^2}. \tag{12}$$

The stalling limit count $L_f(\cdot)$ determines how long the algorithm is allowed to iterate without changing the ML cost, if stalling occurs. It depends on the quality of the stalled solution in terms of the ML cost in (12). If the stalled solution is far away from the ML solution ($g(\hat{\mathbf{s}})$ is large), the algorithm is allowed to continue looking for better solutions

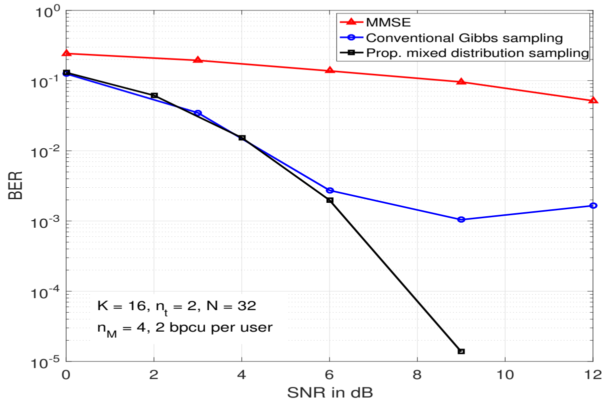

Fig. 3. BER performance of multiuser system with $K = 16$, $n_t = 2$, $N = 32$, $n_M = 4$ (2 bpcu per user) with i) MMSE detection, ii) conventional Gibbs sampling based detection, and iii) proposed detection using mixed distribution sampling.

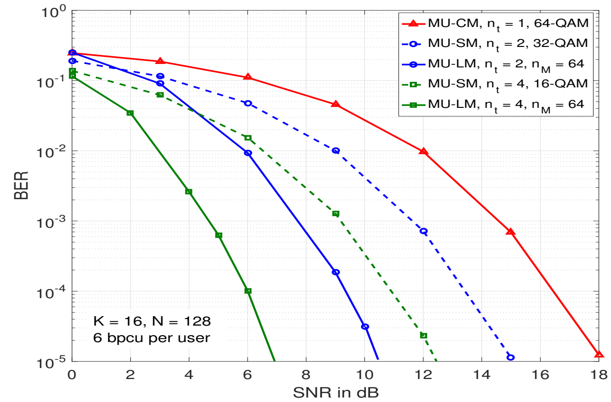

Fig. 5. Comparison between the BER performance of three different single-RF chain multiuser systems with $K = 16$, $N = 128$, 6 bpcu per user, proposed detection for MU-LM, MU-SM, and sphere decoding for MU-CM.

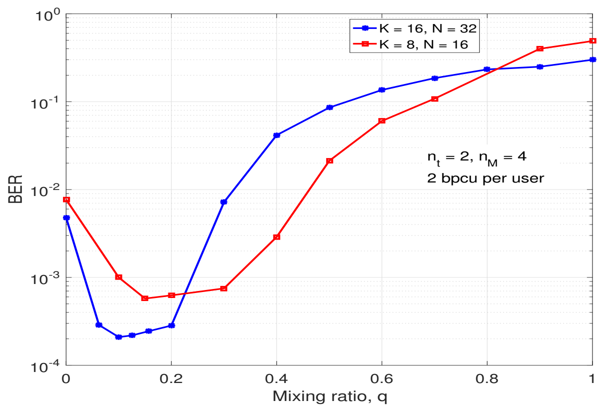

Fig. 4. BER performance of the proposed detection algorithm as a function of the mixing ratio q for $(K = 8, N = 16)$, $(K = 16, N = 32)$, $n_t = 2$, $n_M = 4$ (2 bpcu per user), and SNR = 7.5 dB.

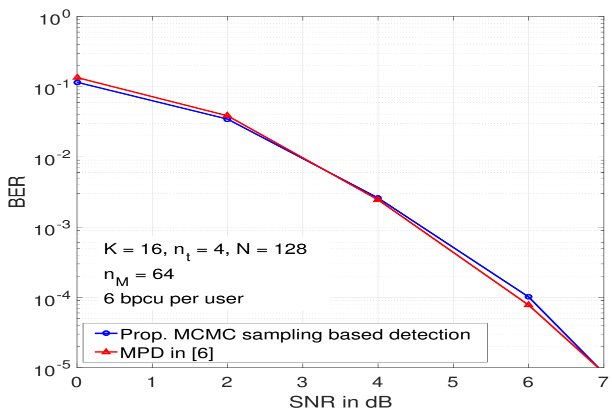

Fig. 6. Comparison between the BER performance of the proposed detection and MPD in [6] for a system with $K = 16, n_t = 4, N = 128$ and 6 bpcu per user.

for more iterations. However, if the stalled solution is close to the ML solution, the algorithm spends less time with the stalled ML cost [9]. Based on the above discussion, the following rule is adopted to compute the stalling limit count: $L_c(\hat{\mathbf{s}}) = \lceil \max(t_{\min}, k_1 e^{g(\hat{\mathbf{s}})}) \rceil$, with k_1 being chosen suitably proportional to n_M.

C. Performance results and discussions

In this subsection, we present the BER performance of the proposed detection algorithm and also present performance comparison between multiuser LM system and other single-RF chain multiuser systems using conventional modulation (CM) and spatial modulation (SM).

In Fig. 3, we show the performance of conventional Gibbs sampling detector and the proposed detector that uses mixed distribution for sampling. The system parameters considered are: $K = 16$, $n_t = 2$, $N = 32$, $n_M = 4$, random initial vector, mixing ratio $q = \frac{1}{K} = \frac{1}{16}$, and 256 iterations. MMSE detection performance is also shown for comparison. It can be seen that MMSE detection performance is rather poor. Also, we observe that the BER of conventional Gibbs sampling detector increases for SNRs more than 9 dB. This behavior is due to the stalling problem discussed before. The proposed detector is found to alleviate the stalling problem and achieve increasingly better BER for increasing SNRs. This shows the effectiveness of the sampling from the mixed distribution with a uniform distribution embedded in it.

In Fig. 4, we show the variation in the BER performance of the proposed detection algorithm as a function of the mixing ratio q. The following system parameters are considered: $(K = 8, N = 16)$, $(K = 16, N = 32)$, $n_t = 2$, $n_M = 4$ (2 bpcu per user), and SNR = 7.5 dB. Note that $q = 0$ corresponds to the case of conventional sampling from the true distribution and $q = 1$ corresponds to the case of sampling from a pure uniform distribution. For both these values of q, it is seen that the performance poor and the best performance is achieved at an optimum mixing ratio. The plots show that this optimum q is $\frac{1}{K}$, which is the inverse of the number of coordinates in the signal vector to be detected. Henceforth, we will use this optimum $q = \frac{1}{K}$ in our simulations.

In Fig. 5, we present a performance comparison between MU-LM, MU-CM, and MU-SM in large systems ($K = 16$, $N = 128$). All the systems are configured for 6 bpcu per user. The following systems are considered: MU-LM with

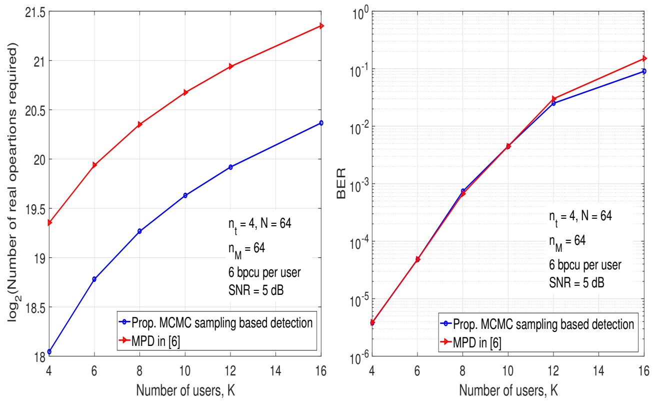

Fig. 7. Computational complexity and BER performance comparison of proposed detection and MPD in [6] for multiuser systems as a function of K, with $n_t = 4, N = 64$ and 6 bpcu per user.

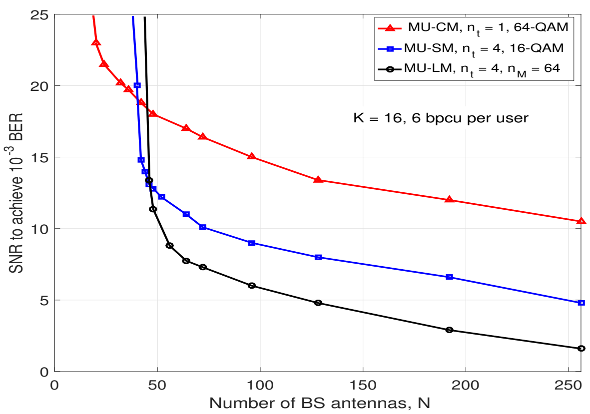

Fig. 8. Comparison of SNRs required by different multiuser systems with $K = 16$ with 6 bpcu per user to achieve 10^{-3} BER: i) MU-LM with ($n_t = 4$, $n_M = 64$), ii) MU-SM with ($n_t = 4$, 16-QAM), and iii) MU-CM with ($n_t = 1$, 64-QAM).

($n_t = 2$, $n_M = 64$) and ($n_t = 4$, $n_M = 64$), MU-SM with ($n_t = 2$, 32-QAM) and ($n_t = 4$, 16-QAM), and MU-CM with ($n_t = 1$, 64-QAM). For MU-CM, ML detection using sphere decoding is used. For MU-LM and MU-SM, the proposed detection algorithm is used. The parameters used in the proposed algorithm are: $t_{\min} = 20$, $k_1 = 10 \log_2 n_M$, max-iter = $16K$, $q = \frac{1}{K}$, and random initial vector. We observe that MU-LM achieves significantly better performance compared to MU-SM and MU-CM. For example, with $n_t = 4$, MU-LM performs better by about 5 dB and 10 dB compared to MU-SM and MU-CM, respectively. This superior performance achieved by MU-LM with low RF hardware complexity at the user terminals makes it attractive for large-scale multiuser MIMO systems.

In fig. 6, we compare the BER performance of the proposed detection algorithm obtained above with that of the message passing detection (MPD) in [6] for a system with $K = 16, n_t = 4, N = 128$ and 6 bpcu per user. It is seen that that the two perform the same. To justify the effectiveness of the proposed scheme, we compare the computational complexities of the two algorithms next.

Fig. 7(a) shows the computational complexity of the proposed scheme in terms of the number of real operations required for systems with $n_t = 4, N = 64$ and 6 bpcu per user. Also shown for comparison is the complexity of MPD algorithm. We see that the complexity of both the schemes grows quadratically in the number of users K. However, even with a lesser number of computations, it can be seen from Fig. 7(b) that the proposed scheme achieves the same BER performance as that achieved by MPD.

Finally, in Fig. 8, we present the effect of varying the number of BS antennas N on the BER performance of MU-LM, MU-SM, and MU-CM systems with $K = 16$ and 6 bpcu per user. The SNRs required in these systems to achieve a target BER of 10^{-3} are plotted as a function of N. The following systems are considered: i) MU-LM with ($n_t = 4, n_M = 64$), ii) MU-SM with ($n_t = 4$, 16-QAM), and iii) MU-CM with ($n_t = 1$, 64-QAM). It can be observed that as the number of antennas at the BS increases, the required SNR to achieve the target BER decreases because of the increased receive diversity. The degradation observed for small values of N is because the systems become under-determined when $Kn_t > N$, and hence the required SNRs shoot up. For $Kn_t \leq N$, MU-LM outperforms MU-SM by 3 to 4 dB and MU-CM by about 9 dB.

IV. Conclusions

We studied LMAs (an emerging and promising multiantenna transmitter architecture offering reduced RF complexity, size, and cost) in multiuser communication on the uplink. For this system, we presented a Monte Carlo sampling based detection algorithm at the BS receiver. The proposed algorithm scaled well in complexity as well as achieved good BER performance. Our results indicate that LMAs hold lot of promise and present interesting research and development possibilities that can lead to the adoption of LMAs in future wireless systems. LMAs on multiuser downlink and design of efficient channel estimation schemes can be investigated as future work.

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