Block-Sparse Compressive Sensing Based Multi-User and Signal Detection for Generalized Spatial Modulation in NOMA

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***Abstract*—The non-orthogonal multiple access (NOMA) technology has been proposed and regarded as one of the potential promising technologies for the future 5G network. The extension of generalized spatial modulation multiple-input multiple-output (MIMO) to NOMA system improves both the spectral and energy efficiencies of the system, while maintaining the massive connectivity and low latency advantages, but it puts forward challenges for the multi-user and signal detection as well. In this paper, we propose a joint user activity and signal detection scheme based on the block-sparse compressive sensing (BS-CS) method in the uplink NOMA system, in which the generalized spatial modulation MIMO technology is used. By exploiting the structure and sparsity of the multi-user generalized spatial modulation signals, we formulate the detection problem into a block-sparse recovery problem. Then a BS-CS based detection algorithm, enhanced structured block-sparse compressive sampling matching pursuit (ESB-CoSaMP), is proposed to detect the active users and transmitted data efficiently. Moreover, the information of active antennas at each user is exploited in ESB-CoSaMP to further improve the accuracy. Simulations show that the proposed detection scheme outperforms the conventional CS and BS-CS based schemes.**

***Index Terms*—non-orthogonal multiple access, generalized spatial modulation, block sparse, compressive sensing.**

I. Introduction

Recent years, there has been a tremendous growth in the world's wireless communications, which puts forwards higher requests for the fifth generation (5G) communication systems. Non-orthogonal multiple access (NOMA) technology, which can support massive connectivity and low transmission latency, has been regarded as one of the potential promising technologies for the future 5G network [1]. In NOMA systems, non-orthogonal resources are allocated to different users rather than orthogonal resource distribution in conventional orthogonal multiple access (OMA) schemes. Thus the base station is able to support much more users with limited resources in the uplink scenario. However, it is worth mentioning that the number of active users is much smaller than the number of totally supported users according to the statistics in [2], which introduces sparsity of the user activity in the NOMA system. So far, several NOMA schemes have been investigated to improve the system performance, which can be divided into two categories, the power-domain NOMA [3] and the code-domain NOMA. The code-domain one includes low-density spreading CDMA (LDS-CDMA) [4], sparse code multiple access (SCMA) [5], multi-user shared access (MUSA) [6] and so on.

The multiple-input multiple-output (MIMO) technology is getting increased research attention by using more antennas on the device terminals to achieve better spectral efficiency and throughput [7]. However, the complexity of signal processing at each mobile device and the expensive energy consuming radio frequency (RF) chains cause trouble for the traditional MIMO communication in practice. Based on the considerations, the spatial modulation (SM) technology, which uses the single-RF chain and spatial constellation to transmit signals came into being to meet with the demand of spectral efficiency (SE) and energy efficiency (EE) [8]. The generalized spatial modulation technology is a generalization of SM by using more than one active antenna at the same time to further improve the spectral efficiency. Because of the sparsity of the SM and generalized SM signals, detectors based on the compressive sensing (CS) [9] method become competitive alternatives with quite low complexity especially in the large-scale scenario [10] [11] [12]. CS is one of the efficient signal processing techniques, which has been utilized in many aspects in communication systems, such as interference cancelation [13] [14], noise elimination [15] [16], channel estimation [17] [18] and so on [19] [20]. The extension of generalized SM technology to NOMA system improves the SE and EE, but puts forward challenges for the detection scheme as well.

In this paper, we introduce generalized SM technology to NOMA systems in the uplink scenario and formulate the system into a block-sparse model. Accordingly, we propose a novel detection scheme based on the block-sparse compressive sensing (BS-CS) method [21] [22], which is referred to as Enhanced Structured Block-sparse Compressive Sensing Matching Pursuit (ESB-CoSaMP). We look into the algorithm

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of Block-based CoSaMP and make use of the structure of the multiuser generalized SM signals to improve performance. Simulations show that the proposed scheme outperforms the conventional CS and BS-CS based detection schemes.

The rest of the paper is organized as follows. In Section II, we present the generalized spatial modulation MIMO and NOMA system model and explore the block-sparsity in the transmitted signals. In Section III, the details of the proposed ESB-CoSaMP detection scheme is explained. The simulation results and discussion are presented in Section IV, and finally we come to the conclusion in Section V.

Notation: Column vectors and matrices are denoted by lowercase and uppercase boldface letters; $(\cdot)^{\mathrm{H}}$, $(\cdot)^{\dagger}$ and $\|\cdot\|_p$ denote the conjugate transposition, pseudo-inversion and ℓ_p-norm respectively; $|\Phi|$ and Φ^{C} denote the cardinality and complementary of set Φ; $\binom{\cdot}{\cdot}$ denotes the binomial coefficient; $\mathbf{v}_i$ represents the i-th sub-block of vector $\mathbf{v}$; $\mathbf{v}|_{\Phi}$ represents the components of vector $\mathbf{v}$ in the index set Φ; $\mathbf{M}_i$ represents the i-th sub-matrix of matrix $\mathbf{M}$ in columns; $\mathbf{M}|_{\Phi}$ represents the sub-matrix of matrix $\mathbf{M}$ with columns in the index set Φ.

II. System Model

A. Generalized Spatial Modulation MIMO in Uplink NOMA

We consider an uplink NOMA system which can support K users with J orthogonal resources and $S(S < K)$ users are active at the same time, as illustrated in Fig. 1. Under the condition of generalized spatial modulation, each user was equipped with n_t antennas. Thus, the total number of transmit antennas is $N = K \times n_t$. The base station is equipped with M receive antennas and the communication system can be described as

$$\mathbf{y} = \mathbf{H}\mathbf{x} + \mathbf{w}, \tag{1}$$

where $\mathbf{y} \in \mathbb{C}^{M\times 1}$ is the received signal at the base station. $\mathbf{H} \in \mathbb{C}^{M\times N}$ is the channel matrix which represents the frequency flat fading channel. $\mathbf{w} \in \mathbb{C}^{M\times 1} \sim \mathcal{CN}(\mathbf{0}, \sigma_n^2\mathbf{I}_M)$ represents the additive white Gaussian noise (AWGN) with variance σ_n^2. $\mathbf{x} \in \mathbb{C}^{N\times 1}$ is the multiuser generalized SM signal transmitted by users. In the scenario considered throughout this paper, the multiuser generalized SM signal $\mathbf{x}$ is written as the combination of the signals of each possible user, which can be expressed as

$$\mathbf{x} = [\mathbf{x}_1^T, \mathbf{x}_2^T, ..., \mathbf{x}_K^T]^T, \tag{2}$$

where $\mathbf{x}_i \in \mathbb{C}^{n_t\times 1}$ denotes the transmitted signal of user i. In generalized spatial modulation MIMO, only n_a antennas of each user are active at each time slot to transmit signals. So $\log_2\binom{n_t}{n_a}$ bits of information can be transmitted through the active antenna indices in each symbol, which can be expressed as

$$\mathbf{x}_i = [0, ..., s_{p_1}, ..., s_{p_{n_a}}, ..., 0]^T, \tag{3}$$

where $p_i \in [1, n_t], i \in [1, n_a]$ represents the indices of active antennas and $s_{p_i}, i \in [1, n_a]$ represents the symbol chosen from a given constellation set $\mathcal{C}$, such as PSK, QAM and so on. Thus the rate of each user is

$$R_{\mathrm{generalizedSM,each}} = \log_2\binom{n_t}{n_a} + n_a \times \log_2|\mathcal{C}| \tag{4}$$

bits per channel use (bpcu).

B. Block-sparse Formulation

Block sparsity. For a vector $\mathbf{c} \in \mathbb{C}^{N\times 1}$, we can always write it into a concatenation of $P(P \le N)$ sub-blocks, i.e, $\mathbf{c} = [\mathbf{c}_1^T, \mathbf{c}_2^T, ..., \mathbf{c}_P^T]^T$, where $\mathbf{c}_l$ is the l-th sub-block of vector $\mathbf{c}$. Intuitively, we call it *k-block-sparse*, if at most k sub-blocks of $\mathbf{c}$ are nonzero. Mathematically, the $\ell_{2,0}$-norm can be used to define block sparsity as in [21], which is expressed as

$$\|\mathbf{c}\|_{2,0} = \sum_{l=1}^{P} I(\|\mathbf{c}_l\|_2), \tag{5}$$

where $I(\cdot)$ is the indicator function which means $I(\|\mathbf{c}_l\|_2) = 1$ if $\|\mathbf{c}_l\|_2 > 0$ and 0 otherwise. Then a vector $\mathbf{c}$ is *k-block-sparse* if $\|\mathbf{c}\|_{2,0} \le k$.

According to the statistics in [2], the supported users in a NOMA system are not always active at the same time. Actually, only a small number of users are active simultaneously even in busy hours. We denote $\mathbf{x}_i = \mathbf{0}$ if user i is not active. As a consequence, the multiuser generalized SM signal $\mathbf{x}$ has a block-sparse structure, i.e.,

$$\mathbf{x} = [..., \underbrace{0, ..., 0}_{\mathbf{x}_i^T}, ..., \underbrace{x_{j,1}, ..., x_{j,n_t}}_{\mathbf{x}_j^T}, ...]^T, \tag{6}$$

where $x_{j,l}, j \in [1, K], l \in [1, n_t]$ denotes the symbol at the l-th antenna of user j. In the scenario considered in this paper, all the users are equipped with the same number of antennas, so each sub-block of $\mathbf{x}$ has the same length n_t.

Block RIP. As defined in [23], the block restricted isometry property of a matrix $\mathbf{B}$ is the smallest constant $\delta_{B,k}$, such that

$$(1 - \delta_{B,k})\|\mathbf{c}\|_2^2 \le \|\mathbf{B}\mathbf{c}\|_2^2 \le (1 + \delta_{B,k})\|\mathbf{c}\|_2^2 \tag{7}$$

holds for every *k-block-sparse* vector $\mathbf{c}$. As shown in [23], if the block RIP condition holds, i.e., $\delta_{B,2k} < \sqrt{2} - 1$, the $\ell_{2,0}$-norm minimum recovery problem could be relaxed to convex $\ell_{2,1}$-norm minimum recovery problem.

Block-sparse Based Detection. As talked above, the recovery of multiuser generalized SM signal $\mathbf{x}$ in NOMA systems can be formulated into a block-sparse recovery problem, which can be described as

$$\min_{\mathbf{x}} \|\mathbf{x}\|_{2,0} = \min_{\mathbf{x}} \sum_{l=1}^{K} I(\|\mathbf{x}_l\|_2) \ \text{ s.t. } \ \mathbf{y} = \mathbf{H}\mathbf{x}. \tag{8}$$

In our scenario, the frequency flat fading channel matrix $\mathbf{H}$ comprised of i.i.d. Gaussian random variables is known to satisfy the Block RIP condition with high probability, as shown in [24], and thus the recovery problem can be relaxed to a $\ell_{2,1}$-norm minimum problem, which is

$$\min_{\mathbf{x}} \|\mathbf{x}\|_{2,1} = \min_{\mathbf{x}} \sum_{l=1}^{K} \|\mathbf{x}_l\|_2 \ \text{ s.t. } \ \mathbf{y} = \mathbf{H}\mathbf{x}. \tag{9}$$

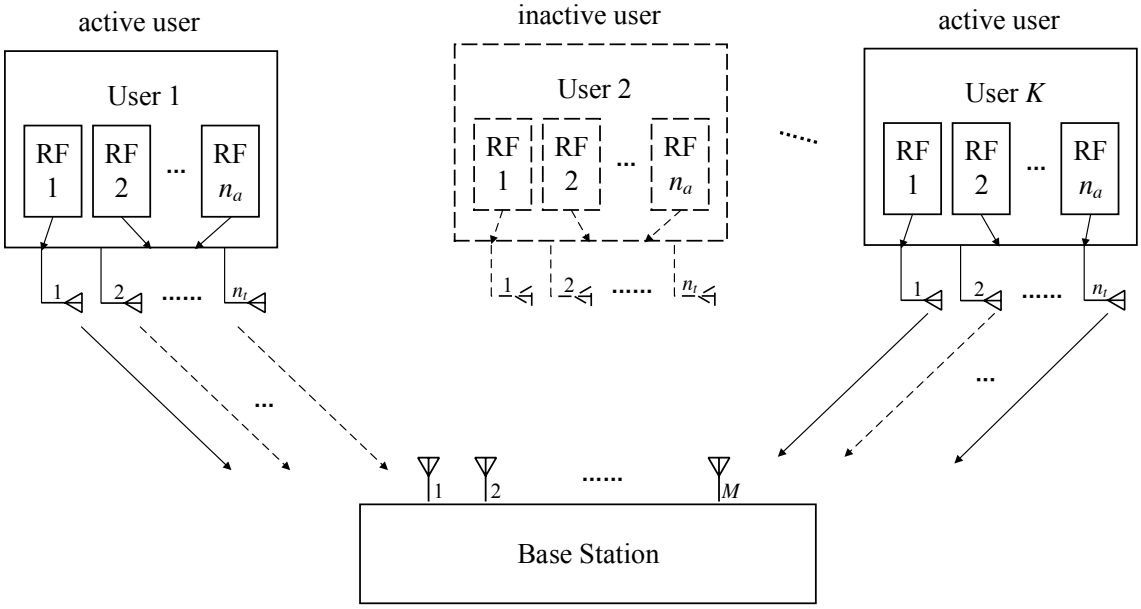


Fig. 1. Generalized spatial modulation MIMO in uplink NOMA system

So far, there have been many efficient block-sparse recovery algorithms based on the compressive sensing methods, such as block orthogonal matching pursuit (BOMP) [21], block-based compressive sampling matching pursuit (Block-based CoSaMP) [25], block iterative hard thresholding (Block IHT) [26] and so on.

III. Proposed BS-CS Based Detection Scheme

The conventional CS and BS-CS algorithms can be applied to the detection problem, however, it cannot achieve ideal performance. In this section, we present the details of the proposed BS-CS based detection scheme, which utilizes the information of active antennas at each user to achieve better performance. It is worth mentioning that the modification of the block-based CoSaMP can also be applied to other BS greedy recovery algorithms. The pseudo-code of the proposed ESB-CoSaMP detection scheme is summarized in **Algorithm 1** and the details are discussed as follows. The overall algorithm consists of three steps.

Step 1: Initialize the iterative variable i, recovery signal $\hat{\mathbf{x}}^{(0)}$, residual $\mathbf{r}^{(0)}$and support set $\Psi^{(0)}$

We set $i = 0$, $\hat{\mathbf{x}}^{(0)} = \mathbf{0}$ and $\mathbf{r}^{(0)} = \mathbf{y}$, respectively, at the beginning of the algorithm. Unlike conventional BS-CS algorithms, we introduce the support set $\Psi^{(i)}$ which is used to describe the support of $\hat{\mathbf{x}}^{(i)}$ more exactly and is initialized as $\varnothing$.

Step 2: Iterate to calculate $\hat{\mathbf{x}}^{(i)}$, $\Psi^{(i)}$ and $\mathbf{r}^{(i)}$ until halting criterion is true

A simple variable $i_{\max}$ is utilized as the halting criterion to control the iteration, which can be adjusted according to the requirement of the communication system.

In **Phase 7**, the estimation of signal residual in the block level is calculated, which is denoted as $\mathbf{e}_\omega \in \mathbb{C}^{n_t \times 1}$ and calculated by

$$\mathbf{e}_\omega = \mathbf{H}_\omega^{\mathrm{H}} \mathbf{r}^{(i-1)}, \omega \in [1, K], \tag{10}$$

where $\mathbf{H}_\omega$ is the ω-th sub-block of $\mathbf{H}$.

In **Phase 8**, the estimation of signal residual is pruned to be *S-block-sparse* by choosing S indexes of blocks with the largest ℓ_2-norm to form support set Ω_{b}, i.e.,

$$\Omega_{\mathrm{b}} = \{\omega_k | \omega_k = arg \max_{\omega_k; k \in [1,S]} \|\mathbf{e}_{\omega_k}\|_2\}. \tag{11}$$

As in conventional block-based CoSaMP, the support set of the estimation of signal residual is found in the block level, which utilize the block-sparse structure of the multiuser generalized SM signals and achieves better performance than the conventional CS algorithm.

In **Phase 9-10**, different from the conventional block-based CoSaMP, the support set Ω_{b} in the block level is transformed to Ω in the index level and then it is merged with the support set $\Psi^{(i-1)}$, which is derived from the $(i-1)$-th estimation of signal $\hat{\mathbf{x}}$. The derivation of $\Psi^{(i)}$ will be talked about later. And thus we can get a more exact merged set T.

In **Phase 11-12**, the approximation of the target signal, denoted as $\mathbf{b} \in \mathbb{C}^{N \times 1}$, is derived by solving a least squares problem on the merged set of components. The other components of $\mathbf{b}$ are simply set to be $\mathbf{0}$.

In **Phase 13-14**, the estimation of the target signal is derived. Different from the conventional block-based CoSaMP, which directly select S sub-blocks of $\mathbf{b}$ with the largest ℓ_2-norm, we introduce a preprocessing of $\mathbf{b}$ to get $\hat{\mathbf{b}}$. The proposed $\hat{\mathbf{b}}$ is

Algorithm 1 Enhanced structured block-sparse compressive sampling matching pursuit (ESB-CoSaMP)

Inputs:

1) System parameters: N, M, K, S, n_t, n_a
2) Channel matrix $\mathbf{H}$
3) Received signal at the base station: $\mathbf{y}$
4) Iteration times $i_{\max}$

Output:

The estimated sparse signal $\hat{\mathbf{x}}$

Initialization:

$i \leftarrow 0$
$\hat{\mathbf{x}}^{(0)} \leftarrow \mathbf{0}$
$\mathbf{r}^{(0)} \leftarrow \mathbf{y}$
$\Psi^{(0)} \leftarrow \varnothing$

Iteration:

while $i \leq i_{\max}$ **do**
  $i \leftarrow i + 1$
  $\mathbf{e}_\omega \leftarrow \mathbf{H}_\omega^{\mathrm{H}} \mathbf{r}^{(i-1)}$ {signal residual estimation}
  $\Omega_{\mathrm{b}} \leftarrow arg \max_{\omega} \|\mathbf{e}_\omega\|_2$ {prune signal residual}
  $\Omega \leftarrow \Omega_{\mathrm{b}}$ {transform to the index level}
  $T \leftarrow \Omega \cup \Psi^{(i-1)}$ {merge supports}
  $\mathbf{b}|_T \leftarrow \mathbf{H}|_T^{\dagger} \mathbf{y}$ {form signal approximation}
  $\mathbf{b}|_{T^{\mathrm{c}}} \leftarrow \mathbf{0}$
  $\hat{\mathbf{b}}_{\psi,j} \leftarrow \max_{j} \|\mathbf{b}_{\psi,j}\|_2, \psi \in [1, K]$ {preprocessing}
  $\hat{\mathbf{x}}^{(i)} \leftarrow \max_{\psi} \|\hat{\mathbf{b}}_\psi\|_2$ {form signal estimation}
  $\Psi^{(i)} \leftarrow \mathrm{supp}(\hat{\mathbf{x}}^{(i)})$ {update support set}
  $\mathbf{r}^{(i)} \leftarrow \mathbf{y} - \mathbf{H}\hat{\mathbf{x}}^{(i)}$ {update residual}
end while

Result Construction:

$\hat{\mathbf{x}} \leftarrow \hat{\mathbf{x}}^{(i_{\max})}$

derived by choosing n_a largest components of each block of $\mathbf{b}$ and setting other small components to be $\mathbf{0}$, i.e.,

$$J_\psi = \{j_k | j_k = \max_{j_k; k \in [1, n_a]} \|\mathbf{b}_{\psi, j_k}\|_2\}, \psi \in [1, K], \tag{12}$$

$$\hat{\mathbf{b}}_\psi|_{J_\psi} = \mathbf{b}_\psi|_{J_\psi}, \hat{\mathbf{b}}_\psi|_{J_\psi{}^{\mathrm{C}}} = \mathbf{0}, \tag{13}$$

where $\mathbf{b}_{\psi,j}$ and $\hat{\mathbf{b}}_{\psi,j}$ denotes the j-th component of the ψ-th sub-block of the vectors respectively. And then the estimation of the target signal $\hat{\mathbf{x}}^{(i)}$ is derived by selecting S sub-blocks of $\hat{\mathbf{b}}_\psi$ with the largest ℓ_2-norm.

Actually, each active user activates n_a antennas to transmit signals. After our preprocessing procedure, the estimation of the target signal $\hat{\mathbf{x}}^{(i)}$ contains n_a non-zero components in each sub-block, which is consistent with the facts. The small components of each sub-blocks introduce errors in the pruning procedure, and the removal of them improves the performance during iteration.

In **Phase 15-16**, the support set $\Psi^{(i)}$ and the residual $\mathbf{r}^{(i)}$ are updated. After the preprocessing procedure, the updated $\Psi^{(i)}$ is derived by

$$\Psi^{(i)} = \mathrm{supp}(\hat{\mathbf{x}}^{(i)}), \tag{14}$$

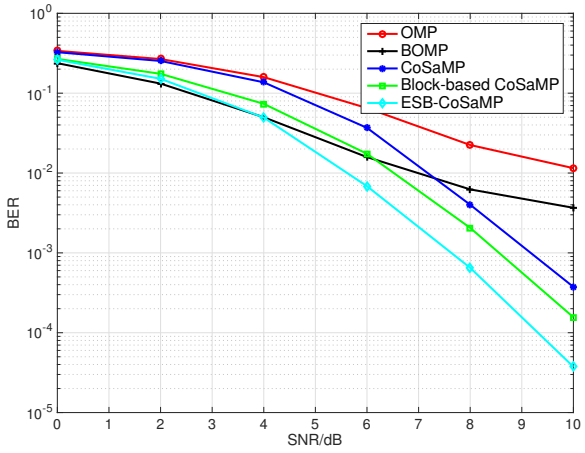


Fig. 2. BER comparison between OMP, BOMP, CoSaMP, Block-based CoSaMP and the proposed ESB-CoSaMP.

where $\mathrm{supp}(\hat{\mathbf{x}}^{(i)})$ denotes the index of non-zero components in $\hat{\mathbf{x}}^{(i)}$.Remarkably, there are only $n_a \times S$ elements in $\Psi^{(i)}$, which is much smaller than $n_t \times S$ in conventional block-sparse CoSaMP. And the complexity is also reduced in the solving of least squares problems in Phase 11, since less columns are selected to form $\mathbf{H}|_T$.

Step 3: Derive the estimated signal $\hat{\mathbf{x}} = \hat{\mathbf{x}}^{(i_{\max})}$

Once the estimated multiuser generalized SM signal $\hat{\mathbf{x}}$ is derived, we can easily derive the indexes of active users and active antennas of each user from $\mathrm{supp}(\hat{\mathbf{x}})$.

IV. Simulation Results

In this section, we present the simulation results of the proposed detection scheme. We consider an uplink NOMA system using multiuser generalized SM technology as described in Sec.II-A. In the Rayleigh flat fading channel, the base station is equipped with M receive antennas. The number of supported users is K and each user is equipped with n_t antennas. S users are active at the same time and each of them activates n_a antennas to transmit signals. We implement conventional CS and BS-CS based detection schemes, i.e., OMP, CoSaMP, BOMP and Block-based CoSaMP as comparison.

The bit error rate (BER) of the proposed detection scheme and the comparison are shown in Fig. 2. Here $M = 50$, $K = 32$, $n_t = 4$, $S = 4$ and $n_a = 2$ and the 4QAM modulation is applied. The simulation results demonstrate that the BS-CS based detectors outperform the conventional CS based detectors because of the usage of the block-sparse structure of the multiuser generalized SM signals. And the proposed ESB-CoSaMP method outperforms both the conventional CS and BS-CS methods by exploiting the active antenna information at each user.

We further investigate the BER performance of the detectors under different numbers of receive antennas at the base station. The simulations are carried out with the same parameters adopted in Fig. 2 and 6 dB signal to noise ratio (SNR). It can

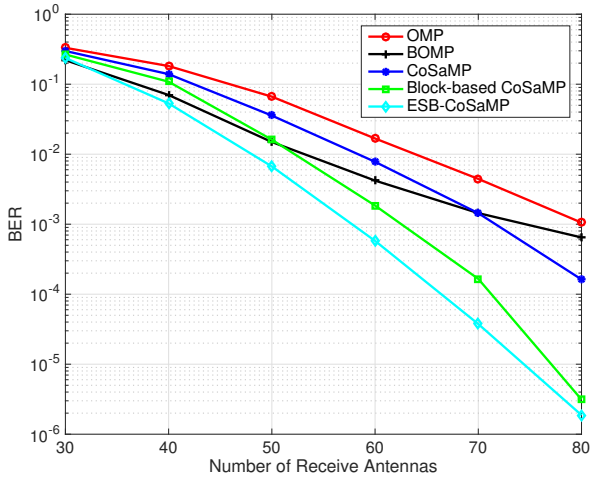


Fig. 3. BER comparison with different number of receive antennas at the base station.

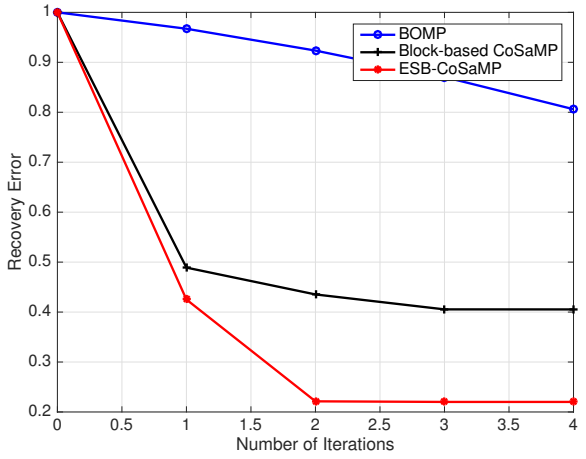


Fig. 4. Recovery error comparison between the block-sparse compressive sensing based detection schemes.

be seen from Fig. 3 that the performance of all the detectors improves with the increase of the number of receive antennas. The detectors can not detect the signals without enough receive antennas, which is consistent with the CS theory. The proposed detection scheme still enjoys BER advantages in each case.

In Fig. 4, the recovery error performance of the block-sparse compressive sensing based detection schemes is investigated, which is defined as $\|\hat{\mathbf{x}}-\mathbf{x}\|_2$. The simulations are carried out with $M = 80$, $K = 32$, $n_t = 4$, $S = 8$, $n_a = 2$ and 10 dB SNR. It can be seen from the figure that the proposed detection scheme enjoys the best recovery error performance and fastest convergence rate in the three BS-CS based detection schemes.

V. Conclusion

In this paper, generalized SM-MIMO technology is introduced into NOMA systems to improve the SE and EE. By exploiting the structure and sparsity of the multiuser generalized SM signals, we formulate the detection problem into a block-sparse recovery problem. Then a detection scheme based on the BS-CS algorithm is proposed to detect the active users and signals efficiently. It is shown by simulations that the proposed detection scheme outperforms the conventional CS and BS-CS based schemes.

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