Compressive sensing based multiuser detector for massive MBM MIMO uplink

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Abstract: Media based modulation (MBM) is expected to be a prominent modulation scheme, which has access to the high data rate by using radio frequency (RF) mirrors and fewer transmit antennas. Associated with multiuser multiple input multiple output (MIMO), the MBM scheme achieves better performance than other conventional multiuser MIMO schemes. In this paper, the massive MIMO uplink is considered and a conjunctive MBM transmission scheme for each user is employed. This conjunctive MBM transmission scheme gathers aggregate MBM signals in multiple continuous time slots, which exploits the structured sparsity of these aggregate MBM signals. Under this kind of scenario, a multiuser detector with low complexity based on the compressive sensing (CS) theory to gain better detection performance is proposed. This detector is developed from the greedy sparse recovery technique compressive sampling matching pursuit (CoSaMP) and exploits not only the inherently distributed sparsity of MBM signals but also the structured sparsity of multiple aggregate MBM signals. By exploiting these sparsity, the proposed CoSaMP based mutliuser detector achieves reliable detection with low complexity. Simulation results demonstrate that the proposed CoSaMP based multiuser detector achieves better detection performance compared with the conventional methods.

Keywords: media based modulation (MBM), radio frequency (RF) mirror, compressive sensing (CS), multiple input multiple output (MIMO), multiuser detector, compressive sampling matching pursuit (CoSaMP).

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1. Introduction

The explosive growth of data rate requirements and user equipment (UE) will be involved in the next generation wireless communication systems [1]. To solve this issue, massive multiple input multiple output (MIMO) is considered as a promising technology to improve the spectral efficiency by employing hundreds of antenna elements (AEs) at the base station (BS). For the uplink transmission, multiple users transmit signals synchronously at the UE equipped with multiple antennas. However, one specific radio frequency (RF) chain is usually equipped with each AE, which leads to considerable power consumption and hardware cost. To mitigate the influences caused by the increased RF chains, innovative schemes such as spatial modulation (SM) [2–5], space shift keying (SSK) [6–8] and media-based modulation (MBM) [9–13] are proposed to improve the performance via using fewer RF chains than the traditional methods.

SM provides a low complexity spectral enhancing way for the MIMO system [14]. In the SM scheme system, each user is equipped with RF chains and multiple antennas at the transmitter. Only one transmit antenna is selected in a given channel use and the signal constellation symbol set $\Omega$ with $M$-ary modulation, e.g., 16 quadrature amplitude modulation (QAM), is transmitted by the selected antenna. Assuming that there are $N_t$ transmit antennas to achieve the throughput of each user is $\log_2(N_t) + \log_2 M$ bits per channel use (bpcu) in the case of one active RF chain. For instance, the spectral efficiency of four information bits can be achieved with the use of 8 phase shift keying (8PSK) and two transmit antennas. To improve the throughput, the number of the transmit antennas should be increased exponentially. However, there is no enough space for each user to own an excess of transmit AEs.

SSK is a modulation scheme based on SM and can be considered as a particular case of SM [15]. In SSK transmission, only one RF chain is connected to multiple antennas and the antenna index is used for relaying information instead of transmitting symbols. In this way, the detection complexity of SSK is lower than SM. For $m$ information bits, $N_t = 2^m$ transmit antennas are utilized to achieve the throughput of $\log_2(N_t)$ bpcu. Similarly, only one transmit antenna is activated to convey the information bits in the SSK scheme. The spectral efficiency of SSK also improves with the exponential increase of transmit antennas, which
is expensive from the perspectives of the hardware cost and energy consumption increase.

MBM as a novel technology can be combined with conventional MIMO and even massive MIMO to solve the issues of the hardware cost and energy consumption in the SM or SSK scheme [14]. The basic idea of MBM is to generate various channel states between the transmitter and receiver by changing the RF properties near transmit antennas. In an MBM system, RF mirrors are placed around a transmit antenna. Each RF mirror represents an ON/OFF status, which is called ‘mirror activation pattern (MAP)’ and a different combination of MAPs maps into different information bits. When the RF mirror is in ON status, the signals will pass through. On the other hand, the OFF status indicates that the RF mirror turns into a barrier and the signals will not pass through. Each combination of ON/OFF status, which results in a variety of different channel states, is large [19]. The linear low complexity detection algorithm such as minimum mean square error (MMSE) performs well for conventional massive MIMO schemes [20], but it is inadaptable due to the exploding increased number of transmit AEs and reduced number of RF chains at BS. Compressive sensing (CS) based detection algorithms leveraged in [21—23] are efficient approaches for multiuser detection, but they are valid only in small scale MIMO systems.

In this paper, a conjunctive MBM transmission scheme for each user is employed and a multiuser detector with low complexity based on compressive sampling matching pursuit (CoSaMP) is proposed. The multiuser detectors of SM systems by using the CS theory were developed by some researchers. A CS based detector was proposed by exploiting the structured sparsity of SM [24]. By utilizing the distributed sparsity in SM systems, a CS based multiuser detection algorithm was exploited in [25]. Similar as SM, MBM also possesses such kind of distributed sparsity and structured sparsity. This conjunctive MBM transmission scheme gathers aggregate MBM signals in multiple continuous time slots, which exploits the structured sparsity of these aggregate MBM signals. The transmission scheme and the proposed detector aim to utilize the inherently distributed sparsity of the MBM signal and the structured sparsity of multiple MBM signals. The simulation results demonstrate that the proposed CoSaMP based multiuser detector outperforms the conventional detectors.

The rest of this paper is organized as follows. Section 2 introduces the multiuser MBM system model. The proposed CoSaMP based multiuser detector is described in Section 3. Section 4 presents the simulation results. Finally, Section 5 concludes this paper.

**Notation**  The italic boldface lowercase and uppercase symbols denote vectors and matrices, respectively. Superscripts \((\cdot)^T, (\cdot)^H\) and \((\cdot)^\dagger\) denote the transpose, conjugate transpose, and Moore-Penrose inversion operators, respectively. \(I_n\) and \(O_n\) denote the \(n \times n\) identity and null matrices, respectively, while \(0_n\) is the vector of the size \(n\) with all the elements being 0. \([A]_{m,n}\) denotes the \(m\)th row and \(n\)th column element of \(A\). The \(\ell_0\) and \(\ell_2\) norm operations are given by \(\|\cdot\|_{\ell_0}\) and \(\|\cdot\|_{\ell_2}\), respectively. The support set of the vector \(x\) is denoted by \(\text{supp}\{x\}\). \(A|_{\Gamma}\) denotes the submatrix whose columns comprise the columns of \(A\) defined in the set \(\Gamma\). \(\langle x \rangle_A|_{\Lambda}\) denotes the sub-vector whose elements comprise the nonzero elements defined in the set \(\Lambda\). \(\Theta = \max(a; n)\) stands for a set whose elements are the indices of the largest \(n\) elements of the vector \(a\). \(|a|\) denotes a vector consisting of the modulus of the elements of \(a\).

### 2. System model

Consider an MBM based massive MIMO multiuser uplink
SONG Wei et al.: Compressive sensing based multiuser detector for massive MBM MIMO uplink system, as shown in Fig. 1, where BS employs $N_{BS}$ receive antennas to serve $K$ UEs with each UE equipped with a single transmit antenna and $N_{RF}$ RF mirrors. These RF mirrors generate $S = 2^{N_{RF}}$ possible MAPs with each MAP involving ON/OFF status associated with one RF mirror, where the UE can transmit one of the MAPs mapped to a bit sequence that contains $N_{RF}$ information bits for a given channel use [26]. To illustrate the mapping relationship between the bit sequences and MAPs, Table 1 shows a mapping example for $N_{RF} = 3$ bits.

![Fig. 1 Block diagram of MBM based multiuser detection for massive MIMO uplink systems](image)

| MAP index | Information bit sequence | Mirror 1 status | Mirror 2 status | Mirror 3 status |
|-----------|--------------------------|-----------------|-----------------|-----------------|
| 1         | 000                      | ON              | ON              | ON              |
| 2         | 001                      | ON              | ON              | OFF             |
| 3         | 010                      | ON              | OFF             | ON              |
| 4         | 011                      | ON              | OFF             | OFF             |
| 5         | 100                      | OFF             | ON              | ON              |
| 6         | 101                      | OFF             | ON              | OFF             |
| 7         | 110                      | OFF             | OFF             | ON              |
| 8         | 111                      | OFF             | OFF             | OFF             |

The uplink multiuser detection lasts $T$ time slots and the MBM signal vector of the $k$th UE in the $t$th time slot $x_{k,t} \in \mathbb{C}^{S}$ ($1 \leq k \leq K, 1 \leq t \leq T$) can be expressed as $x_{k,t} = e_{k,t}s_{k,t}$, where $e_{k,t} \in \mathbb{C}^{S}$ is the selected MAP index vector corresponding to a specified information bit sequence and $s_{k,t} \in \mathbb{C}$ denotes the signal constellation symbol transmitted by a UE. Due to only one of $S$ MAPs selected by each UE, only one entry of $e_{k,t}$ is set to 1, and the residual entries in $e_{k,t}$ are 0. Therefore, the support set of $e_{k,t}$ can be determined as

$$\text{supp}\{e_{k,t}\} \in \Pi, \quad \|e_k\|_0 = 1; \quad \|e_k\|_2 = 1$$

where $\Pi = \{1, 2, \ldots, S\}$ is the MAP index set. On the other hand, the transmit signal constellation symbol $s_{k,t}$ comes from the signal constellation symbol set $\Omega$ with $M$-ary modulation (e.g., $M$-QAM), i.e., $s_{k,t} \in \Omega$. Therefore, the overall throughput in the uplink for an MBM based massive MIMO system having $K$ UEs is $K(N_{RF} + \log_2 M)$ bpcu. For example, the total throughput of an MBM based multiuser system with $K = 4$, $N_{RF} = 4$ and $M = 16$ is 32 bpcu.

For multiuser detection in the uplink, the signal vector $y_t \in \mathbb{C}^{N_{BS}}$ received by BS in the $t$th time slot is given by

$$y_t = \sum_{k=1}^{K} H_k x_{k,t} + z_t$$

where $H_k = [h_{k,1}^1 \ h_{k,2}^2 \ \cdots \ h_{k,S}^S] \in \mathbb{C}^{N_{BS} \times S}$ is the MBM channel gain matrix of the $k$th UE with $h_{k,i}^i \in \mathbb{C}^{N_{BS}}$ being the channel gain vector corresponding to the $i$th MAP for $1 \leq i \leq S$, and $z_t \in \mathbb{C}^{N_{BS}}$ is the complex additive white Gaussian noise (AWGN) vector with the covariance matrix $\sigma_n^2 I_{N_{BS}}$, i.e., $z_t \sim \mathcal{CN}(0_{N_{BS}}, \sigma_n^2 I_{N_{BS}})$.

By collecting an all $K$ channel matrix associated with $K$ UEs, we have the aggregated channel gain matrix $H =$
\[ [H_1, H_2, \ldots, H_K] \in \mathbb{C}^{N_{BS} \times KS}. \] Furthermore, due to the close placement of RF mirrors at the UEs, the channels associated with different MAPs exhibit typical spatial correlation, and the similar spatial correlation can be also established among the receive antennas equipped at the BS. Hence, \( H \) is the correlated flat Rayleigh fading MIMO channel gain matrix, which can be expressed by using the Kronecker model \([27]\), i.e.,

\[
H = R_{BS}^{1/2} H R_{UE}^{1/2}
\]  \hspace{1cm} (3)

where each entry of \( H \in \mathbb{C}^{N_{BS} \times KS} \) obeys the independent and identically distributed (i.i.d.) \( \mathcal{CN}(0,1) \), and \( R_{UE} \in \mathbb{C}^{KS \times KS} \) and \( R_{BS} \in \mathbb{C}^{N_{BS} \times N_{BS}} \) are the correlation matrices at the BS and UEs, respectively. The transmit correlation matrix \( R_{UE} \) can be expressed as

\[
R_{UE} = \begin{bmatrix}
R_1 & O_S & \cdots & O_S \\
O_S & R_2 & \cdots & O_S \\
& \vdots & \ddots & \vdots \\
O_S & O_S & \cdots & R_K
\end{bmatrix}
\]  \hspace{1cm} (4)

where \( R_k \in \mathbb{C}^{S \times S} \) is the RF mirror correlation matrix of the \( k \)th UE that reveals the spatial correlation among the channels corresponding to different MAPs. For the \( k \)th RF mirror correlation matrix, given the correlation value \( \rho_k \), \( R_k \ (1 \leq k \leq K) \) is given by

\[
R_k = \begin{bmatrix}
1 & \rho_t & \cdots & \rho_t \\
\rho_t & 1 & \cdots & \rho_t \\
& \vdots & \ddots & \vdots \\
\rho_t & \rho_t & \cdots & 1
\end{bmatrix}
\]  \hspace{1cm} (5)

In terms of the receive correlation matrix \( R_{BS} \), its element follows the exponentially decreasing correlation model, i.e., given the correlation value \( \rho_r \), \( [R_{BS}]_{m,n} = \rho_r^{m-n} \). Thus \( R_{BS} \) can be expressed as

\[
R_{BS} = \begin{bmatrix}
1 & \rho_r & \rho_r^2 & \cdots & \rho_r^{N_r-1} \\
\rho_r & 1 & \rho_r & \cdots & \rho_r^{N_r-2} \\
& \vdots & \ddots & \ddots & \vdots \\
\rho_r^{N_r-1} & \rho_r^{N_r-2} & \rho_r^{N_r-3} & \cdots & 1
\end{bmatrix}
\]  \hspace{1cm} (6)

According to the aggregated channel gain matrix \( H \), (2) can be rewritten as

\[
y_t = H x_t + z_t
\]  \hspace{1cm} (7)

where \( x_t = [x_{1,t}^T, x_{2,t}^T, \ldots, x_{K,t}^T]^T \in \mathbb{C}^{K S} \) is the aggregated MBM signal vector and \( H \) in continuous time slots can be regarded as quasi static. Finally, by aggregating the received signal vectors \( y_t \) of (7) over the \( T \) time slots into \( Y = [y_1, y_2, \ldots, y_T] \in \mathbb{C}^{N_{BS} \times T} \), we have

\[
Y = H X + Z
\]  \hspace{1cm} (8)

where \( X = [x_1, x_2, \ldots, x_T] \in \mathbb{C}^{K S \times T} \) and \( Z = [z_1, z_2, \ldots, z_T] \in \mathbb{C}^{N_{BS} \times T} \) are the aggregated MBM signal and noise matrices, respectively.

According to (8), the optimal ML detection criterion for the MBM signal matrix \( X \) is given by

\[
\hat{X}_{ML} = \arg \min_X \| Y - H \|_2^2
\]

s.t. \( \text{supp}(e_{k,t}) \in \Pi, s_{k,t} \in \Omega, 1 \leq k \leq K, 1 \leq t \leq T \).  \hspace{1cm} (9)

Although the ML signal detector in (9) is optimal, its computational complexity exhibits exponential increase with the amount of users since the size of exhaustive search is equal to \( (S \cdot M)^{KT} \) \([28]\). The excessively high computational complexity can be unavoidable in practice for the multiuser MIMO systems where the number of the UE \( K \) tends to be very large. As the near-optimal solutions, the sphere decoding detectors \([29]\) are indeed capable of reducing the computational complexity, but they may still suffer from prohibitive complexity cost when the values of \( S, M, K \) and \( T \) are very large. Moreover, some suboptimal low complexity linear algorithms, such as matched filter (MF), zero forcing (ZF) and MMSE, which are applied in traditional MIMO systems to solve the overdetermined signal detection problem \([30]\), are not suitable to addressing the large-scale underdetermined (e.g., \( N_{BS} < KS \)) multiuser signal detection problem in (9). According to (1), we can observe that the sparsity level of the MBM signal vector \( x_{k,t} \) is equal to 1, so the aggregated MBM signal matrix \( X \) has a sparsity level of \( K \) when its columns share the same common sparse support set. To fully exploit this sparsity of the MBM signals and further improve the performance of signal detection, we propose a CS-based multiuser detection algorithm in the next section.

3. Proposed CoSaMP based multiuser detector for MBM MIMO uplink

In this section, a successive MBM signal design employed at the UEs is first proposed to present the common sparse support set in (8). Then, by exploiting the sparsity of MBM signals, a multiuser detection algorithm is proposed based on the CS theory. Furthermore, the computational complexity of the proposed multiuser detection algorithm is evaluated. Specifically, for an MBM signal vector, there is only one non-zero element in \( S \) elements, which means the MBM signal vectors are inherently sparse and their sparsity factor is \( 1/S \). According to (7), the aggregated MBM signal vector \( x_t \) in the 4th time slot consists of \( K \) subvectors with sparsity level one, and thus its sparsity factor is \( K/(KS) = 1/S \). This inherent sparse property in the
CS theory can be utilized to improve the accuracy of signal detection, and then a greedy sparse recovery technique based algorithm is proposed to solve the CS problem.

3.1 Successive MBM signal design

The successive $T$ time slots at the data transmission stage are considered as a group to design MBM signals. To effectively reduce the switching frequency of RF mirrors at the UEs, the same selected MAP index vector is adopted in different time slots, i.e., $e_{k,t} = e_{k,t-1} = \cdots = e_{k,T}$ ($1 \leq k \leq K$), but the signal constellation symbols are different for every time slot. Therefore, the MBM signal vectors in different time slots share the same common sparse support set, i.e.,

$$\text{supp}\{x_{k,1}\} = \text{supp}\{x_{k,2}\} = \cdots = \text{supp}\{x_{k,T}\},$$

$$1 \leq k \leq K. \quad (10)$$

Due to the same common sparse support set sharing by different time slots for all UEs, the aggregated MBM signal vectors also share the same common sparse support set, i.e.,

$$\text{supp}\{x_1\} = \text{supp}\{x_2\} = \cdots = \text{supp}\{x_T\}. \quad (11)$$

According to (8) and (11), we can observe that different columns of the aggregated MBM signal matrix $X$ have the same common sparse support set. By exploiting this sparsity, a modified CoSaMP algorithm is proposed, named partitioned CoSaMP (PCoSaMP) algorithm and detailed in the next subsection, to improve the performance of signal detection significantly.

3.2 Proposed PCoSaMP algorithm

Based on the analysis above, all the columns of the aggregated received signal matrix $Y$ can be addressed simultaneously to solve the following optimization problem:

$$\hat{X} = \arg \min_{\{x_t\}_{t=1}^T} \sum_{t=1}^T \|y_t - Hx_t\|_2^2 =$$

$$\arg \min_{\{x_{k,t}\}_{k=1,t=1}^{K,T}} \sum_{t=1}^T \|y_t - Hx_t\|_2^2$$

s.t. $\|x_{k,t}\|_0 = 1, \quad 1 \leq k \leq K; \quad 1 \leq t \leq T. \quad (12)$

To solve the optimization problem (12) above, a PCoSaMP multiuser detection algorithm is proposed by exploiting the common sparse support set among measurements of multiple time slots and the priori sparse information of the MBM signal vector. By utilizing the proposed PCoSaMP multiuser detection algorithm, the MBM signal vectors of $K$ users in $T$ successive time slots can be estimated, i.e., $\hat{x}_{k,t} = \hat{e}_{k,t}\hat{s}_{k,t}$ ($1 \leq k \leq K, 1 \leq t \leq T$), where $\hat{e}_{k,t}$ and $\hat{s}_{k,t}$ are the estimated selected MAP index vector and signal constellation symbol, respectively.

The proposed PCoSaMP algorithm is summarized in Algorithm 1. Specifically, the residual vector $r_t$ ($1 \leq t \leq T$) and the support set $\Xi^{(i)}$ can be initialized in Step 2. According to the priori sparse information of the constraint condition in (12), i.e., $\|x_t\|_0 = K$, Step 3 means that the total number of iterations is equal to that of UEs $K$. Step 5 performs the correlation calculation between the channel matrices and the residual in previous iteration, and Step 7 attempts to obtain the most likely preliminary support set based on the correlation values of Step 5. Step 9 acquires the union set by combining the support sets in the current and previous iterations, and this union set is used to solve the least squares (LS) problem in Step 11, which contributes to discarding the incorrect indices and update the most likely support set of the current iteration in Step 13, i.e., $\Xi^{(i)}$. Step 15 calculates the MBM signal estimation in the current iteration by using the LS criterion, and Step 17 updates the residue estimates based on this estimation and the refined support set $\Xi^{(i)}$. Then, the ultimate MBM signal estimation $\hat{x}_t$ ($1 \leq t \leq T$) and the support set $\Xi^{(K)}$ are in Step 20. Finally, because $\hat{x}_{k,t} = \hat{e}_{k,t}\hat{s}_{k,t}$ ($1 \leq k \leq K, 1 \leq t \leq T$), the support set $\Xi^{(K)}$ can directly determine the estimated selected MAP index vectors and its information bit sequences, and the estimated signal constellation symbols can be obtained by minimizing the Euclidean distance between $\hat{s}_{k,t}$ and the legitimate signal constellation symbols in the set $\Omega$.

Algorithm 1 Proposed PCoSaMP algorithm

Input: Received signal matrix $Y = [y_1 \; y_2 \; \cdots \; y_T]$, channel matrix $H$, and sparsity level $K$

1 \% Initialization

2 $\Xi^{(0)} = \{\emptyset\}, i = 1, r_t = y_t, \hat{x}_t = 0_{KS}$ for $1 \leq t \leq T$

3 while $i \leq K$

4 \% Correlation

5 $c_t = H^H r_t, \forall t$

6 \% Preliminary support set

7 $\phi = \max(\sum_{t=1}^T |c_t|; 2K)$

8 \% Combine support set

9 $\psi = \Xi^{(i-1)} \cup \phi$

10 \% First least squares

11 $b_t^i \psi = (H \psi)^+ y_t, \forall t$

12 \% Update support set

13 $\Xi^{(i)} = \max(\sum_{t=1}^T |b_t^i \psi|; K)$

14 \% Second least squares
based signal detector for the massive MIMO uplink system. The BER performance influenced by different arguments’ values of the transmitter and receiver is also compared. In addition, the proposed algorithm is implemented by using Matlab 2017a.

Fig. 2 describes the BER performance achieved by different signal detectors as a function of the SNR under the MBM massive MIMO uplink system for $K = 8$, $M = 64$, $N_{RF} = 3$, $\rho_t = 0$, $\rho_r = 0.5$, and $N_{BS} = 32$. The traditional MMSE and MF based detectors suffer from a BER performance floor when the SNR value is greater than 10 dB, but the BER performance of the MF based detector works inferior than the MMSE based detector. The BER performance of the CoSaMP based detector works superior than the MF based detector when the SNR value is greater than 10 dB and works superior than the MMSE based detector when the SNR value is greater than 15 dB. When $T = 4$, the advantage of the proposed detector becomes clearer. The performance gap between the situation of $T = 2$ and $T = 4$ becomes larger when the SNR value is greater than 4 dB. In conclusion, relative to using the traditional signal detector, the proposed PCoSaMP based multiuser detector only suffers from little BER loss in the massive MIMO uplink system. It can be observed from Fig. 2 that the proposed PCoSaMP based multiuser detector achieves better BER performance than the other conventional CS based detectors mentioned in Fig. 2 and has near optimal performance compared with the ML detector.

3.3 Computational complexity evaluation

In terms of optimal ML detector in (9), its computational complexity is $O((MN_{RF}K)^3)$, which is excessively high due to the exponential order. Therefore, the ML detection algorithm is not suitable for the multiuser MBM system in this paper. By contrast, the MMSE based detector for massive MIMO and the CS based SM detector [21] for general MIMO have low computational complexity, and their computational complexities are $O(N_{BS}(N_{RF}K)^2 + (N_{RF}K)^3)$ and $O(2(N_{BS}K)^2 + (K)^3)$, respectively. As for the proposed PCoSaMP multiuser signal detector, its computational requirements mainly come from the LS operations, whose computational complexity is $O(T(2N_{BS}(K)^2 + (K)^3))$. By comparing the computational complexity of these multiuser signal detectors mentioned above, it should be pointed out that the orders of magnitude of the proposed PCoSaMP based detector are lower than those of the traditional MMSE or CS based detector.

4. Simulation results

To verify our proposed algorithm, the bit error rate (BER) performance of the proposed detector is carried out to be compared with that of the other multiuser systems by using the traditional MMSE based, MF based and CoSaMP based signal detector for the massive MIMO uplink system. The BER performance influenced by different arguments’ values of the transmitter and receiver is also compared. In addition, the proposed algorithm is implemented by using Matlab 2017a.

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bers of users and RF mirrors, where $T = 2$, $M = 48$, $\rho_r = 0.4$, $\rho_t = 0$ and $N_{BS} = 64$ are considered. Considering the situation of $K = 8$ or $K = 16$ and $N_{RF} = 3$ or $N_{RF} = 4$, the result indicates that the BER performance of $K = 8$ approaches better BER performance. The different values of $K$ have a prominent impact on BER performance. The problem that we challenge is a large scale underdetermined problem and the values of $K$ have an influence on the dimension of the transmit signals. When the value of $K$ increases, the dimension of transmit signals also increases. This will make the underdetermined problem more serious and obtain worse BER performance. With the SNR increasing, the gap of the BER performance between the $K = 8$ and $K = 16$ situations becomes wider. We can find that the different values of $N_{BS}$ hardly have any effect on the BER performance. It indicates that the proposed PCoSaMP multiuser detector possesses robustness.

![Fig. 3 BER performance of proposed PCoSaMP multiuser detector versus SNRs with different values of $K$ and $N_{RF}$](image)

Fig. 3 BER performance of proposed PCoSaMP multiuser detector versus SNRs with different values of $K$ and $N_{RF}$

Finally, comparing the BER performance achieved by the proposed PCoSaMP based multiuser detector for different arguments’ values at the receiver, where $K = 8$, $M = 48$, $\rho_r = 0.4$ and $N_{RF} = 3$. When $\rho_r = 0$ and $\rho_t = 0$, and the channels become uncorrelated Rayleigh fading MIMO channels. The improvement of performance is achieved at the expense of reduced uplink throughput and the antenna number increment of the receiver will alleviate this situation. The different values of $N_{BS}$ affect the dimension of received signals and further influence the calculating results of the large scale underdetermined problem to be solved. For instance, when the value of $N_{BS}$ decreases from 48 to 32, the BER performance degrades. Meanwhile, the different values of the correlation coefficient $\rho_t$ make the receive correlation matrix $R_{BS}$ change and finally have an effect on the channel matrix. The decreased $\rho_t$ has a positive effect on the BER performance. In the situation of $N_{BS} = 48$, the BER performance degrades a lot when the value of $\rho_r$ changes from 0.8 to 0.4. However, the BER performance degrades a little when the value of $\rho_r$ changes from 0.4 to 0. Meanwhile, the decreased $\rho_r$ has a positive effect on the BER performance. In Fig. 4, the best BER performance is the situation of $N_{BS} = 48$ transmitted by the uncorrelated Rayleigh fading MIMO channels.

![Fig. 4 BER performance of proposed PCoSaMP multiuser detector versus SNRs with different values of $\rho_r$ and $N_{BS}$](image)

Fig. 4 BER performance of proposed PCoSaMP multiuser detector versus SNRs with different values of $\rho_r$ and $N_{BS}$

Finally, comparing the BER performance achieved by the proposed PCoSaMP based multiuser detector in Fig. 5 with different values of $\rho_t$ and $M$, where $K = 8$, $T = 2$, $N_{RF} = 3$, $\rho_r = 0$ and $N_{BS} = 48$ are considered. The probability of each signal constellation points in $M$-ary modulation is $1/M$ and this indicates the BER performance will be worse when the value of $M$ becomes larger. Comparing the BER performance of 16QAM and 64QAM, the results show that the BER performance of 16QAM is better than 64QAM. Similarly, the different values of the correlation coefficient $\rho_t$ make the receive correlation matrix $R_{TX}$ change and finally have an effect on the channel matrix. The simulation results show that the better BER performance can be gained when the values of $M$ and $\rho_t$ are both lower.
Fig. 5 BER performance of proposed PCoSaMP multiuser detector versus SNRs with different values of $\rho_t$ and $M$

5. Conclusions

MBM is considered as a potential modulation scheme as it reduces RF hardware consumption and offers performance advantages. In this paper, a signal detector with low complexity for MBM based MIMO uplink transmission is proposed. The joint MBM transmission scheme is leveraged by the users to introduce the structured sparsity of multiple aggregate MBM signals. The proposed method based on CoSaMP obtains reliable multiuser signal detection performance by exploiting the inherently distributed sparsity of MBM signals and the structured sparsity of multiple MBM signals. The simulation results demonstrate that the proposed CoSaMP based multiuser detector outperforms other traditional methods.

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