Signal Detection with Parallel Orthogonal Matching Pursuit in Multi-User Spatial Modulation Systems

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***Abstract*—In this paper, we propose a novel signal detection technique with *parallel* orthogonal matching pursuit (POMP) for a multi-user spatial modulation (SM) uplink network which consists of a single base station (BS) with N_r antennas and K users with N_t antennas. Each user utilizes the SM, and thus it sends a modulated symbol via a *single* antenna among N_t antennas. The BS tries to estimate the symbols simultaneously received from K users. In the proposed signal detection technique, the BS modifies the conventional OMP algorithm, known as one of the most promising detection techniques in sparse signal processing field, by selecting multiple candidates M at the first iteration of the OMP algorithm. Simulation results show that the proposed technique significantly outperforms the OMP algorithm in terms of symbol-error rate. It is worth noting that the proposed technique requires M-times more complexity than the OMP-based technique, but it has still much lower complexity than the maximum likelihood detector.**

***Index Terms*—Spatial modulation, massive MIMO, parallel orthogonal matching pursuit, multi-user detection, compressed sensing.**

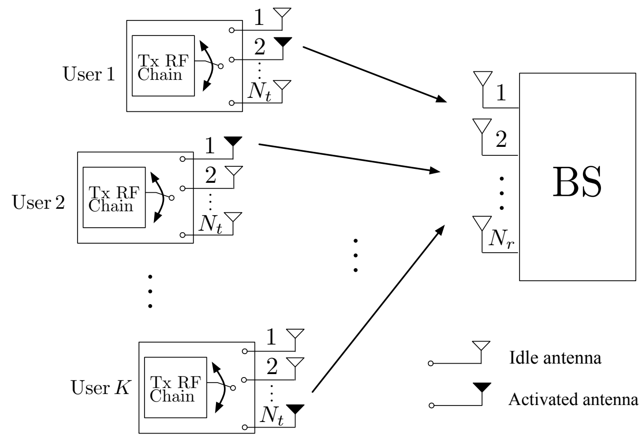

Fig. 1: Uplink multi-user access network with SM.

I. Introduction

Massive multiple-input and multiple-output (MIMO) technique is being considered as one of the most promising techniques for the next generation mobile communication systems, called 5G, because it can improve system performances such as error probability and spectral efficiency [1], [2]. However, the massive MIMO technique has known to suffer from several technical challenges such as inter-channel interference among antennas, high receiver complexity, energy inefficiency, difficulty on inter-antenna synchronization, etc [3]. Recently, spatial modulation (SM) techniques have been proposed as another way of utilizing multiple antennas, coping with the demerits of the conventional MIMO techniques [4]. With the SM, a transmitter activates a single antenna to send data while remaining antennas are not utilized, and digital information is sent according to the index of the activated antenna in addition to modulation symbols like QAM. The SM technique results in improved energy efficiency (EE) due to reduced number of radio frequency (RF) chains at the transmitter.

The SM has been applied to multiple access networks [5], [6]. In [5], the maximum likelihood detector (MLD) was assumed at a base stations (BS) to detect uplink signals, but the complexity of the MLD is exponentially increased as the number of antennas at users or the number of users in the network increases. In [6], two signal detection algorithms with low complexity were proposed for multi-user SM-based MIMO uplink, where SM-based MIMO techniques with the proposed detection algorithms are compared with the massive MIMO technique having the same spectral efficiency. On the other hand, a computationally efficient signal detection technique based on compressed sensing (CS) theory was proposed for the SM technique [7], which exploits the orthogonal matching pursuit (OMP) algorithm [8]. However, the signal detection performance of the OMP-based technique is much worse than the MLD.

In this paper, we propose a signal detection technique based on *parallel* OMP (POMP) [9] for uplink multi-user SM (MU-SM) systems. In the proposed technique, the receiver (BS) performs M parallel OMP processes simultaneously. Extensive simulation results show that the proposed technique significantly outperforms the conventional OMP algorithm, while reducing the computational complexity, compared to the MLD.

II. System Model

Fig. 1 illustrates an uplink multi-user MIMO network with the SM. Let K, N_t, and N_r denote the number of users in the network, the number of transmit antennas at each user, and the number of receive antennas at the BS, respectively. Each user employs the SM for transmission, and thus it transmits a symbol from a modulation alphabet $\mathbb{A}$ via a single activated antenna among N_t antennas. The number of transmitted bits per channel use through the modulation symbol is given by $\log_2\lfloor|\mathbb{A}|\rfloor$, where $|\cdot|$ denotes the cardinality of a set. In addition, the number of transmitted bits through the index of the activated transmit antenna is given by $\lfloor\log_2 N_t\rfloor$. Then, the total number of bits that can be transmitted per channel use is given by

$$N_b = K\left(\lfloor\log_2 N_t\rfloor + \log_2\lfloor|\mathbb{A}|\rfloor\right). \tag{1}$$

For example, $N_b = 12$ when $K = 3$, $N_t = 4$, and QPSK modulation is used, i.e., $|\mathbb{A}| = 4$. The SM signal set $\mathbb{S}_{N_t,\mathbb{A}}$ for each user is given by $\mathbb{S}_{N_t,\mathbb{A}} = \{\mathbf{s}_{j,l} : j = 1, \cdots, N_t,\ l = 1, \cdots, |\mathbb{A}|\}$, where

$$\mathbf{s}_{j,l} = [0, \ldots, 0, \underbrace{s_l}_{\text{j-th coordinate}}, 0, \ldots, 0]^T, s_l \in \mathbb{A}. \tag{2}$$

Let $\mathbf{x}_k \in \mathbb{S}_{N_t,\mathbb{A}}$ denote the transmit signal vector of the k-th user and let $\mathbf{x} \triangleq \left[\mathbf{x}_1^T\mathbf{x}_2^T\cdots\mathbf{x}_k^T\cdots\mathbf{x}_K^T\right]^T$ denote the vector comprising of transmit vectors from all users. Let $\mathbf{H} \triangleq [\mathbf{h}_1\cdots\mathbf{h}_{KN_t}] \in \mathbb{C}^{N_r\times KN_t}$ denote the channel coefficient matrix, where $\mathbf{h}_{(k-1)\cdot N_t+j} \in \mathbb{C}^{N_r\times 1}$ indicates the channel vector from the j-th antenna of the k-th user to the BS. Then, the received signal vector at the BS is described as

$$\mathbf{y} = \mathbf{H}\mathbf{x} + \mathbf{z}, \tag{3}$$

$\mathbf{z} \in \mathbb{C}^{N_r\times 1}$ denotes an additive white Gaussian noise (AWGN) vector. In this paper, the received signal-to-noise ratio (SNR) is defined as

$$\mathsf{SNR} = \frac{\mathbb{E}\left[\|\mathbf{H}\mathbf{x}\|^2\right]}{\mathbb{E}\left[\|\mathbf{z}\|^2\right]}. \tag{4}$$

With a receiver with the optimal MLD, for example, the detection rule is given by

$$\hat{\mathbf{x}}_{\mathsf{ML}} = \arg\min_{\mathbf{x}} \|\mathbf{y} - \mathbf{H}\mathbf{x}\|_2^2. \tag{5}$$

Although the the MLD achieves the optimal performance, it requires tremendous amount of computations at the receiver because it searches all possible candidates. For a MU-SM system shown in Fig. 1, the computational complexity of the MLD increases exponentially as N_b increases. For example, the complexity becomes 10^{13} when $N_t = 5$, QPSK, and $K = 4$. Thus, the MLD can not be applied to the practical systems.

III. Signal Detection with POMP Algorithm

In this section, we describe the proposed POMP-based signal detection technique for MU-SM systems. The POMP algorithm was proposed to improve the detection performance of the OMP with tolerable complexity increment [9]. The POMP algorithm has never been applied to multi-user MIMO systems so far. In this paper, therefore, we apply the POMP algorithm to the signal detection in MU-SM systems. The POMP algorithm consists of M parallel OMP processes. At the first iteration, M indices having the largest correlation value between channel matrix $\mathbf{H}$ and received signal $\mathbf{y}$ are selected, and each index is allocated to each OMP process as

Iter	OMP	POMP($M=3$)		
1	$\Lambda_1 = \{3\}$	Initialization $\Lambda_1^0 = \{3, 5, 12\}$		
2	$\Lambda_2 = \{3, 7\}$	$\Lambda_2^1 = \{3, 7\}$	$\Lambda_2^2 = \{5, 15\}$	$\Lambda_2^3 = \{12, 14\}$
3	$\Lambda_3 = \{3, 7, 16\}$	$\Lambda_3^1 = \{3, 7, 16\}$	$\Lambda_3^2 = \{5, 15, 10\}$	$\Lambda_3^3 = \{12, 14, 2\}$
$\cdots$	$\cdots$	$\cdots$	$\cdots$	$\cdots$
		1st OMP process	2nd OMP process	3rd OMP process

Fig. 2: Example of index set generation of POMP when $M = 3$

the first index. Then, each process independently executes the conventional OMP algorithm with the allocated index. Fig. 2 illustrates procedures of OMP and POMP for each iteration when $M = 3$. Λ_t^m denotes the index set of the m-th OMP process after t iterations. Contrary to OMP selecting a single index with the largest correlation at the first iteration, the POMP algorithm selects 3 indices (3, 5, and 12) to be allocated to each OMP process in Fig. 2. After K iterations, the estimate $\hat{\mathbf{x}}$ with the minimum residual among M support sets. Overall procedure is summarized in Algorithm 1. In the algorithm, $\mathbf{H}_{\Lambda_t^m} \in \mathbb{C}^{N_r\times|\Lambda_t^m|}$ denotes a submatrix of $\mathbf{H}$ that only contains columns indexed by Λ_t^m.

IV. Numerical Results

In this section, performance of the proposed POMP-based signal detection technique is compared with that of the OMP-based technique in terms of symbol error rate (SER) Figs. 3 and Figs. 4 show the SER of the proposed POMP-based signal detection technique for an uplink multi-user access network with SM, where $K = 4, N_t = 8, N_r = 16, N_b = 20$, and $K = 4, N_t = 8, N_r = 16, N_b = 12$, respectively. In Fig. 3, QPSK scheme is used for symbol modulation. In Fig. 4, space-shift keying (SSK) technique is used. In both figures, the proposed POMP-based detection technique outperforms the conventional OMP-based technique, and the performance gap between the proposed technique and the conventional one increases as M increases. However, the computational complexity of the proposed technique also increases as as M increases, and M needs to be chosen carefully by considering both performance and complexity.

V. Conclusion

We proposed a low-complexity signal detection technique for a multi-user multiple access network, where each user utilizes a spatial modulation technique. In the proposed signal detection technique at the BS, the BS exploits M parallel OMP processes, and thus the BS selects M indices with largest correlation value between channel matrix and received signal at the first iteration of the OMP algorithm. Extensive simulation results show that the proposed technique significantly outperforms the conventional OMP-based detection technique in terms of SER, while it requires M times more complexity than the OMP-based scheme. Therefore, we need to adjust M in the proposed signal detection technique by considering

Algorithm 1 Proposed POMP-based algorithm

Input:

  $\mathbf{y}$: Received signal

  $\mathbf{H}$: Channel matrix

  K : Number of users

  M : Number of parallel OMP processes

Initialize:

  $\mathbf{r}_0^m = \mathbf{y},\ \Lambda_0^m = \emptyset, \Omega = \{1, 2, \ldots, n\}$

  $m = \{1, 2, \ldots, M\}$

for $t = 1$ to K **do**

  if $t == 1$ **then**

    $\lambda_t^1 = \arg\max_{i \in \Omega} \left\| \left\langle \mathbf{r}_{t-1}^m, \mathbf{h}_i / \|\mathbf{h}_i\| \right\rangle \right\|^2$

    $\lambda_t^2 = \arg\max_{i \in \Omega \setminus \{\lambda_t^1\}} \left\| \left\langle \mathbf{r}_{t-1}^m, \mathbf{h}_i / \|\mathbf{h}_i\| \right\rangle \right\|^2$

    $\vdots$

    $\lambda_t^M = \arg\max_{i \in \Omega \setminus \{\lambda_t^1, \ldots, \lambda_t^{M-1}\}} \left\| \left\langle \mathbf{r}_{t-1}^m, \mathbf{h}_i / \|\mathbf{h}_i\| \right\rangle \right\|^2$

    for $m = 1$ to M **do**

      $\Lambda_t^m = \Lambda_{t-1}^m \cup \{\lambda_t^m\}$

      $\mathbf{P}^m = \left\{ \left(\mathbf{H}_{\Lambda_t^m}\right)^T \mathbf{H}_{\Lambda_t^m} \right\}^{-1} \left(\mathbf{H}_{\Lambda_t^m}\right)^T$

      $\hat{\mathbf{x}}_t^m = \mathbf{P}^m \mathbf{y}$

      $\hat{\mathbf{y}}_t^m = \mathbf{H}_{\Lambda_t^m} \hat{\mathbf{x}}_t^m$

      $\mathbf{r}_t^m = \mathbf{y} - \hat{\mathbf{y}}_t^m$

    end for

  else

    for $m = 1$ to M **do**

      $\lambda_t^m = \arg\max_{i \in \Omega \setminus \{\lambda_{t-1}^m\}} \left\| \left\langle \mathbf{r}_{t-1}^m, \mathbf{h}_i / \|\mathbf{h}_i\| \right\rangle \right\|^2$

      $\Lambda_t^m = \Lambda_{t-1}^m \cup \{\lambda_t^m\}$

      $\mathbf{P}^m = \left\{ \left(\mathbf{H}_{\Lambda_t^m}\right)^T \mathbf{H}_{\Lambda_t^m} \right\}^{-1} \left(\mathbf{H}_{\Lambda_t^m}\right)^T$

      $\hat{\mathbf{x}}_t^m = \mathbf{P}^m \mathbf{y}$

      $\hat{\mathbf{y}}_t^m = \mathbf{H}_{\Lambda_t^m} \hat{\mathbf{x}}_t^m$

      $\mathbf{r}_t^m = \mathbf{y} - \hat{\mathbf{y}}_t^m$

    end for

  end if

end for

$\hat{m} = \arg\min_m \|\mathbf{r}_K^m\|^2$

$\hat{\mathbf{x}} = \mathbf{x}_K^{\hat{m}}$

the system requirements such as complexity, cost, storage requirement, and detection performance, etc.

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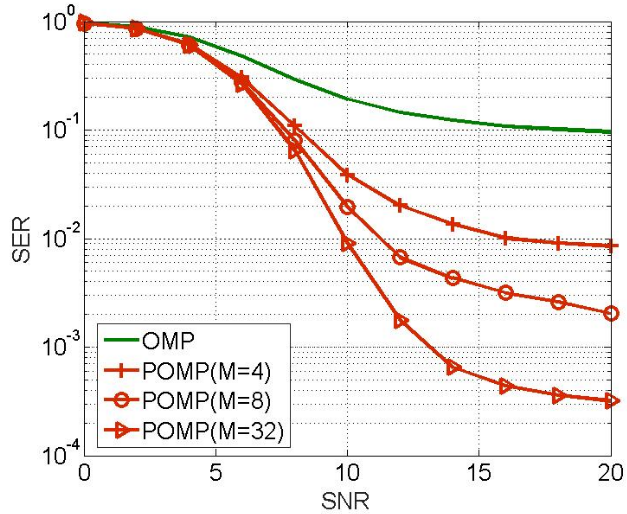

Fig. 3: Symbol error rates (SER) when $N_t = 8, N_r = 16, K = 4, QPSK$ and $N_b = 20$.

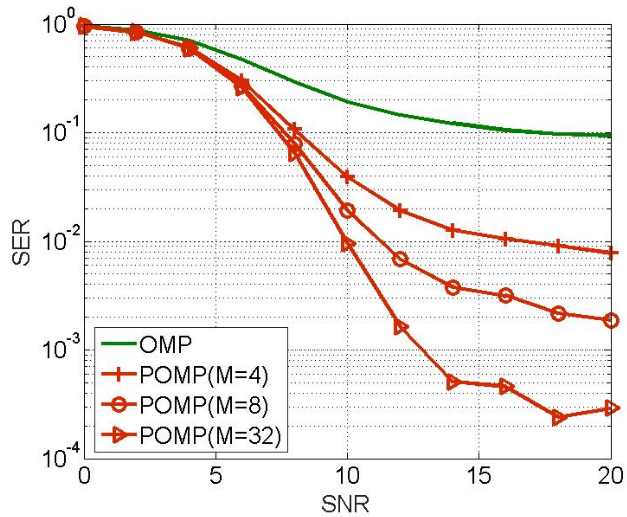

Fig. 4: Symbol error rates (SER) when $N_t = 8, N_r = 16, K = 4, SSK$ and $N_b = 12$.

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