Generalized Spatial Modulation-Based Multi-User and Signal Detection Scheme for Terrestrial Return Channel With NOMA

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***Abstract*—The terrestrial return channel provides interactive services in digital television terrestrial broadcasting systems to meet various consumers' demands around the world. The extension of non-orthogonal multiple access and generalized spatial modulation multiple-input multiple-output to the terrestrial return channel improves both the spectral and energy efficiencies of the system, but it puts forward detection challenges. In this paper, a joint user activity and signal detection scheme based on the block-sparse compressive sensing (BS-CS) method in the terrestrial return channel is proposed, in which the generalized spatial modulation technology is used. By exploiting the structure and sparsity of the multi-user generalized spatial modulation signal, 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*—Interactive broadcasting, terrestrial return channel, generalized spatial modulation, block sparse, compressive sensing.**

I. Introduction

RECENT years, new digital television based services such as t-commerce, t-banking and t-learning are arousing increasingly interests among people [1]. The terrestrial return channel is proposed to meet the demands of the aforementioned interactive services. A generic model of the interactive system is shown in Fig. 1. In this system, the broadcast channel and the return channel are established between the base station and the users to provide the interactive services. The return channel terrestrial terminals (RCTTs) are deployed to provide interface of the both channel. The RCTT consists of the set up unit (STU) and the network interface unit (NIU), and NIU consists of the broadcast interface module (BIM) and the interactive interface module (IIM). The increasingly interactive services around the world put forward higher request for the spectral efficiency in the terrestrial return channel.

In conventional terrestrial return channel systems, the orthogonal multiple access (OMA) schemes are applied to allocate resources [2], [3], which limit the spectral efficiency and the number of users supported [4]. With the non-orthogonal multiple access (NOMA) technology, non-orthogonal resources are allocated to different users rather than orthogonal resource distribution in conventional OMA schemes. So far, several NOMA schemes have been investigated to improve the system performance, which can be divided into two categories, the power-domain NOMA [5] and the code-domain NOMA. The code-domain one includes low-density spreading CDMA (LDS-CDMA) [6], sparse code multiple access (SCMA) [7], multi-user shared access (MUSA) [8], and so on.

The MIMO technology is getting increased research attention by using more antennas on the device terminals to achieve better spectral efficiency and throughput [9]. There has been some related work that combines the MIMO technology with the terrestrial return channel systems [10], [11]. However, the complexity of signal processing at each mobile device and the expensive energy consuming radio frequency (RF) chains

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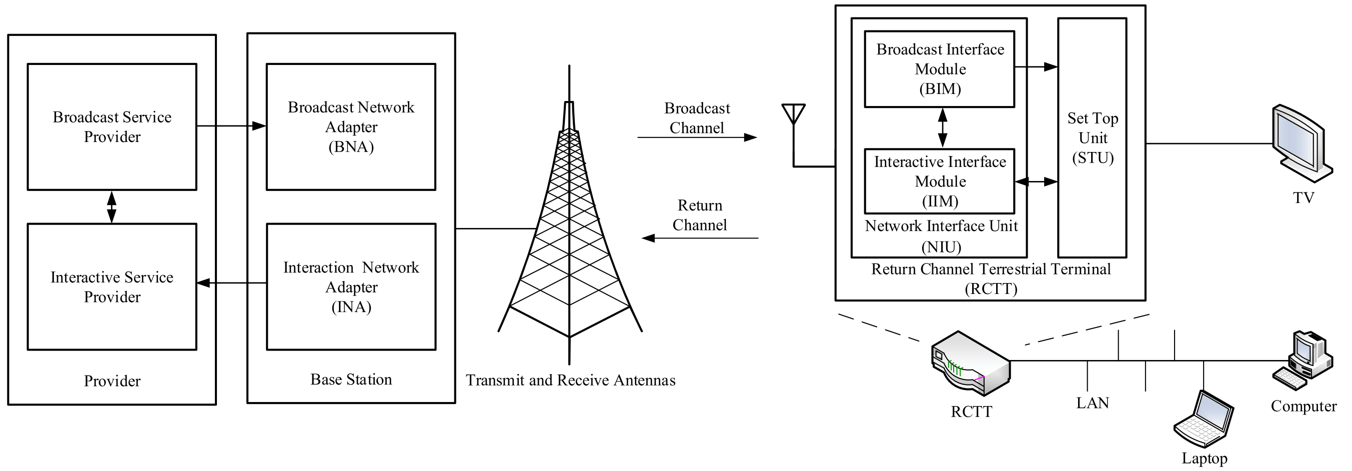

Fig. 1. A generic model of the interactive systems.

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 signal, emerges to meet with the demand of spectral efficiency and energy efficiency [12]. The generalized spatial modulation technology is a generalization of SM by using more than one active antennas at the same time to further improve the spectral efficiency. The extension of generalized SM technologies to the terrestrial return channel improves the spectral efficiency and energy efficiency, but puts forward challenges for the detection scheme.

The conventional generalized SM detection schemes include the maximum likelihood (ML) detection and linear detection schemes. However, the ML detection has unacceptable complexity, and the linear detection schemes such as zero-forcing (ZF) detection and minimum mean-squared error (MMSE) detection have limited performance. In [13] and [14], detection schemes based on message passing are proposed and achieve superior performance than the conventional detection schemes. However, they are limited by high complexity when the scale is large. Because of the sparsity of the generalized SM signal, the detection schemes based on the compressive sensing (CS) [15] method become competitive alternatives with low complexity, especially in the large-scale scenario [16]–[18]. CS is one of the efficient signal processing techniques, which has been utilized in many aspects in communication systems, such as interference cancellation [19], [20], noise elimination [21], channel estimation [22]–[24], and so on [25].

In this paper, we introduce the generalized SM technology to the terrestrial return channel and formulate the system into a block-sparse model. Accordingly, a novel detection scheme is proposed based on the block-sparse compressive sensing (BS-CS) method [26]–[28], which is referred to as enhanced structured block-sparse compressive sensing matching pursuit (ESB-CoSaMP). We look into the algorithm of block-based CoSaMP and make use of the structure of the multiuser generalized SM signal to improve detection performance. Simulations show that the proposed scheme outperforms the conventional BS-CS methods and linear detection schemes.

The rest of the paper is organized as follows. In Section II, we present the system model of the terrestrial return channel with generalized spatial modulation. In Section III, the details of the proposed ESB-CoSaMP detection scheme is explained. In Section IV, the computational complexity analysis is provided. The simulation results and discussion are presented in Section V, and finally we come to the conclusion in Section VI.

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, respectively; $\binom{\cdot}{\cdot}$ denotes the binomial coefficient; $\mathbf{v}_i$ and $\mathbf{v}|_{\Phi}$ represent the i-th sub-block of vector $\mathbf{v}$ and the components of vector $\mathbf{v}$ in the index set Φ, respectively; $\mathbf{M}_i$ and $\mathbf{M}|_{\Phi}$ represent the i-th sub-matrix of matrix $\mathbf{M}$ and the sub-matrix of matrix $\mathbf{M}$ with columns in the index set Φ, respectively.

II. System Model

A. Terrestrial Return Channel With Generalized SM-MIMO

An interactive system is considered, which can support K users and S ($S < K$) users are active at the same time, as illustrated in Fig. 2. Under the condition of generalized spatial modulation, each user is 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 signal of each possible user, which can be expressed as

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

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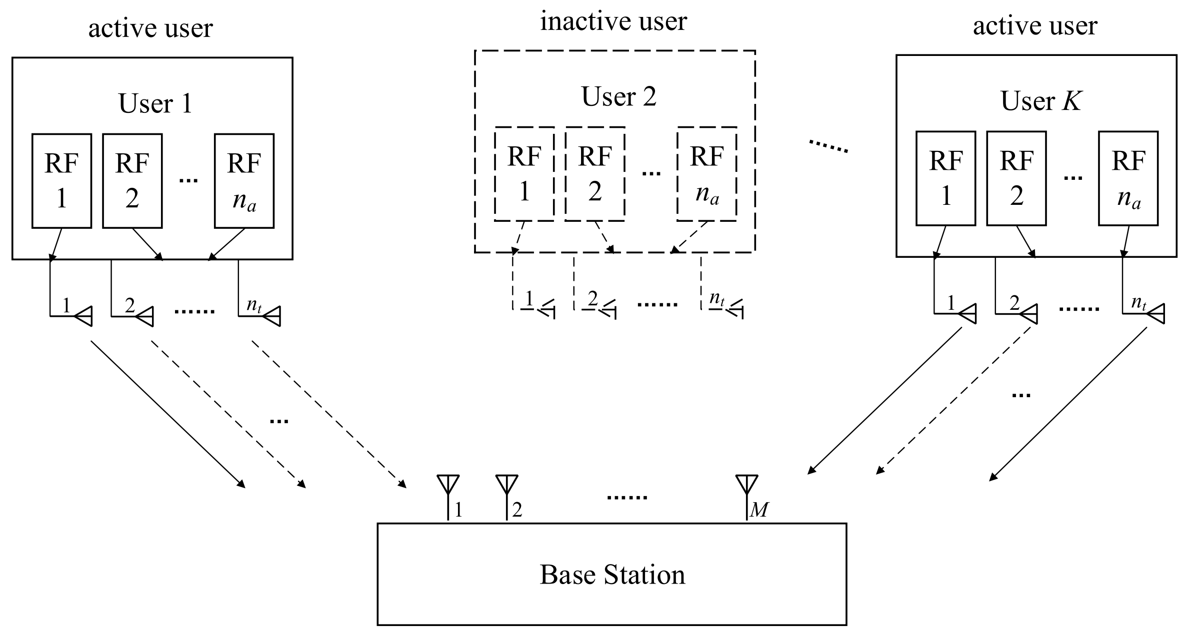

Fig. 2. Terrestrial return channel with generalized SM-MIMO.

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 signal. 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

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

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

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

bits per channel use (bpcu).

B. Block-Sparse Signal Detection

Block sparsity: For a vector $\mathbf{c} \in \mathbb{C}^{N \times 1}$, it can always be written into a concatenation of P ($P \leq N$) sub-blocks, i.e, $\mathbf{c} = [\mathbf{c}_1^T, \mathbf{c}_2^T, \ldots, \mathbf{c}_P^T]^T$, 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 $\mathbf{c}$ is nonzero. Mathematically, the $\ell_{2,0}$-norm can be used to define block sparsity [26], 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 $\|\mathbf{c}\|_{2,0} \leq k$.

Block RIP: As defined in [29], the block restricted isometry property of a matrix $\mathbf{B}$ is the smallest constant $\delta_{B,k}$, such that

$$\left(1 - \delta_{B,k}\right)\|\mathbf{c}\|_2^2 \leq \|\mathbf{B}\mathbf{c}\|_2^2 \leq \left(1 + \delta_{B,k}\right)\|\mathbf{c}\|_2^2 \tag{6}$$

holds for every *k-block-sparse* vector $\mathbf{c}$. As shown in [29], if the block RIP condition holds, i.e., $\delta_{B,2k} < \sqrt{2} - 1$, the $\ell_{2,0}$-norm minimum recovery problem can be relaxed to a convex $\ell_{2,1}$-norm minimum recovery problem.

So far, there have been many efficient block-sparse recovery algorithms based on the compressive sensing methods, such as block orthogonal matching pursuit (BOMP) [26], block-based compressive sampling matching pursuit (block-based CoSaMP) [28], block iterative hard thresholding (Block IHT) [30], and so on.

III. Proposed BS-CS Based Detection Scheme

In this section, an enhanced BS-CS based detection scheme is proposed. It will begin with the block-sparse formulation of the multi-user and signal detection problem. And then a theoretical analysis is provided based on the block RIP. Finally the details of the proposed detection scheme is given.

A. Block-Sparse Formulation

According to the statistics in [31], the supported users 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.,

$$\mathbf{x} = \left[\ldots, \underbrace{0, \ldots, 0}_{\mathbf{x}_i^T}, \ldots, \underbrace{x_{j,1}, \ldots, x_{j,n_t}}_{\mathbf{x}_j^T}, \ldots,\right]^T, \tag{7}$$

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.

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As talked above, the recovery of multiuser generalized SM signal $\mathbf{x}$ in the terrestrial return channel can be formulated into a block-sparse recovery problem, which can be described as

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

B. Block RIP Analysis

In the terrestrial return channel, the Rayleigh flat fading channel is usually considered and the channel matrix $\mathbf{H}$ is comprised of i.i.d. Gaussian random variables. We follow [32] and [33] to show that the Rayleigh flat fading channel matrix can satisfy the block RIP condition with a high probability.

The analysis in [32] is based on the Johnson-Lindenstrauss (JL) Lemma and it is proven that the random matrix drawn according to i.i.d. Gaussian distribution can satisfy the concentration inequality (9),

$$\Pr\Big(\big|\|\mathbf{H}\mathbf{x}\|_2^2 - \|\mathbf{x}\|_2^2\big| \geq \epsilon\|\mathbf{x}\|_2^2\Big) \leq 2e^{-Mc_0(\epsilon)}, \tag{9}$$

where $\epsilon \in (0,1)$ and $c_0(\epsilon)$ is a positive constant depending on ϵ. And then for any *k-sparse* vector $\mathbf{x}$ and any $0 < \delta_k < 1$, we have

$$(1-\delta_k)\|\mathbf{x}\|_2^2 \leq \|\mathbf{H}\mathbf{x}\|_2^2 \leq (1+\delta_k)\|\mathbf{x}\|_2^2 \tag{10}$$

with probability

$$\Pr \geq 1 - 2(12/\delta_k)^k e^{c_0(\delta_k/2)M}. \tag{11}$$

Let $k = S{*}n_t$, and the standard RIP is satisfied with probability

$$\Pr \geq 1 - 2\big(12/\delta_{S*n_t}\big)^{S*n_t} e^{c_0\left(\delta_{S*n_t}/2\right)M}. \tag{12}$$

In the scenario considered in this paper, the multi-user signal $\mathbf{x}$ is *S-block-sparse* and has at most n_t non-zero elements in each block, which can be seen as a special case of the *$(S*n_t)$-sparse* vector. Since the block RIP only cares about the *$(S*n_t)$-sparse* vectors with block structures which are subsets of the *$(S*n_t)$-sparse* vectors, it can be satisfied with a smaller coefficient $\delta_{B,S} < \delta_{S*n_t}$.

Thus if we have enough receive antennas at the base station, the channel matrix can satisfy the RIP condition with a high probability and the recovery problem can be relaxed to a $\ell_{2,1}$-norm minimum problem, which is

$$\begin{aligned} \min_{\mathbf{x}} \|\mathbf{x}\|_{2,1} &= \min_{\mathbf{x}} \sum_{l=1}^{K} \|\mathbf{x}_l\|_2 \\ \text{s.t.} \quad \mathbf{y} &= \mathbf{H}\mathbf{x}. \end{aligned} \tag{13}$$

Thus the conventional CS and BS-CS algorithms, especially the greedy algorithms, can be applied to the detection problem.

C. Details of the Proposed Detection Scheme

In this subsection, the details of the proposed BS-CS based detection scheme are provided, which utilizes the information of active antennas at each user to achieve superior 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.

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:
1: $i \leftarrow 0$
2: $\hat{\mathbf{x}}^{(0)} \leftarrow \mathbf{0}$
3: $\mathbf{r}^{(0)} \leftarrow \mathbf{y}$
4: $\Psi^{(0)} \leftarrow \varnothing$

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

Result Construction:
18: $\hat{\mathbf{x}} \leftarrow \hat{\mathbf{x}}^{(i_{\max})}$

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

The variables are initialized as $i=0$, $\hat{\mathbf{x}}^{(0)} = \mathbf{0}$ 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 stopping criterion is true.

A simple variable $i_{\max}$ is utilized as the stopping 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

$$\mathbf{e}_\omega = \mathbf{H}_\omega^{\mathrm{H}}\mathbf{r}^{(i-1)}, \omega \in [1,K], \tag{14}$$

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

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largest ℓ_2-norm to form the support set Ω_{b}, i.e.,

$$\Omega_{\mathrm{b}} = \left\{\omega_k | \omega_k = arg \max_{\omega_k; k\in[1,S]} \|\mathbf{e}_{\omega_k}\|_2\right\}. \tag{15}$$

As in conventional block-based CoSaMP, the support set of the estimation of signal residual is found in the block level, which utilizes the block-sparse structure of the multiuser generalized SM signal 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. In conventional block-based CoSaMP algorithm, the processing of the support set is carried out in the block level to ensure the block-sparse structure of the results. However, for the problem considered in this paper, the multi-user generalized SM signal leads to sparsity in each block, which means not all the elements in each block are non-zero. The processing in the block level contains redundant elements and the transformation to the index level will provide more exact results. Then Ω is merged with the support set $\Psi^{(i-1)}$, which is derived from the $(i-1)$-th estimation of signal $\hat{\mathbf{x}}$. 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-square 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 obtain $\hat{\mathbf{b}}$. The proposed $\hat{\mathbf{b}}$ is derived by choosing n_a largest components of each block of $\mathbf{b}$ and setting other small components to be $\mathbf{0}$, i.e.,

$$J_\psi = \left\{j_k | j_k = \max_{j_k; k\in[1,n_a]} \|\mathbf{b}_{\psi,j_k}\|_2\right\}, \psi \in [1, K], \tag{16}$$

$$\hat{\mathbf{b}}_\psi|_{J_\psi} = \mathbf{b}_\psi|_{J_\psi}, \hat{\mathbf{b}}_\psi|_{{J_\psi}^C} = \mathbf{0}, \tag{17}$$

where $\mathbf{b}_{\psi,j}$ denotes the j-th component of the ψ-th sub-block of vector $\mathbf{b}$. 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 signal. 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 recovery 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

$$\Psi^{(i)} = \mathrm{supp}\left(\hat{\mathbf{x}}^{(i)}\right), \tag{18}$$

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-square 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 derive the indexes of active users and active antennas of each user from $\mathrm{supp}(\hat{\mathbf{x}})$, where $\mathrm{supp}(\hat{\mathbf{x}})$ denotes the support set of $\hat{\mathbf{x}}$.

TABLE I
COMPLEXITY OF SOLVING AN $m \times n$ LEAST-SQUARE PROBLEM

Method	Complexity in flops
QR Decomposition	$8n^2m - \frac{8}{3}n^3 + 8mn + 4n^2$
Cholesky Decomposition	$4n^2m + \frac{4}{3}n^3 + 8mn + 11n^2$
Conjugate Gradient	$16mn + 18n + i_{ls} \times (16mn + 27n)$

IV. COMPUTATIONAL COMPLEXITY ANALYSIS

In this section, the complexity analysis of the proposed detection method is provided and the complexity of the conventional CS and BS-CS based detection methods is also addressed as comparison. As adopted in [11] and [17], the total number of real multiplications and additions of each method is considered for the computational complexity analysis, which is also called the number of real floating-point operations (flops). Therefore, one complex multiplication is counted as four real multiplications.

Thus, the computational complexity of each operation of the proposed ESB-CoSaMP detection scheme in each iteration can be summarized as follows.

Phase 7: In this operation, the signal residual is estimated by the complex multiplications of $\mathbf{H}_\omega^{\mathrm{H}}$ and $\mathbf{r}^{(i-1)}$. Thus the complexity is $O(8MN)$.

Phase 8: The ℓ_2-norm of $\mathbf{e}_\omega$ is calculated and the total complexity is $O(4N)$.

Phase 11: The signal approximation is derived by solving the least-square problem $\mathbf{H}|_T^\dagger\mathbf{y}$. The computational complexity of the least-square problem can be determined by the dimension of the problem and the specific method applied. We denote the complexity of an $m \times n$ least-square problem using a specific method as $C_{m\times n}^{ls}$. And some complexity analysis results are provided in Table I [17], where i_{ls} denotes the maximum number of iteration in the conjugate gradient method.

Phase 13: In this step, the ℓ_2-norm of each component of $\mathbf{b}$ is calculated to find n_a largest components in each block. Thus the complexity is $O(3N)$.

Phase 14: After the preprocessing method, there are at most $n_a \times K$ non-zero components in $\mathbf{b}$, and the ℓ_2-norm of each component is calculated in the preprocessing step. Thus only $n_a \times K$ real additions are needed to obtain each $\mathbf{b}_\psi$.

Phase 16: The residual is updated by $\mathbf{r}^{(i)} = \mathbf{y} - \mathbf{H}\hat{\mathbf{x}}^{(i)}$, where $\hat{\mathbf{x}}^{(i)}$ is a (Sn_a)-*sparse* vector. Thus the complexity of this step is $O(8MSn_a)$.

Therefore, the total computational complexity of the proposed detection method is given by

$$C_{\mathrm{ESB}} \simeq i_{max} \times (8MN + 8MSn_a + 7N + Kn_a) + C_{M\times Sn_t}^{ls} + C_{M\times S(n_t+n_a)}^{ls} \times (i_{max} - 1), \tag{19}$$

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TABLE II
COMPLEXITY ANALYSES OF THE PROPOSED METHOD AND THE CONVENTIONAL CS AND BS-CS BASED METHODS

Detection Method	Complexity in flops
OMP	$C_{\text{OMP}} \simeq Sn_a \times (8MN + 4MSn_a + 3N + 4M) + \sum_{j=1}^{Sn_a} C_{M\times j}^{ls}$
BOMP	$C_{\text{BOMP}} \simeq S \times (8MN + 4MSn_t + 4N + 4Mn_t) + \sum_{j=1}^{S} C_{M\times jn_t}^{ls}$
CoSaMP	$C_{\text{CoSaMP}} \simeq i_{max} \times (8MN + 8MSn_a + 6N) + C_{M\times Sn_a}^{ls} + C_{M\times 2Sn_a}^{ls} \times (i_{max} - 1)$
Block-based CoSaMP	$C_{\text{Block-based}} \simeq i_{max} \times (8MN + 8MSn_a + 8N) + C_{M\times Sn_t}^{ls} + C_{M\times 2Sn_t}^{ls} \times (i_{max} - 1)$
ESB-CoSaMP	$C_{\text{ESB}} \simeq i_{max} \times (8MN + 8MSn_a + 7N + Kn_a) + C_{M\times Sn_t}^{ls} + C_{M\times S(n_t+n_a)}^{ls} \times (i_{max} - 1)$

where i_{max} is the maximum number of iteration in the ESB-CoSaMP method. The computational complexity analyses of the conventional CS and BS-CS based detection methods are given in Table II, where j denotes the iteration index of the detection methods.

It can be seen from Table II that in the OMP and BOMP based methods, the dimensions of the least-square problems are lower in the first couple of iteration; however, they become larger with the increase of the iteration index. Moreover, the iteration time is equal to the sparse level in these two methods. Thus, the complexity will increase significantly with the increase of the sparse level. As for the CoSaMP, the block-based CoSaMP and the proposed ESB-CoSaMP methods, the CoSaMP method has the lowest computational complexity without considering the block structure of the signal. And the proposed ESB-CoSaMP method enjoys lower complexity than the block-based CoSaMP method because of the more exact selection of the merged support set.

V. SIMULATION RESULTS

In this section, the simulation results of the proposed detection scheme are presented in a terrestrial return channel using multiuser generalized SM technology over the Rayleigh flat fading channel as described in Section II-A. 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 signal. To show the performance improvement of the proposed scheme, the conventional CS and BS-CS based detection scheme, i.e., OMP [34], CoSaMP [35], BOMP [26] and block-based CoSaMP [28] are implemented for comparison.

In the first scenario, we investigate the bit error rate (BER) of the proposed detection scheme and the simulation results are shown in Fig. 3. The base station is equipped with $M = 50$ antennas, which can support $K = 32$ users with $n_t = 4$ antennas each. $S = 4$ users are active at the same time and each of them activates $n_a = 2$ antennas to transmit signal. The 4QAM modulation is applied. The simulation results demonstrate that the CoSaMP based detectors (CoSaMP and block-based CoSaMP) outperform the OMP based detectors (OMP and BOMP), which is because the inherent pruning and support update steps in the CoSaMP algorithm can correct some wrong detections of the active antennas during iterations. It also shows that the block-sparse CS based detectors (BOMP and block-based CoSaMP) outperform the corresponding conventional CS based detectors because of the

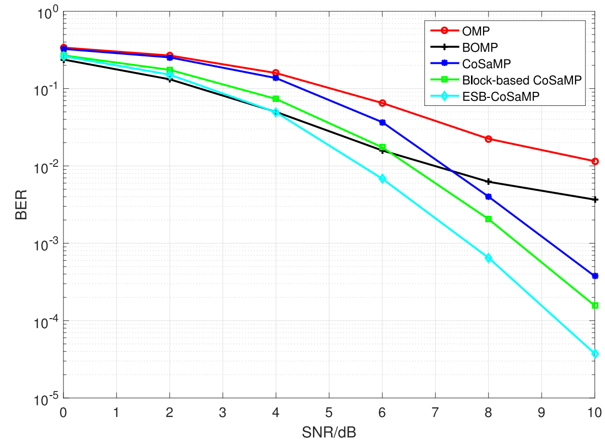

Fig. 3. BER comparisons between OMP, BOMP, CoSaMP, block-based CoSaMP and the proposed ESB-CoSaMP for the first scenario.

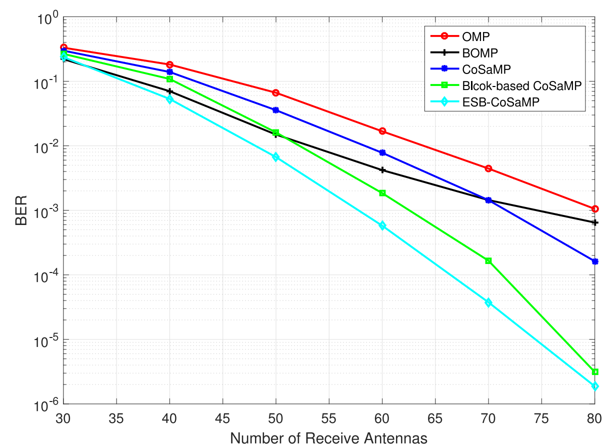

Fig. 4. BER comparisons with different number of receive antennas at the base station for the first scenario when SNR = 6 dB.

utilizing of the block-sparse structure of the multiuser generalized SM signal. Among all the simulated detectors, the proposed ESB-CoSaMP based detector enjoys the lowest BER and the performance gap becomes large with the increase of the signal to noise ratio (SNR). The reason behind this is that not only the block-sparse structure, but also the structure of each generalized SM signal is taken into consideration in the proposed method.

We further investigate the BER performance of the detectors under different numbers of receive antennas at the base station. The simulations are carried out in the same scenario as in Fig. 3 and the SNR is 6 dB. It can be seen from Fig. 4 that the detectors cannot detect the signal without enough receive

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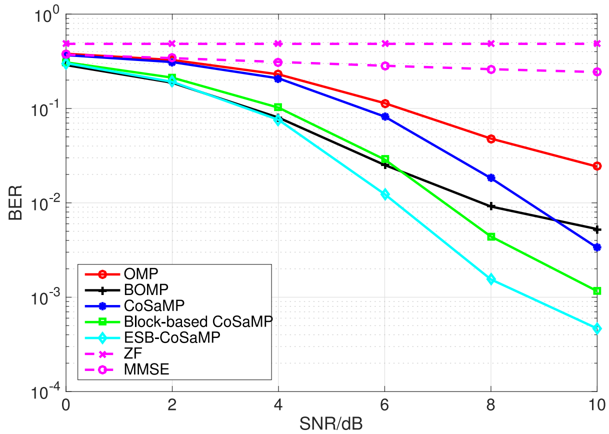

Fig. 5. BER comparisons between OMP, BOMP, CoSaMP, block-based CoSaMP, ESB-CoSaMP, ZF and MMSE for the second scenario.

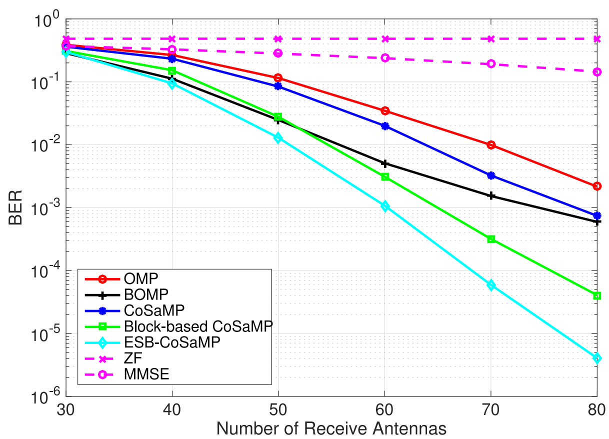

Fig. 6. BER comparisons with different number of receive antennas at the base station for the second scenario when SNR = 6 dB.

TABLE III
DATA RATE AND BER COMPARISONS WITH DIFFERENT n_a

n_a	1	2	3
Data rate	4 bpcu	6.585 bpcu	8 bpcu
BER	$2.25 * 10^{-4}$	$6.59 * 10^{-3}$	$2.12 * 10^{-2}$

antennas, which is consistent with the CS theory. And the performance of all the detectors improves with the increase of the number of receive antennas. The proposed detection scheme still enjoys BER advantages in each case.

The number of active antennas n_a not only affects the signal sparsity but also controls the data rate of each user according to (4). Then the detection performance with different n_a is investigated in the first scenario when SNR $= 6$ dB. The data rates of each user and the BER simulation results are shown in Table III. It can be seen that the date rates increase with n_a, since more antennas are activated to transmit signal. However, the BER performance gets worse with increased n_a. This is because more active antennas increase the interference and decrease the signal sparsity, which cause difficulty for the detection of generalized SM signal.

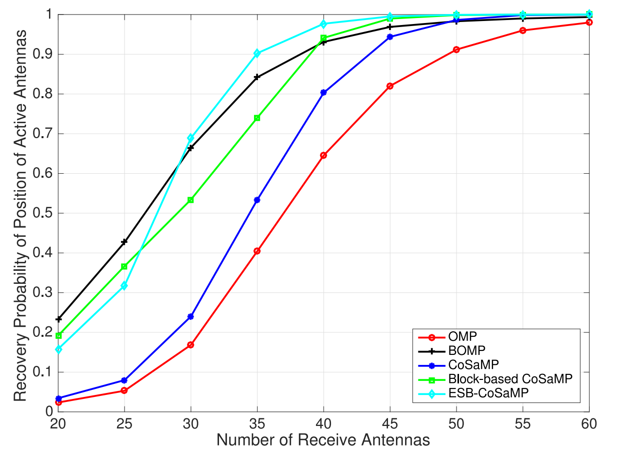

Fig. 7. Recovery probability comparisons of the active antennas between different compressive sensing based detection schemes, SNR = 10 dB.

In the second scenario, we consider an interactive system with more supported users, the number of which becomes $K = 64$ and the numbers of antennas at the base station and each user remain $M = 50$ (in Fig. 5) and $n_t = 4$. Other parameters remain the same as in the first scenario. The simulation results are shown in Fig. 5 and Fig. 6. It can be seen from the figures that the BER performance of all the simulated detectors gets worse because of the increase of supported users. This is due to the dimension of the multiuser generalized SM signal doubles, which causes more difficulties in the detection process. It is worth noting that the proposed ESB-CoSaMP method still enjoys the best BER performance under different SNRs and different numbers of receive antennas with an increased number of supported users. The BER performance of linear detection schemes is also investigated for this scenario. Two kinds of linear detection schemes, i.e., zero-forcing (ZF) and minimum mean-squared error (MMSE) are investigated for comparison. According to [17], the linear detection matrix $\mathbf{D}$ is given by

$$\mathbf{D}^{\mathrm{ZF}} = \mathbf{H}^{\dagger} = \left(\mathbf{H}^{\mathrm{H}}\mathbf{H}\right)^{-1}\mathbf{H}^{\mathrm{H}}, \tag{20}$$

$$\mathbf{D}^{\mathrm{MMSE}} = \left(\mathbf{H}^{\mathrm{H}}\mathbf{H} + \frac{1}{\mathrm{SNR}}\mathbf{I}\right)^{-1}\mathbf{H}^{\mathrm{H}}. \tag{21}$$

It can be seen from Fig. 5 and Fig. 6 that the BER of linear detection schemes is much higher than the compressive sensing based schemes. Since the number of receive antennas at the base station is much less than the total number of transmit antennas at the users, the detection problem is under-determined, which causes performance degradation for the linear detection schemes.

In Fig. 7, the recovery probability of the position of the active antennas with different numbers of receive antennas is investigated in the second scenario when the SNR is 10 dB. It is shown that the proposed detection scheme enjoys a better recovery probability with enough receive antennas. It can be seen that the recovery probability of BOMP and block-based CoSaMP is a little bit higher when the number of receive antennas is low; however, the BER is only about 0.3 in this situation according to Fig. 6, where the number of receive antennas is not sufficient.

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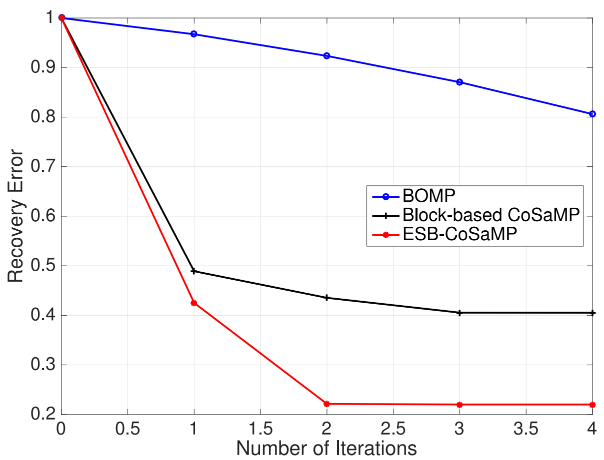

Fig. 8. Recovery error comparisons between the block-sparse compressive sensing based detection schemes, SNR = 10 dB.

In Fig. 8, the average recovery error performance of the block-sparse compressive sensing based detection scheme is investigated, which is defined as $\|\hat{\mathbf{x}} - \mathbf{x}\|_2$. The simulations are carried out in the third scenario 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 the fastest convergence rate in the three BS-CS based detectors. In the BOMP algorithm, it only selects one new block into the support set in each iteration, thus it needs S iterations to find all the supports. So it has the slowest convergence rate. However, the block-based CoSaMP and the proposed ESB-CoSaMP algorithms select S blocks in each iteration, resulting in faster convergence rate. Moreover, in the ESB-CoSaMP algorithm, new support set is found in the block level to ensure the block-sparse structure and is processing in the index level to provide more exact support set. Thus the convergence rate of ESB-CoSaMP is much faster. It can also be seen from the simulation that the average recovery error floor of the proposed ESB-CoSaMP is lower than that of the block-based CoSaMP. This is because of the preprocessing step introduced in Phase 13 in the ESB-CoSaMP algorithm. Due to the preprocessing step, the influence of the signal approximation of non-active antennas is decreased. Thus during iterations, the ESB-CoSaMP algorithm has smaller chances choosing wrong active users. As a consequence, the ESB-CoSaMP algorithm achieves lower recovery error floor.

VI. Conclusion

In this paper, generalized SM-MIMO technology is introduced into terrestrial return channel to improve the spectral efficiency and energy efficiency. By exploiting the structure and sparsity of the multiuser generalized SM signal, 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 signal efficiently. Simulation results show that the proposed detection scheme outperforms the conventional CS and BS-CS based schemes with lower BER under different SNRs, numbers of receive antennas, and numbers of supported users. The proposed detection scheme also enjoys better performance in convergence rate, recovery error, and recovery probability of the active antennas compared to conventional CS and BS-CS based ones.

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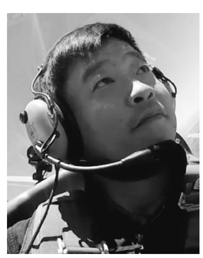

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