Message Passing Receivers for Large-scale Multiuser Media-based Modulation

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***Abstract*—In this paper, we consider the problem of low-complexity detection and channel estimation in multiuser media-based modulation (MBM). MBM is an attractive modulation scheme which can achieve high data rates using multiple radio frequency (RF) mirrors (parasitic elements) and fewer transmit antennas/RF chains. A large-scale multiuser system with tens of users and a base station with tens to hundreds of receive antennas is considered. Each user employs MBM for transmission using one transmit antenna surrounded by multiple RF mirrors. We propose message passing based detection algorithms which provide very good bit error performance at low computational complexities. For the proposed message passing detection, we present a low-complexity channel estimation scheme exploiting the 'channel hardening' phenomenon that occurs in large MIMO channels. We compare the performance of the proposed receiver algorithms with that of the minimum mean square error based receiver and compressive sensing based reconstruction algorithms, and show that the proposed algorithms are not only computationally less complex but also provide better performance in large-scale multiuser MBM systems.**

Keywords *– Media-based modulation, RF mirrors, multiuser MIMO, message passing receiver, channel hardening.*

I. Introduction

Recently, media-based modulation (MBM) is attracting research attention for high data rate wireless communications in rich scattering multipath fading environments [1]-[5]. A key advantage in MBM over conventional modulation schemes arises from the usage of multiple RF mirrors and fewer transmit antenna elements/RF chains to achieve high spectral efficiency. The RF mirrors are digitally controlled parasitic elements (e.g., varactors, switched capacitors) which do not require complex RF hardware like mixers, filters, etc. These RF mirrors controlled by information bits create different channel fade realizations, which are used as the channel modulation alphabet.

The concept of MBM can be briefly explained as follows. The RF mirrors placed around a transmit antenna act as RF signal scatterers, thereby modifying the propagation environment and the channel gains from the transmitter to the receiver. Each RF mirror can be switched ON (reflects incident RF signal) or OFF (transparent to incident RF signal) digitally. The ON/OFF status of the mirrors is called the 'mirror activation pattern' (MAP). If there are m_{rf} mirrors around a transmit antenna, then $2^{m_{rf}}$ MAPs are possible. Each of these MAPs corresponds to a unique channel geometry. In a rich scattering environment, even a small perturbation in the channel geometry results in an independent fading channel. Thus, each MAP creates a corresponding independent fade realization. The transmitter can select one of the $2^{m_{rf}}$ MAPs using m_{rf} input information bits. The antenna element transmits a symbol from a conventional modulation alphabet (e.g., QAM) denoted by $\mathbb{A}$. The spectral efficiency of MBM, therefore, is $\eta_{\text{MBM}} = m_{rf} + \log_2 |\mathbb{A}|$ bits per channel use (bpcu). The spectral efficiency increases by 1 bit with the addition of every single RF mirror. Thus, the MBM scheme not only assures a channel with rich scattering and independent fade states, but also provides high spectral efficiency. A practical implementation of the MBM scheme with 14 RF mirrors and a dipole transmit antenna is reported in [3]. A scheme similar to MBM was reported earlier as 'aerial modulation' in [7].

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It has been shown in [2] that MBM with n_r receive antennas can asymptotically (as $m_{rf} \to \infty$) achieve the capacity of n_r parallel AWGN channels. This encourages the use of MBM scheme in a large-scale multiuser wireless communication setup. One of the main bottlenecks in such a setup is devising practical receiver algorithms to detect large-dimensional MBM signals. In this paper, we propose to overcome this challenge by developing low-complexity detection algorithms, namely, belief propagation based MBM signal detector (BP-MSD) and channel hardening exploiting message passing based MBM signal detector (CHEMP-MSD). BP-MSD models the multiuser MBM system as a bipartite graph and performs message passing over it to detect the MBM signals. CHEMP-MSD exploits the 'channel hardening' phenomenon that occurs in large MIMO channels to detect the MBM signals. In large-dimensional systems, the channel matrices are well conditioned – this is referred to as the channel hardening phenomenon [8]. Further, CHEMP technique facilitates the use of a simple and low-complexity technique for channel estimation. Our results show that the proposed algorithms are not only computationally less complex but also provide better performance compared to other receivers based on minimum mean square error (MMSE) and compressive sensing (CS) based reconstruction algorithms.

II. Multiuser MBM system model

Consider a large-scale multiuser system with K users, each having a single transmit antenna and m_{rf} RF mirrors surrounding the antenna, and a base station (BS) with n_r receive antennas (Fig. 1). Here, K is in the order of tens and n_r is in the order of tens to hundreds. The users employ MBM for transmission. In a given channel use, each user selects one of the $2^{m_{rf}}$ possible MAPs. The choice of this MAP is made using m_{rf} information bits. The MBM channel alphabet is defined as the set of all channel gain vectors corresponding to all the MAPs. Let $\mathbf{h}_k^m$ denote the $n_r \times 1$ channel gain vector that is observed at the BS when the mth MAP of the kth user is activated, where $\mathbf{h}_k^m = [h_{1,k}^m \ h_{2,k}^m \ \cdots \ h_{n_r,k}^m]^T$, $h_{i,k}^m$ is the channel gain corresponding to the mth MAP of the kth user and the ith receive antenna, $i = 1, \cdots, n_r$, $k = 1, \cdots, K$, $m = 1, \cdots, N_m$, and $N_m \triangleq 2^{m_{rf}}$. The channel gains $h_{i,k}^m$s are assumed to be i.i.d Gaussian with mean zero and unit variance. The MBM channel alphabet for the kth user, denoted by $\mathbb{H}_k$, is now defined as the collection of the channel gain vectors, i.e., $\mathbb{H}_k = \{\mathbf{h}_k^1, \mathbf{h}_k^2, \cdots, \mathbf{h}_k^{N_m}\}$. Therefore, in multiuser MBM, information bits are conveyed to the BS by each user through two entities: $i)$ the choice of the MAP from the channel alphabet, and $ii)$ the symbol transmitted from a conventional modulation alphabet $\mathbb{A}$ (e.g., QAM, PSK). Thus, the spectral efficiency of a K-user MBM system is given by

$$\eta = \sum_{k=1}^{K} (\log_2 |\mathbb{H}_k| + \log_2 |\mathbb{A}|) = K(m_{rf} + \log_2 |\mathbb{A}|) \ \text{ bpcu}. \tag{1}$$

Note that the per-user spectral efficiency increases linearly with the number of RF mirrors. For example, a multiuser MBM system with $K = 5$, $m_{rf} = 2$, and 4-QAM has a throughput of 20 bpcu (4 bpcu per user).

The MBM signal set, denoted by $\mathbb{S}$, is the set of all $N_m \times 1$-sized MBM signal vectors, which is given by

$$\mathbb{S} = \Big\{ \mathbf{s}_{m,q} \in \mathbb{A}_0^{N_m} : m = 1, \cdots, N_m, \ q = 1, \cdots, |\mathbb{A}| \Big\}$$
$$\text{s.t } \mathbf{s}_{m,q} = [0 \cdots 0 \underbrace{s_q}_{m\text{th coordinate}} 0 \cdots 0]^T, s_q \in \mathbb{A}, \tag{2}$$

where k is the index of the MAP and $\mathbb{A}_0 \triangleq \mathbb{A} \cup 0$. The size of the MBM signal set is $|\mathbb{S}| = N_m |\mathbb{A}|$. For example, if $m_{rf} = 2$ and $|\mathbb{A}| = 2$ (BPSK), then the MBM signal set is given by

$$\mathbb{S} = \left\{ \begin{bmatrix}1\\0\\0\\0\end{bmatrix}, \begin{bmatrix}-1\\0\\0\\0\end{bmatrix}, \begin{bmatrix}0\\1\\0\\0\end{bmatrix}, \begin{bmatrix}0\\-1\\0\\0\end{bmatrix}, \begin{bmatrix}0\\0\\1\\0\end{bmatrix}, \begin{bmatrix}0\\0\\-1\\0\end{bmatrix}, \begin{bmatrix}0\\0\\0\\1\end{bmatrix}, \begin{bmatrix}0\\0\\0\\-1\end{bmatrix} \right\}. \tag{3}$$

An MBM signal vector from $\mathbb{S}$ is transmitted by each of the K users. Let $\mathbf{x}_k \in \mathbb{S}$ denote the MBM vector of size $N_m \times 1$ transmitted by the kth user. Now, the received signal vector at the BS can be represented as

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

where $\mathbf{n}$ is the noise vector of size $n_r \times 1$ with $\mathbf{n} \sim \mathcal{CN}(0, \sigma^2 \mathbf{I}_{n_r})$, $\mathbf{x}$ is the multiuser transmit vector of size $KN_m \times 1$ given by $\mathbf{x} = \begin{bmatrix}\mathbf{x}_1^T & \mathbf{x}_2^T & \cdots & \mathbf{x}_K^T\end{bmatrix}^T$,

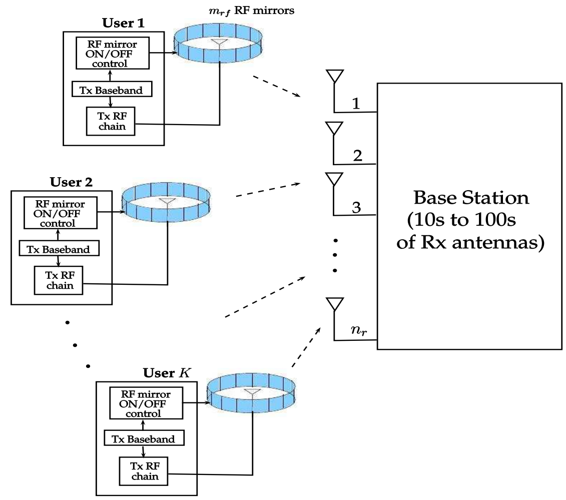

Fig. 1. Large-scale multiuser MBM system.

and $\mathbf{H} \in \mathbb{C}^{n_r \times KN_m}$ denote the multiuser channel gain matrix given by $\mathbf{H} = [\mathbf{H}_1 \ \mathbf{H}_2 \ \cdots \ \mathbf{H}_K]$, where $\mathbf{H}_k = [\mathbf{h}_k^1 \ \mathbf{h}_k^2 \ \cdots \ \mathbf{h}_k^{N_m}] \in \mathbb{C}^{n_r \times N_m}$, and $\mathbf{h}_k^m$ is the channel gain vector of the kth user corresponding to the mth MAP as defined before. The received signal-to-noise ratio (SNR) is given by $E_s K/\sigma^2$, where E_s is the average symbol energy and σ^2 is the variance of the additive noise. The maximum likelihood (ML) detection rule for this system is given by

$$\widehat{\mathbf{x}} = \underset{\mathbf{x} \in \mathbb{S}}{\text{argmin}} \ ||\mathbf{y} - \mathbf{H}\mathbf{x}||^2. \tag{5}$$

It has to be noted that the complexity of ML detection is exponential in m_{rf} and K. This complexity is prohibitively high for large-scale systems. Hence, low complexity receiver algorithms are required for detection of large-dimensional signals. In the following sections, we propose low complexity message passing based receiver algorithms for large-scale multiuser MBM systems.

III. Large-scale multiuser MBM signal detection

In this section, we propose two message passing based detection algorithms. Here we assume perfect channel state information (CSI) at the BS; we shall relax this assumption in the next section. First, we model the system as a bipartite graph and develop a detection algorithm using belief propagation (BP) over the bipartite graph. Second, we exploit the channel hardening phenomenon that occurs in large MIMO channels to develop a detection algorithm for multiuser MBM signals. The detection algorithms are described below.

A. BP based MBM signal detector (BP-MSD)

The multiuser MBM system model described in (4) can be represented using a bipartite graph. This graphical model used for the detection of MBM signals is illustrated in Fig. 2. The bipartite graph consists of K variable nodes, each corresponding to a user's transmit vector $\mathbf{x}_j$, and n_r observation nodes, each corresponding to a received signal value y_i. We develop a BP based detection algorithm that estimates $\mathbf{x}$ given the observation

$\mathbf{y}$ and the channel matrix $\mathbf{H}$. Here, we assume that the BS has perfect knowledge of $\mathbf{H}$. From (4), the received signal y_i can be written as

$$y_i = \mathbf{h}_{i,[j]}\mathbf{x}_j + \underbrace{\sum_{l=1,l\neq j}^{K} \mathbf{h}_{i,[l]}\mathbf{x}_l + n_i}_{\triangleq\, q_{i,j}}, \tag{6}$$

where $\mathbf{h}_{i,[l]}$ is a row vector of length N_m, given by $\left[H_{i,(l-1)N_m+1} \;\; H_{i,(l-1)N_m+2} \;\; \cdots \;\; H_{i,lN_m}\right]$, and $H_{i,j}$ is the (i,j)th entry of the matrix $\mathbf{H}$. In large-scale multiuser MBM systems, the value of KN_m is large. Hence, we employ Gaussian approximation of interference. That is, we approximate the interference term $q_{i,j}$ to be Gaussian with mean $\mu_{i,j}$ and variance $\sigma^2_{i,j}$, where

$$\mu_{i,j} = \mathbb{E}\Big[\sum_{l=1,l\neq j}^{K} \mathbf{h}_{i,[l]}\mathbf{x}_l + n_i\Big] = \sum_{l=1,l\neq j}^{K}\sum_{\mathbf{s}\in\mathbb{S}} p_{li}(\mathbf{s})\mathbf{h}_{i,[l]}\mathbf{s}, \tag{7}$$

$$\begin{aligned}\sigma^2_{i,j} &= \mathrm{Var}\Big(\sum_{\substack{l=1,\\ l\neq j}}^{K} \mathbf{h}_{i,[l]}\mathbf{x}_l + n_i\Big)\\ &= \sum_{\substack{l=1,\\ l\neq j}}^{K}\Big(\sum_{\mathbf{s}\in\mathbb{S}} p_{li}(\mathbf{s})\mathbf{h}_{i,[l]}\mathbf{s}\mathbf{s}^H\mathbf{h}^H_{i,[l]} - \big|\sum_{\mathbf{s}\in\mathbb{S}} p_{li}(\mathbf{s})\mathbf{h}_{i,[l]}\mathbf{s}\big|^2\Big) + \sigma^2; \end{aligned} \tag{8}$$

where $p_{ji}(\mathbf{s})$ is the message passed by the jth variable node to the ith observation node. Further, $p_{ji}(\mathbf{s})$ also denotes the a posteriori probability (APP) or 'belief' $p(\mathbf{x}_j = \mathbf{s}|\mathbf{y}_{\setminus i})$, where $\mathbf{y}_{\setminus i}$ denotes the vector of all elements in $\mathbf{y}$ except y_i. The message $p_{ji}(\mathbf{s})$ can be evaluated as

$$p_{ji}(\mathbf{s}) \propto \prod_{m=1,\; m\neq i}^{n_r} \exp\Big(\frac{-\big|y_m - \mu_{m,j} - \mathbf{h}_{m,[j]}\mathbf{s}\big|^2}{\sigma^2_{m,j}}\Big). \tag{9}$$

The belief propagation schedule is given below.

1) Initialize $p_{ji}(\mathbf{s}) = \frac{1}{|\mathbb{S}|}$, $\forall j, i, \mathbf{s}$.
2) Compute μ_{ij} and $\sigma^2_{i,j}$, $\forall i, j$.
3) Compute p_{ji}, $\forall j, i$.

We perform damping of the belief values evaluated through (9) with a damping factor $\beta \in (0, 1]$ to improve the convergence [11]. Steps 2 and 3 are repeated for a fixed number of iterations. At the end of these iterations, the probabilities $p(\mathbf{x}_j = \mathbf{s})$, $j = 1, 2, \cdots, K$, are computed as

$$p_j(\mathbf{s}) \propto \prod_{i=1}^{n_r} \exp\Big(\frac{-\big|y_i - \mu_{i,j} - \mathbf{h}_{i,[j]}\mathbf{s}\big|^2}{\sigma^2_{i,j}}\Big), \tag{10}$$

Finally, the estimates $\widehat{\mathbf{x}}_j$s are obtained by choosing the MBM signal vector $\mathbf{s} \in \mathbb{S}$ that has the largest APP. That is,

$$\widehat{\mathbf{x}}_j = \underset{\mathbf{s}\in\mathbb{S}}{\mathrm{argmax}}\; p_j(\mathbf{s}). \tag{11}$$

The $\widehat{\mathbf{x}}_j$s obtained are demapped to get the MAP, which are then demapped to obtain the bits corresponding to the MAP of each user. The non-zero entry in $\widehat{\mathbf{x}}_j$ is demapped to get the conventional modulation symbol bits transmitted by each of the K users.

B. Channel hardening exploiting message passing for MBM signal detection (CHEMP-MSD)

In this subsection, we present another message passing detector. The difference of this detector compared to the detector in the previous subsection is that it exploits the channel hardening phenomenon that occurs in large

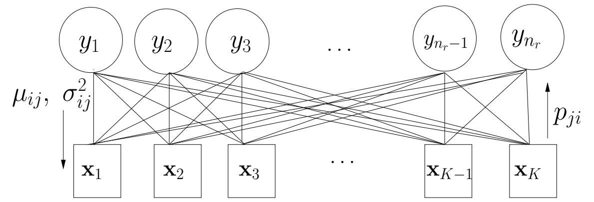

Fig. 2. Graphical model for BP-MSD.

MIMO channels. In an $m \times n$ channel matrix, when m and n are increased keeping their ratios fixed, the distribution of the singular values of the matrix becomes less sensitive to the actual distribution of the entries of the matrix (as long as the entries are i.i.d.) [8,12,13]. This is called the channel hardening phenomenon. Because of the channel hardening effect, very tall or very wide channel matrices become very well conditioned. As a consequence, the off-diagonal terms of the $\mathbf{H}^H\mathbf{H}$ matrix become increasingly weaker compared to the diagonal terms as the size of the channel matrix $\mathbf{H}$ increases. This effect is exploited here for efficiently recovering the large-scale multiuser MBM signals.

In order to exploit the channel hardening effect, the detection algorithm works on the matched filtered received signal vector, which can be obtained as

$$\mathbf{H}^H\mathbf{y} = \mathbf{H}^H(\mathbf{H}\mathbf{x} + \mathbf{n}). \tag{12}$$

In the above equation, since the matrix $\mathbf{H}^H$ is a large matrix with i.i.d. complex Gaussian entries, it exhibits channel hardening phenomenon, and hence the matrix $\mathbf{H}^H\mathbf{H}$ has strong diagonal components. After scaling by n_r, the system model in (12) can be written as

$$\mathbf{z} = \mathbf{G}\mathbf{x} + \mathbf{w}, \tag{13}$$

$$\mathbf{z} \triangleq \frac{\mathbf{H}^H\mathbf{y}}{n_r}, \quad \mathbf{G} \triangleq \frac{\mathbf{H}^H\mathbf{H}}{n_r}, \quad \mathbf{w} \triangleq \frac{\mathbf{H}^H\mathbf{n}}{n_r}. \tag{14}$$

As in (4), $\mathbf{z}$ in (13) can be expressed as a concatenation of K vectors, each of length N_m, i.e., $\mathbf{z} = [\mathbf{z}_1^T\mathbf{z}_2^T \cdots \mathbf{z}_i^T \cdots \mathbf{z}_K^T]^T$. Similarly, $\mathbf{w} = [\mathbf{w}_1^T\mathbf{w}_2^T \cdots \mathbf{w}_i^T \cdots \mathbf{w}_K^T]^T$, where $w_j = \sum_{l=1}^{n_r} \frac{H^*_{lj} n_l}{n_r}$ is the jth element of $\mathbf{w}$ and H_{ji} is the (j,i)th element of $\mathbf{H}$. For large values of n_r (tens to hundreds), w_j can be approximated to be Gaussian with zero mean and variance $\sigma^2_w \triangleq \frac{\sigma^2}{n_r}$. We employ Gaussian approximation of interference in the generation of the messages in the message passing algorithm. From (13), $\mathbf{z}_i$ can be expressed as

$$\mathbf{z}_i = \mathbf{G}_{ii}\mathbf{x}_i + \underbrace{\sum_{j=1,j\neq i}^{K} \mathbf{G}_{ij}\mathbf{x}_j + \mathbf{w}_i}_{\triangleq\, \mathbf{g}_i}, \tag{15}$$

where $\mathbf{G}_{ij}$ is a $N_m \times N_m$ sub-matrix of $\mathbf{G}$ formed by taking the elements in rows $(i-1)N_m + 1$ to iN_m and columns $(j-1)N_m + 1$ to jN_m. The matrix $\mathbf{G}$ can thus be written in terms of the sub-matrices as

$$\mathbf{G} = \begin{bmatrix} \mathbf{G}_{11} & \mathbf{G}_{12} & \cdots & \mathbf{G}_{1K} \\ \mathbf{G}_{21} & \mathbf{G}_{22} & \cdots & \mathbf{G}_{2K} \\ \vdots & & \ddots & \vdots \\ \mathbf{G}_{K1} & \mathbf{G}_{K2} & \cdots & \mathbf{G}_{KK} \end{bmatrix}.$$

The interference-plus-noise term $\mathbf{g}_i$, for the ith user, is formed by the off-diagonal elements of $\frac{\mathbf{H}^H\mathbf{H}}{n_r}$ (i.e., G_{ij}, $i \neq j$). Due to the channel hardening effect, the matrix $\mathbf{G}$ has strong diagonal elements compared to the off-diagonal elements for large n_r and K. We approximate $\mathbf{g}_i$ to be a multivariate Gaussian random vector with mean $\boldsymbol{\mu}_i$ and variance $\boldsymbol{\Sigma}_i$, which can be obtained as

$$\boldsymbol{\mu}_i = \mathbb{E}(\mathbf{g}_i) = \sum_{j=1,j\neq i}^{K} \mathbf{G}_{ij}\mathbb{E}(\mathbf{x}_j), \tag{16}$$

$$\boldsymbol{\Sigma}_i = \text{Var}(\mathbf{g}_i) = \sum_{j=1,j\neq i}^{K} \mathbf{G}_{ij}\text{Var}(\mathbf{x}_j)\mathbf{G}_{ij}^H + \sigma_w^2\mathbf{I}_{N_m} \tag{17}$$

Let $\mathbf{p}_i$ denote the $|\mathbb{A}|N_m \times 1$ vector of probability values corresponding to the MBM signal vector $\mathbf{x}_i$. The entries of $\mathbf{p}_i$ are given by

$$p_i(\mathbf{s}) = \Pr\big(\mathbf{x}_i = \mathbf{s}\big), \ \mathbf{s} \in \mathbb{S}. \tag{18}$$

Now, we have

$$\mathbb{E}(\mathbf{x}_j) = \sum_{\forall \mathbf{s},\ \mathbf{s}\in\mathbb{S}} \mathbf{s}p_j(\mathbf{s}) \tag{19}$$

$$\text{Var}(\mathbf{x}_j) = \sum_{\forall \mathbf{s},\ \mathbf{s}\in\mathbb{S}} \mathbf{s}\mathbf{s}^H p_j(\mathbf{s}) - \mathbb{E}(\mathbf{x}_j)\mathbb{E}(\mathbf{x}_j)^H. \tag{20}$$

We approximate $\mathbf{p}_i$s with the corresponding APPs, i.e.,

$$p_i(\mathbf{s}) \leftarrow \Pr(\mathbf{x}_i = \mathbf{s}|\mathbf{z}_i, \mathbf{G}), \tag{21}$$

where
$\Pr(\mathbf{x}_i = \mathbf{s}|\mathbf{z}_i, \mathbf{G}) \propto e^{-\frac{1}{2}(\mathbf{z}_i - \mathbf{G}_{ii}\mathbf{s} - \boldsymbol{\mu}_i)^H \boldsymbol{\Sigma}_i^{-1}(\mathbf{z}_i - \mathbf{G}_{ii}\mathbf{s} - \boldsymbol{\mu}_i)}$.

Message passing: In CHEMP-MSD, the system model can be represented by a fully-connected graph with K nodes, where the ith node is an approximate APP processor corresponding to the ith user's transmit vector $\mathbf{x}_i$. Each node computes the APP as a function of the incoming messages and the knowledge of $\mathbf{G}$ and $\mathbf{z}_i$. The message passing schedule is as follows.

1) Initialize the probability vectors $\mathbf{p}_i$s with equiprobable masses.
2) Each node computes $\mathbf{p}_i$ as per (21). This, in turn, requires the computation of (16) and (17).

Steps 1 and 2 are repeated for a fixed number of iterations. Damping of messages is done to improve the convergence rate [11]. At the end of the tth iteration, the messages are damped with a damping factor $\beta \in [0, 1)$. Thus, if $\tilde{\mathbf{p}}_i^t$ is the computed probability vector at the tth iteration, the message at the end of tth iteration is

$$\mathbf{p}_i^t = (1-\beta)\tilde{\mathbf{p}}_i^t + \beta\mathbf{p}_i^{t-1}. \tag{22}$$

The iterative algorithm is terminated after a certain number of iterations. An estimate of the modulation symbol transmitted by the ith user is obtained as

$$\widehat{s}_i = \underset{s\in\mathbb{A}}{\text{argmax}} \sum_{\forall \mathbf{s},\ \mathbf{s}\in\mathbb{S}:\mathcal{X}(\mathbf{s})=s} p_i(\mathbf{s}), \tag{23}$$

where $\mathcal{X}(\mathbf{s})$ gives the non-zero element in $\mathbf{s}$. An estimate of the MAP chosen for transmission by the ith user is obtained as

$$\widehat{q}_i = \underset{q\in\{1,\cdots,N_m\}}{\text{argmax}} \sum_{\forall \mathbf{s},\ \mathbf{s}\in\mathbb{S}:\mathcal{I}(\mathbf{s})=q} p_i(\mathbf{s}), \tag{24}$$

where $\mathcal{I}(\mathbf{s})$ gives the index of the non-zero element in $\mathbf{s}$. The estimated MAP and the modulation symbols obtained are then demapped to obtain the ith user's bits.

C. Computational complexity

In BP-MSD, the computation of the messages from the observation nodes to the variable nodes has an order of $O(n_r N_m^2 K^2 |\mathbb{S}|)$. The messages from the variable nodes to the observation nodes require a computational complexity of $O(n_r^2 N_m K |\mathbb{S}|)$.

In CHEMP-MSD, the complexity for the computation of the APP is $O(N_m^3 K(|\mathbb{S}| + K))$. The computation of $\mathbf{G}$ has a complexity order of $O(n_r K^2 N_m^2)$. For $n_r > K$ and $K > N_m$, the overall complexity of the algorithm gets dominated by the computation of $\mathbf{G}$. However, we shall see in the next section that CHEMP-MSD has both computational complexity and performance advantages over other algorithms when the channel matrix is estimated instead of assuming it to be perfect.

MMSE based detector is a conventionally used detector for large-scale MIMO systems. The complexity of MMSE detector is $O(K^2N_m^2(n_r + KN_m) + KN_m|\mathbb{S}|)$. The computational complexity of ML detection is $O(n_r K N_m |\mathbb{S}|^K)$. Therefore, both the proposed BP-MSD and CHEMP-MSD algorithms have much lesser computational complexity than MMSE and ML detectors for large-scale multiuser MBM signal detection.

IV. MBM SIGNAL DETECTION WITH ESTIMATED CSI

In this section, we consider a practical scenario where perfect CSI is not available and the channel matrix has to be estimated at the BS. We refer to the system with a combined detector and channel estimator as a receiver. We introduce two receivers for large-scale multiuser MBM systems.

In order to estimate the channel matrix, we use pilot symbols. Here, each transmission frame from the users has a pilot part and a data part. The pilot part is used for the transmission of the pilot symbols. Let the length of the transmission frame be F_L. The coherence time of the channel is assumed to be equal to the duration of the frame (hence, the channel becomes invariant over a frame duration). The pilot part has KN_m channel uses, and the data part consists of $F_L - KN_m$ channel uses. Let $\mathbf{X}_\text{p} = A\mathbf{I}_{KN_m}$ denote the pilot matrix. In the ith channel use, $1 \leq i \leq KN_m$, the $\lceil \frac{i}{N_m} \rceil$th user transmits a pilot symbol using a MAP, whose index is given by $\big((i-1) \mod N_m\big)+1$, with amplitude A. Only one user transmits at a time and all other users remain silent. The received signal at the BS during the pilot phase is then

$$\mathbf{Y}_\text{p} = \mathbf{H}\mathbf{X}_\text{p} + \mathbf{N}_\text{p} = A\mathbf{H} + \mathbf{N}_\text{p}, \tag{25}$$

where $A = \sqrt{KE_s}$, E_s is the average symbol energy, and $\mathbf{N}_\text{p}$ denotes the noise matrix.

A. BP receiver

First, we extend the proposed BP-MSD algorithm to formulate the belief propagation based receiver (BP receiver). We use the MMSE channel estimator to estimate the channel matrix $\mathbf{H}$. The estimated channel gain matrix is then used instead of $\mathbf{H}$ in the BP-MSD algorithm as described in the Section III-A.

B. CHEMP receiver

This receiver employs the algorithm described in the Section III-B for the detection of MBM signals. In this receiver, we do not use the conventional method of estimating the channel matrix $\mathbf{H}$ directly (like in MMSE channel estimation). Instead, we directly obtain an estimate of $\mathbf{H}^H\mathbf{H}$ (which is defined as $\mathbf{G}$ in Section III-B). This is because, the equivalent system model obtained in (13) through the matched filtering operation can work with a direct estimate of $\mathbf{G}$. We shall see in the next section that this approach of direct estimation of $\mathbf{G}$ performs better compared to the conventional method of explicitly estimating $\mathbf{H}$ and detecting $\mathbf{x}$. In the CHEMP receiver, the matrix $\mathbf{G}$ is estimated as

$$\widehat{\mathbf{G}} \;=\; \frac{\mathbf{Y}_{\text{p}}^T\mathbf{Y}_{\text{p}}}{n_r A^2} - \frac{\sigma_w^2}{A^2}\mathbf{I}_{KN_m}. \tag{26}$$

An estimate of the vector $\mathbf{z}$ is obtained as

$$\widehat{\mathbf{z}} \;=\; \frac{\mathbf{Y}_{\text{p}}^T\mathbf{y}}{n_r A}, \tag{27}$$

where $\mathbf{y}$ is the received signal vector in each channel use of the data part. These estimates $\widehat{\mathbf{G}}$ and $\widehat{\mathbf{z}}$ obtained in (26) and (27) are used in place of $\mathbf{G}$ and $\mathbf{z}$ in the CHEMP detection algorithm.

C. Computational complexity

It has to be noted that there is no additional computational complexity in the CHEMP receiver for channel estimation. That is, the CHEMP receiver has the same computational complexity as the CHEMP-MSD algorithm despite performing channel estimation. In contrast, other receiver algorithms require additional computational complexity to explicitly estimate the channel matrix $\mathbf{H}$.

V. Results and Discussions

In this section, we present the bit error rate (BER) performance of the proposed BP and CHEMP receivers in multiuser MBM systems.

A. Performance of the proposed algorithms

We simulate a multiuser MBM system with $n_t = 1, m_{rf} = 3, K = 16$, 4-QAM, 5 bpcu per user, and $n_r = 64, 128$. Note that for $n_r = 64$, the multiuser MBM system becomes an under-determined system as the transmit vector $\mathbf{x}$ is of dimension 128×1. For $n_r = 128$, the system is fully-determined.

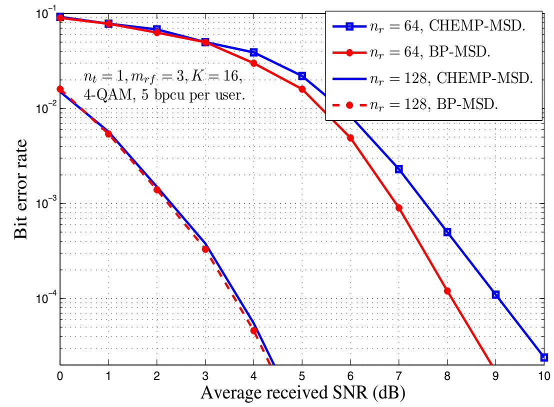

Fig. 3. BER performance of BP-MSD and CHEMP-MSD for multiuser MBM system with $K = 16$, $n_t = 1$, $m_{rf} = 3$, 4-QAM, 5 bpcu per user, and $n_r = 64, 128$.

In Fig. 3, we present the performance of the proposed BP-MSD and CHEMP-MSD algorithms with perfect CSI. From Fig. 3, it can be seen that both the detectors have almost the same BER performance for $n_r = 128$. For $n_r = 64$, BP-MSD performs better than CHEMP-MSD by about 1 dB at 10^{-4} BER. This is because, for under-determined systems, the $\frac{\mathbf{H}^H\mathbf{H}}{n_r}$ matrix will have relatively strong off-diagonal elements. Therefore, the channel hardening effect is less pronounced.

Figure 4 shows the performance of the proposed BP and CHEMP receivers (i.e., with estimated CSI at the receiver). From Fig. 4, it can be seen that the BP receiver performs better than the CHEMP receiver by about 1 dB at 10^{-4} BER for $n_r = 64$. This is because, as seen before, the system is under-determined for $n_r = 64$. For $n_r = 128$, the CHEMP receiver outperforms the BP receiver by about 0.8 dB at 10^{-4} BER. This is because, when the MBM channel is fully-determined, directly estimating $\mathbf{H}^H\mathbf{H}$ in CHEMP without explicitly estimating $\mathbf{H}$ improves the detection performance. This shows that the BP receiver algorithm is efficient for under-determined MBM channels and the CHEMP receiver algorithm is efficient for fully- and over-determined MBM channels.

B. Comparison with other receiver algorithms

Here, we compare the BER performance of the proposed receivers with that of the existing receivers known in the literature for multiuser MBM systems. Low complexity detection and channel estimation techniques for large-scale multiuser MBM systems are not studied well in the literature so far. For comparison with the state-of-art techniques, we choose MMSE detector and a compressed sensing (CS) based detector proposed in [14]. The complexity of the CS based algorithm is $O(K^2N_m^2(|\mathbb{S}|+n_r))$, which is higher than the proposed message passing based receiver algorithms.

In Fig. 5, we present the performance comparisons between (i) MMSE detector (perfect CSI) and MMSE

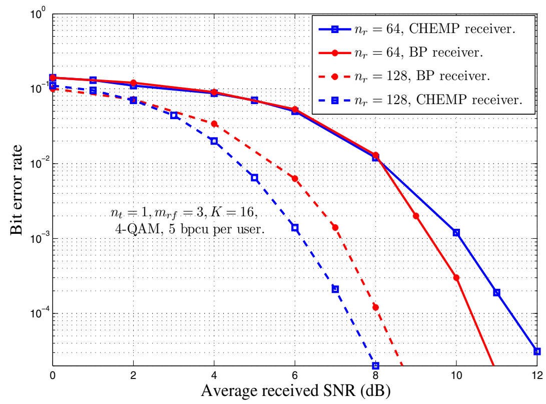

Fig. 4. BER performance of BP receiver and CHEMP receiver for multiuser MBM system with $K = 16$, $n_t = 1$, $m_{rf} = 3$, 4-QAM, 5 bpcu per user, and $n_r = 64, 128$.

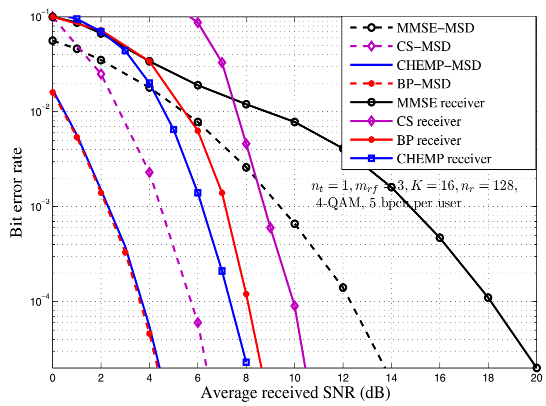

Fig. 5. BER performance comparison between (i) MMSE receiver (MMSE detector + MMSE channel estimator), (ii) CS receiver (SP detector + MMSE channel estimator), (iii) BP receiver, and (iv) CHEMP receiver for multiuser MBM system with $K = 16$, $n_t = 1$, $m_{rf} = 3$, 4-QAM, and 5 bpcu per user, and $n_r = 128$.

receiver (MMSE detector with MMSE channel estimator), (ii) CS based subspace pursuit (SP) detector [14,15] (perfect CSI) and CS based receiver (SP detector with MMSE channel estimator), (iii) BP-MSD and BP receiver, and (iv) CHEMP-MSD and CHEMP receiver. The multiuser MBM system configuration chosen is $n_t = 1, m_{rf} = 3, K = 16, n_r = 128$, 4-QAM, and 5 bpcu per user. From Fig. 5, it can be seen that the proposed BP and CHEMP detectors and receivers outperform all the other detectors and receivers, respectively. For example, at a BER of 10^{-4}, BP-MSD and CHEMP-MSD outperform MMSE detector by about 8.5 dB and CS detector by about 2 dB. The BP receiver outperforms MMSE receiver by about 10 dB and CS receiver by about 2 dB. The CHEMP receiver outperforms MMSE receiver by about 11 dB and CS receiver by about 3 dB.

VI. Conclusions

We proposed receiver algorithms for multiuser MBM and studied their performance and complexity in large-scale multiuser settings. The devised algorithms used message passing techniques. They exploited channel hardening effect that occurs in large MIMO channels and Gaussian approximation of interference, which yielded very good bit error performance as well as low complexity. The proposed receivers were also shown to outperform other receivers such as MMSE receiver and compressed sensing based receiver. With MBM emerging as a promising modulation scheme to achieve high data rates and good performance using low RF hardware complexity, the proposed receiver algorithms demonstrated the feasibility of achieving such good performance in large-scale multiuser MBM systems.

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