Group Sparsity Based Signal Detection for Massive Multi User Spatial Modulation Cyclic Prefix Single Carrier Systems

Sahar Said , Sayed El- Araby
Nuclear Research Center
Atomic Energy Authority
Cairo, Egypt
r_sahar10@yahoo.com, selaraby@netscape.net

Waleed Saad , Mona Shokair
Electronic and Electrical Communications Department
Faculty of Electronic Engineering, Menoufia University
Menouf, Egypt
waleedsaad100@yahoo.com, shokair_1999@hotmail.com

Abstract — **Massive spatial modulation (MSM) is considered as an attractive technique for multi antenna wireless communications. That is because, it gives higher energy efficiency and spectral efficiency than small scale multiple-input multiple-output (MIMO) systems. Massive SM-MIMO utilizes multiple transmit antennas for each user with only one transmit radio frequency (RF) chain and hundreds of receive antennas at base station (BS) with small number of RF chain. Owing to large number of TAs at the user and small number of RF chains at BS, multi user signal detection becomes challenging problem. To solve this matter, a joint grouped SM transmission scheme at users and group subspace pursuit (GSP) based signal detection at BS can be proposed to improve the signal detection performance. Owing to joint transmission scheme, SM signals in same transmission group exhibit group sparsity. Also, spatial signal composed of multiple users' SM signals exhibits distributed sparsity. By utilizing these sparse features, the proposed GSP based signal detection can detect SM signals more reliability than other detection techniques. Additionally, the cyclic prefix single carrier (CPSC) is utilized to withstand the multipath channels. Simulation results prove that BER performance of the proposed GSP based signal detection outperforms classical SP based signal detection by 3dB SNR gain at BER=10^{-4}.**

Keywords—Massive SM-MIMO,,Compressive Sensing (CS), Cyclic prefix single carrier (CPSC) ,Subspace Pursuit (SP)

I. INTRODUCTION

Massive spatial modulation (SM-MIMO) systems are attractive for future wireless communication systems due to providing high energy efficiency and high system capacity [1-2]. Where massive MIMO and spatial modulation MIMO systems are considered as promising techniques for 5G systems. Massive MIMO utilizes hundreds of antennas at BS with one RF chain for each antenna (number of antennas equal to number of RF chains). This leads to increase power consumption and hardware cost due to using one RF chain for every antenna element. Therefore, SM-MIMO can utilize to reduce number of RF chains by making multiple of transmit antennas with one RF chain. Moreover, it activates part of available antenna element to send information in spatial domain in addition to information bits that sent through classical modulation symbols (e.g. 16QAM). Therefore, SM-MIMO has high energy efficiency and reduced hardware cost [3-5]. Actually, both techniques have their advantages and disadvantages. Therefore, by combination each of massive MIMO and SM-MIMO, one can imagine win to win situation. In fact, SM-MIMO is an attractive for massive MIMO systems due to reducing number of wanted RF chains. This leads to minify power consumption and hardware cost in massive MIMO. Moreover, massive MIMO with hundreds of antenna elements at BS can increase the system throughput of SM-MIMO. This reciprocity enables massive MIMO and SM-MIMO to enjoy virtual compatibility.

In this paper, massive SM-MIMO can be proposed for merging the benefits of both massive MIMO and SM-MIMO for 5G systems. In this technique, each user utilizes multiple transmit antennas (TAs) with only one RF chain for raising the system throughput. Hundreds of antenna elements at BS with small number of RF chains are made to serve multiple users simultaneously. The CPSC transmission scheme is considered to combat the multipath channels [6]. The direct antenna element selection scheme at BS was introduced to improve the system performance [7-8]. The proposed scheme sums the advantages each of massive MIMO and SM-MIMO while decreasing the power consumption and hardware cost.

In fact, due to large number of TAs at users and limited number of RF chains at BS, multiuser signal detection for massive SM-MIMO becomes challenging problem. The optimum maximum like hood signal detector (ML) suffers from high complexity when the number of transmit antennas (TAs) becomes large [9]. Further, sphere decoding [10] detectors suffer from high complexity for massive SM-MIMO but it can be used with SM-MIMO. Furthermore, minimum mean square error (MMSE) based signal detector [4] is unsuitable for proposed massive SM-MIMO owing to large number of TAs at users and limited number of RF chains at BS. By introducing the idea of inherent sparsity for SM signals, compressive sensing based signal detectors [11-12] were proposed for small scale SM-MIMO. However, their bit error rate (BER) performance has gap contrasted with optimal ML detector and massive SM-MIMO with large TAs and receive antenna at BS.

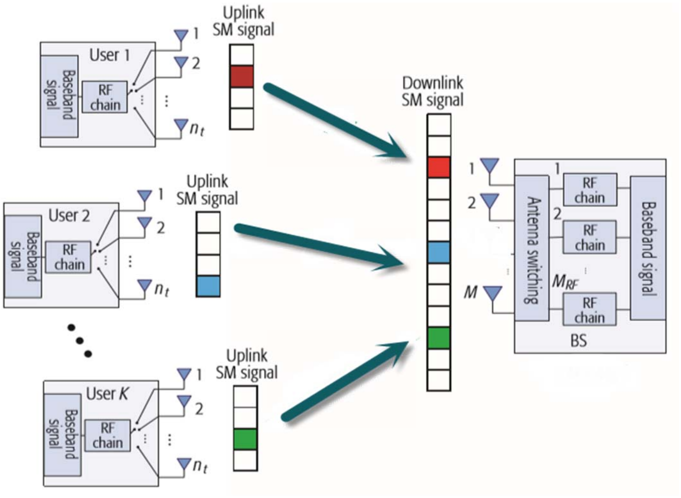

Fig.1 Massive Spatial Modulation System Architecture.

In this paper, GSP based signal detector will be proposed for massive SM-MIMO. By exploiting specific signal structure in massive SM-MIMO, where each user only activates a single antenna element in each time slot. Hence, SM signal consisted of multiple users' SM signals of CPSC block shows distributed sparsity, which can be utilized for improving the signal detection performance. Moreover, a joint grouped transmission scheme will be suggested at the users coupling with GSP based signal detector at the BS. By utilizing both of distributed sparsity of SM signal and group sparsity of multiple SM signals due to joint grouped transmission scheme, the proposed GSP based signal detection can detect SM signals more reliability than classical CS based signal detection.
The contributions of this paper can be summarized as follows:

- Investigating a joint grouped transmission scheme at the users and GSP based signal detector at the BS
- Studying BER performance for detecting each of spatial constellation symbol and signal constellation symbol with different number of BS antennas.
- Studying total BER performance for detecting SM signal with different numbers of users.
- Making comparisons between proposed GSP based signal detector with different detection techniques.

This paper is organized as follows: System model will be illustrated in Section II. The proposed GSP based signal detection will be offered in Section III. Simulation results and discussions will be carried out in Section IV. Finally, in Section V conclusions will be made.

II. SYSTEM MODEL

Consider massive SM-MIMO system with K uplink users , n_t transmit antennas and M receive antennas at BS as shown in Fig. 1. For massive SM-MIMO, large number of transmit antennas at users with only one RF chain and hundreds of antennas at BS with small number of RF chains where $\boldsymbol{M_{RF}} < \boldsymbol{M}$. Hence, using reduced number of RF chain contrasted with total number of antenna elements at the BS can minify both power consumption and hardware cost [3]. Where direct antenna element selection scheme may be adopted for electing the most suitable $\boldsymbol{M_{RF}}$ antenna elements at the BS to receive SM signals [7].

Each SM signal $\boldsymbol{x_K}$ transmitted by Kth users consists of two symbols $\boldsymbol{x_k = s_k e_k}$: signal constellation symbol $s_K \in L$ is coming from signal constellation set of L-ary with information bits equal to $log_2(L)$ where L is signal constellation symbol set (e.g. 16QAM) and spatial constellation symbol e_K is producing by mapping $log_2(n_t)$ bits to index of active TA. Therefore, information bits for each SM signal are equal to $log_2(L) + log_2(n_t)$ bits per channel use (bpcu). Where the overall uplink (UL) throughput is $K(log_2(L) + log_2(n_t))$ bpcu.

Owing to only one RF chain utilized at each user ,only one entry of e_K connected with active antenna is equal to one and the reminder of the entries e_K are zeros, i.e. we have

$$\boldsymbol{supp(e_K) \in A \quad , \quad \|e_k\|_0 = 1 \quad ,\|e_k\|_2 = 2} \tag{1}$$

Where $A = \{1,2, \dots \dots \dots, n_t\}$ is the spatial constellation symbol set.

For transmitting SM signals, CPSC transmission scheme [6] can be considered to combat the multipath channels over P samples. Each CPSC block consists of a cyclic prefix (CP) having the length of $P - 1$ and data block having the length of Q . Therefore, the length of each CPSC block equals to $Q + P - 1$. Also, data block consists of Q sequential SM signals.

After removal of cyclic prefix at the receiver, the received signal $y_q \in C^{M_{RF}}$ for $1 \le q \le Q$ of the qth time slot of CPSC block can be considered as

$$\boldsymbol{y_q} = \sum_{k=1}^{K} \boldsymbol{y_{k,q} + w_q}$$

$$= \sum_{p=0}^{P-1} \sum_{k=1}^{K} \boldsymbol{H}_{k,p}|_{\Theta} \ \boldsymbol{x_{k,mod(q-p,Q)} + w_q}$$

$$= \sum_{p=0}^{P-1} \sum_{k=1}^{K} \boldsymbol{\widetilde{H}_{k,p}\, x_{k\,,mod(q-p,Q)} + w_q} \tag{2}$$

Where $\boldsymbol{\widetilde{H}_{k,p}}$ is $\boldsymbol{M x\, n_t}$ channel matrix for kth user for pth multipath components and Θ is defined by direct antenna element selection scheme [7]. Where direct antenna element selection scheme can be made to select only M_{RF} receive antenna elements that can be exploited to receive signals .That is because ,there is limited number of RF chains at BS. $\boldsymbol{w_q}$ is additive white Gaussian noise (AWGN) with zero mean and noise variance $\sigma^2{}_w$.

By considering the Q SM signals of CPSC block, received signal can be considered by:

$$\boldsymbol{y = \widetilde{H}\, x + w} \tag{3}$$

Where received signal $y = \left[(y_1)^T, (y_2)^T, \dots \dots \dots, (y_Q)^T\right]^T$, SM signal $x = \left[(x_1)^T, (x_2)^T, \dots \dots \dots, (x_Q)^T\right]^T$, $w = \left[(w_1)^T, (w_2)^T, \dots \dots \dots, (w_Q)^T\right]^T$ and

$$\widetilde{\boldsymbol{H}} = \begin{bmatrix} \widetilde{\boldsymbol{H}}_0 & \mathbf{0} & \mathbf{0} & \dots & \widetilde{\boldsymbol{H}}_2 & \widetilde{\boldsymbol{H}}_1 \\ \widetilde{\boldsymbol{H}}_1 & \widetilde{\boldsymbol{H}}_0 & \mathbf{0} & \dots & \vdots & \widetilde{\boldsymbol{H}}_2 \\ \vdots & \widetilde{\boldsymbol{H}}_1 & \widetilde{\boldsymbol{H}}_0 & \dots & \widetilde{\boldsymbol{H}}_{P-1} & \vdots \\ \widetilde{\boldsymbol{H}}_{P-1} & \vdots & \widetilde{\boldsymbol{H}}_1 & \vdots & \mathbf{0} & \widetilde{\boldsymbol{H}}_{P-1} \\ \mathbf{0} & \widetilde{\boldsymbol{H}}_{P-1} & \vdots & \vdots & \vdots & \mathbf{0} \\ \vdots & \mathbf{0} & \widetilde{\boldsymbol{H}}_{P-1} & \vdots & \vdots & \vdots \\ \vdots & \vdots & \mathbf{0} & \dots & \mathbf{0} & \vdots \\ \vdots & \vdots & \vdots & \dots & \widetilde{\boldsymbol{H}}_0 & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{0} & \dots & \widetilde{\boldsymbol{H}}_1 & \widetilde{\boldsymbol{H}}_0 \end{bmatrix} \quad \textbf{(4)}$$

The optimal signal detector for (3) depends on the ML algorithm

$$\min_{\hat{\boldsymbol{x}}} \left\| \boldsymbol{y} - \widetilde{\boldsymbol{H}}\hat{\boldsymbol{x}} \right\|_2 = \min_{\{\hat{x}_{k,q}\}_{k=1,q=1}^{K,Q}} \left\| \boldsymbol{y} - \widetilde{\boldsymbol{H}}\hat{\boldsymbol{x}} \right\|_2$$

$$\boldsymbol{s.t.}\ \ \boldsymbol{supp}(\hat{\boldsymbol{x}}_{k,q}) \in \boldsymbol{A}\ ,\hat{\boldsymbol{x}}_{k,q}|_{supp(\hat{x}_{k,q})} \in \boldsymbol{L},\ \ \mathbf{1} \le \boldsymbol{k} \le \boldsymbol{K}, \mathbf{1} \le \boldsymbol{q} \le \boldsymbol{Q} \quad \textbf{(5)}$$

Increasing the size of the search set for ML detector, leads to increase the complexity which complexity exponentially rises with the number of users. This complexity is un affordable practically. To minify it , sphere decoding detector [9] was proposed ,but it has high complexity ,especially for the systems have large $K, Q, nt\ and\ L$ [13]. Further, near optimal MMSE based signal detector is suitable with massive MIMO but it is unsuitable with massive SM-MIMO due to large number of TAs and limited number of RF chains. Therefore, signal detection problem for massive SM-MIMO systems become challenging problem. By utilizing the sparsity property for SM-signals, compressive sensing (CS)based signal detector can be proposed for small scale SM-MIMO. However, these detectors are unsuitable for massive SM-MIMO. From equation (1), we note that sparse signal $x_{k,q}$ has one sparsity level and consists of multiple user's SM signals in Q time slot ,displays distributed sparsity. This property for sparse signal allows us to utilize the structured compressive sensing (SCS) theory for signal detection [14]. To get better the signal detection performance and to rise the system throughput, joint grouped transmission scheme at users and GSP based signal detection at BS will be suggested for improving the signal detection performance. This technique will be discussed in the next section in detail.

III. PROPOSED GSP BASED SIGNAL DETECTION

To resolve signal detection problem for UL massive SM-MIMO, a joint grouped transmission scheme at the users and GSP based signal detection at the BS will be proposed for improving the signal detection performance by exploiting each of distributed sparsity of the SM signal and group sparsity of multiple SM signals.

A. Joint Grouped Transmission Scheme at the Users

Each sequential J CPSC block for the Kth user in the qth time slot is treated as a group , share the same spatial constellation symbol and share same support set ,i.e.

$$\boldsymbol{supp}\left(\boldsymbol{x}_{k,q}^{(1)}\right) = \boldsymbol{supp}\left(\boldsymbol{x}_{k,q}^{(2)}\right) = \cdots \dots \dots . = \boldsymbol{supp}\left(\boldsymbol{x}_{k,q}^{(J)}\right),$$
$$\mathbf{1} \le \boldsymbol{k} \le \boldsymbol{K}\ , \mathbf{1} \le \boldsymbol{q} \le \boldsymbol{Q} \quad \textbf{(6)}$$

Where J refers to jth CPSC block and is usually small $e.g.\ J = 2$. By utilizing SCS theory, $\boldsymbol{x}_{k,q}^{(1)}, \boldsymbol{x}_{k,q}^{(2)}, \dots \dots, \boldsymbol{x}_{k,q}^{(J)}$ share common support and exhibits group sparsity . Moreover, SM signals exhibit distributed sparsity i.e.,

$$\boldsymbol{supp}\left(\boldsymbol{x}^{(1)}\right) = \boldsymbol{supp}\left(\boldsymbol{x}^{(2)}\right) = \cdots \dots \dots \dots = \boldsymbol{supp}\left(\boldsymbol{x}^{(J)}\right) \quad \textbf{(7)}$$

Although group sparsity may minify the information bits that are carried by spatial constellation symbols, it can improve total bit error rate (BER) performance. This conclusion will be verified in our simulation results.

B. GSP Based Signal Detection at The BS

The received signals at the BS according to (3) can be considered as:

$$\boldsymbol{y}^{(j)} = \widetilde{\boldsymbol{H}}^{(j)}\boldsymbol{x}^{(j)} + \boldsymbol{w}^{(j)}\ \boldsymbol{for}\ \mathbf{1} \le \boldsymbol{j} \le \boldsymbol{J} \quad \textbf{(8)}$$

Where $\boldsymbol{y}^{(j)}$ refers to the received signals in jth CPSC block . $\widetilde{\boldsymbol{H}}^{(j)}$ is channel matrix and $\boldsymbol{w}^{(j)}$ is AWGN vector.

By utilizing each of group sparsity and distributed sparsity for SM signals, signal detection at the BS can be subedited as optimization problem by,

$$\min_{\{\hat{x}^{(j)}\}_{j=1}^{J}} \sum_{j=1}^{J} \left\| \boldsymbol{y}^{(j)} - \widetilde{\boldsymbol{H}}^{(j)}\hat{\boldsymbol{x}}^{(j)} \right\|_2^2$$

$$= \min_{\{\hat{x}_{k,q}^{(j)}\}_{j=1,k=1,q=1}^{J,K,Q}} \sum_{j=1}^{J} \left\| \boldsymbol{y}^{(j)} - \widetilde{\boldsymbol{H}}^{(j)}\hat{\boldsymbol{x}}^{(j)} \right\|_2^2$$

$$\boldsymbol{s.t.}\ \ \left\| \hat{\boldsymbol{x}}_{k,q}^{(j)} \right\|_0 = \mathbf{1}\ , \mathbf{1} \le \boldsymbol{j} \le \boldsymbol{J}, \mathbf{1} \le \boldsymbol{q} \le \boldsymbol{Q}, \mathbf{1} \le \boldsymbol{k} \le \boldsymbol{K} \quad \textbf{(9)}$$

We solve this optimization problem (9) into two stages:

First Stage (Estimation Spatial Constellation Symbols):

A group subspace pursuit algorithm (GSP) derived from conventional subspace pursuit (SP) algorithm [15] was proposed for solving signal detection problem (9). By exploiting each of a prior sparse information $\left\| \hat{\boldsymbol{x}}_{k,q}^{(j)} \right\|_0 = \mathbf{1}$ and group sparsity of $\boldsymbol{x}^{(1)}, \boldsymbol{x}^{(2)}, \dots \dots, \boldsymbol{x}^{(J)}$ to improve the signal detection performance . Where, proposed GSP algorithm

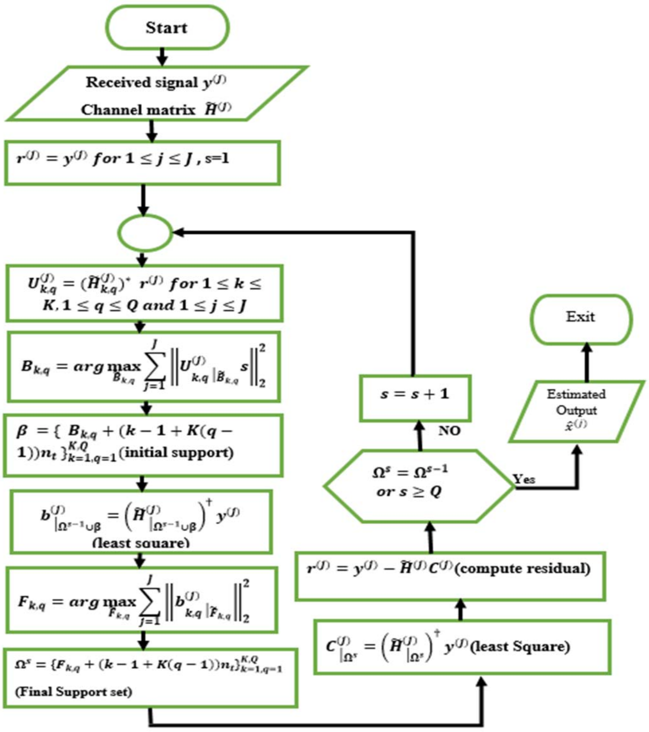

Fig. 2 Flowchart of GSP based Signal Detection.

can estimate SM signal $\{\hat{\boldsymbol{x}}_{k,q}^{(j)}\}_{j=1,k=1,q=1}^{J,K,Q}$ as described in flowchart in Fig. 2.

The flowchart for GSP based signal detection can be demonstrated as follows: First, with received signals $y^{(j)}$ and channel matrices $\widetilde{H}^{(j)}$ as input parameters to GSP algorithm, we measure correlation $U_{k,q}^{(j)}$ between previous residual iteration and MIMO channels , a potential support set $B_{k,q}$ which makes the correlation $U_{k,q}^{(j)}$ largest will be elected from predefined spatial constellation set. Where spatial constellation set can be exploited as prior information, this means that estimated support set during each iteration depends on predefined spatial constellation set. Then, apply least square and make update for current support set $F_{k,q}$, wrong indices will be ejected and most likely indices Ω^{s} will be elected according to least square. After that , compute residual $r^{(j)}$.Finally , repeat iteration index until $\Omega^{s} = \Omega^{s-1}$.

By comparison with conventional SP algorithm, proposed GSP algorithm elects the support set connected with the largest value from local correlation result in every $(\widetilde{\boldsymbol{H}}^{(j)})^{*}\ \boldsymbol{r}^{(j)}$ but conventional SP elects support set linked with the first KQ largest values of the global correlation result $(\widetilde{\boldsymbol{H}}^{(j)})^{*}\ \boldsymbol{r}^{(j)}$**.** Also, proposed GSP based detection can exploit each of distributed sparsity and group sparsity for improving the detection performance.

Second Stage (Estimation Signal Constellation Symbols)

After following stage 1, we can obtain approximate estimate of the signal constellation symbol for each user. By searching for the minimum Euclidian distance between this approximate estimate and reasonable constellation symbols of L .We can acquire the final estimate of the signal estimation symbols.

IV. SIMULATION RESULTS AND DISSCUSTIONS

A. Simulation Setup

In this subsection, many MATLAB programs are executed to compare the performance of proposed GSP based signal detection with each of MMSE based signal detection [4] and conventional SP based signal detection [15-16]. Also, study the performance proposed GSP based signal detection with each of the numbers of users and the numbers of BS antennas at different types of modulation symbols. The system performance is chosen as total bit error rate (BER) which is defined as the number of bit errors divided by total number of transmitted bits during time interval. BER is a uniteless performance measure. Where total BER consist of spatial constellation symbols and signal constellation symbols.

The system model is considered as discussed in Section II with simulation parameters listed in Table I.

Table I: Simulation Parameters

Parameters	Value
Number of receive antennas	M= 64
Number of transmit antennas	n_t=4,8
Numbers of users	K=16
Number of samples	P=8
Modulation Symbols	16QAM or 64QAM
Number of RF chains at BS	M_{RF}=18
Number of RF at MS	Equal 1
Number of active antenna	Equal 1
jth CPSC block	J=1 or 2
Length of data block	Q=64

B. System Performance

The proposed GSP based signal detection performance can be measured in comparison with conventional SP based signal detection. **Fig. 3** contrasts total BER achieved by conventional SP based signal detection and GSP based signal detection with SNR.

No doubt that with the increase of SNR, total BER is decreased due to inverse relationship between SNR and BER. It is shown that proposed GSP based signal detection outperforms on classical SP based signal detection. Where BER performance for PGSP based signal detection improves when J increases. This leads to reduce UL throughput. To relieve this impediment, increasing the numbers of TAs at users for increasing the spatial constellation symbols set constituted by TAs. When n_t increases and J=2, there is about .8 dB BER performance gap for proposed GSP based signal detection at BER=10^{-4}.

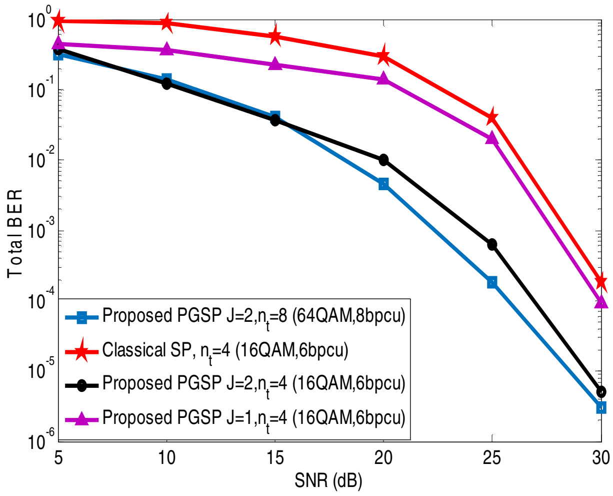

Fig. 3. Total BER with classical SP based signal detection and PGSP based signal detection.

C. The Impact of BS Antennas on BER

In this subsection, the performance of PGSP based signal detection is compared with classical SP based signal detection with different numbers of BS antennas. **Fig. 4** displays BER of spatial constellation symbols with different numbers of BS antennas at different SNR.

The more number of antenna at BS is, the more data rate is. Increasing data rate, leads to reduce BER.

It is shown that performance of PGSP based signal detection outperforms on classical SP based signal detection. The reason is that the proposed GSP based signal detection has two important features such as distributed sparsity and block sparsity. This leads to improve detection performance and achieves a better BER performance than classical SP based signal detection.

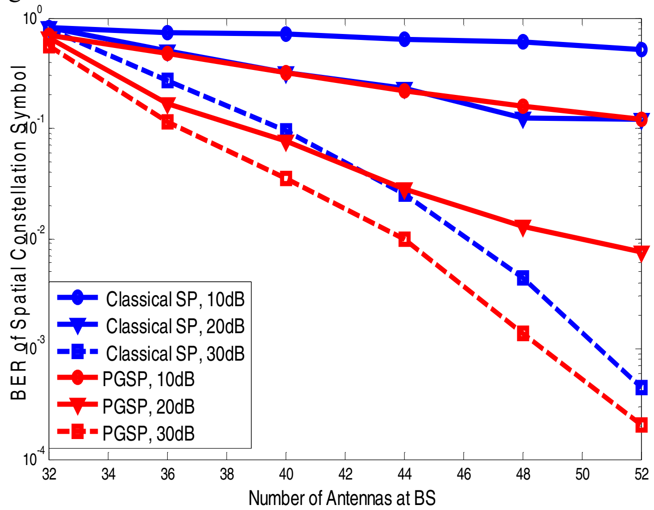

Fig. 4 BER of Spatial Constellation Symbols.

Fig. 5 studies BER of signal constellation symbols with different numbers of BS antennas at different SNR.

It is shown that the proposed GSP based signal detection outperforms on classical SP based signal detection. That is due to reducing the number of samples to restore signal because, PGSP based signal detection has priori sparse information. This gives improving detection performance with low complexity.

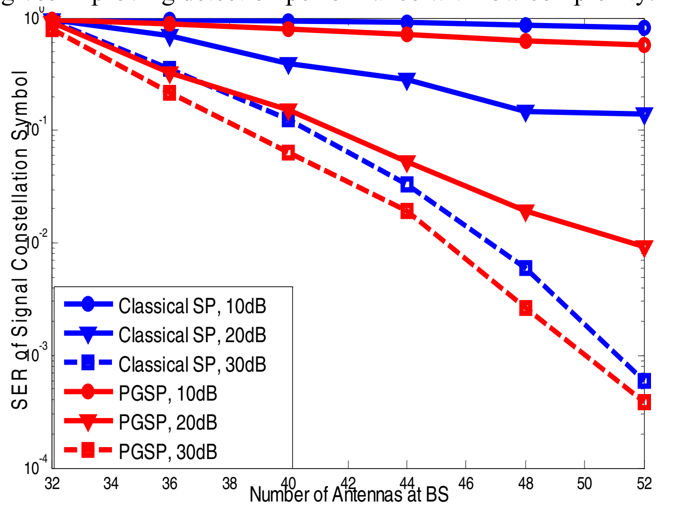

Fig. 5 BER of Signal Constellation Symbols.

Fig. 6 describes total BER of the proposed GSP based signal detection with different numbers of BS antennas at different SNR.

Where, total BER consists of spatial constellation symbols and signal constellation symbols.

Because of the above mentioned, the proposed GSP based signal detection achieves a better BER performance than classical SP based signal detection.

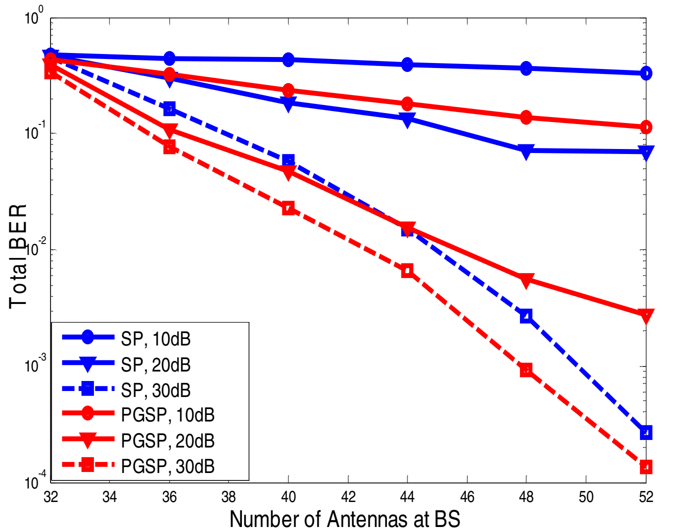

Fig. 6 Total BER performance of massive SM-MIMO.

Fig.7 displays total BER carried out by different signal detectors with different numbers of BS antennas in massive SM-MIMO and massive MIMO.

It is shown that the proposed GSP based signal detection achieves a better performance than MMSE based signal detection and classical SP based signal detection. Also, MMSE is favorable to massive MIMO and is unsuitable for massive

SM MIMO. That is due to increasing TAs at users and reduced numbers of RF chains at BS.

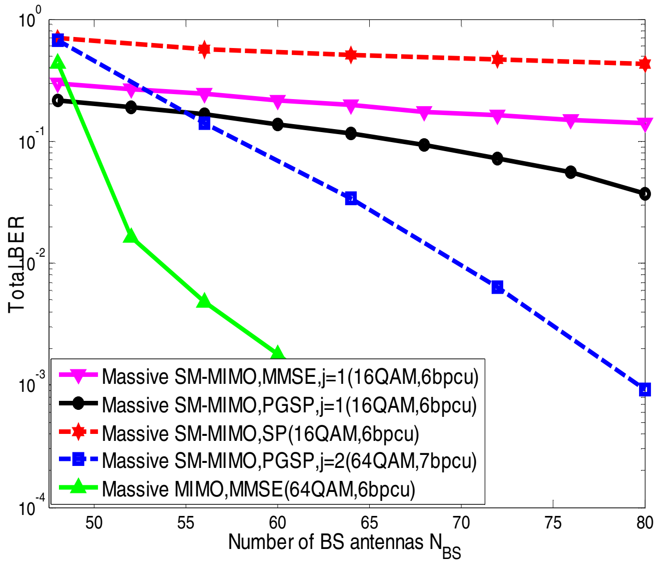

Fig. 7 Total BER of massive SM-MIMO and massive MIMO.

D. The Impact of Numbers of Users on BER

In this subsection, the performance of proposed GSP based signal detection is contrasted with classical SP based signal detection with different numbers of users. **Fig. 8** discusses total BER of massive SM-MIMO with different numbers of users at different SNR.

The more numbers of users are, the more information bits carried by system are. This leads to increase data rate and reduce BER.

It is shown that the proposed GSP based signal detection outperforms on classical SP based signal detection. The reason is that PGSP based signal detection exploits each of distributed sparsity and block sparsity. This leads to improve detection performance and reduces BER.

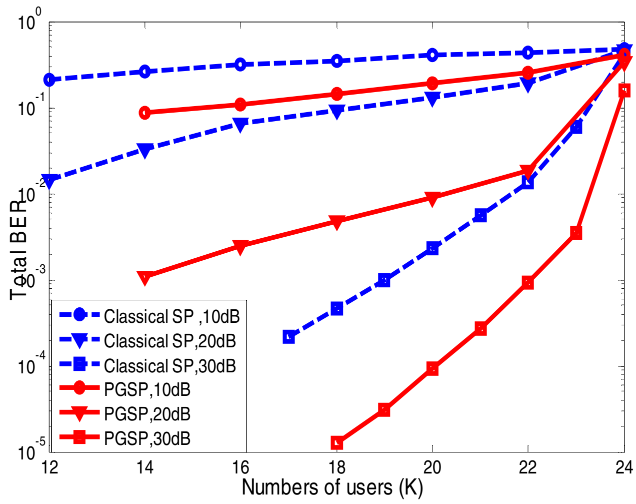

Fig. 8 Total BER performance of massive SM-MIMO with different numbers of users.

Fig. 9 displays total BER performance carried out by different signal detectors with different numbers of users in massive MIMO and massive SM-MIMO**.**

Due to the above mentioned, the proposed GSP based signal detection can obtain a better BER performance than MMSE based signal detection and classical SP based signal detection. Where MMSE based signal detection is superior to massive MIMO than massive SM-MIMO. That is due to increasing numbers of users and numbers of TAs at users.

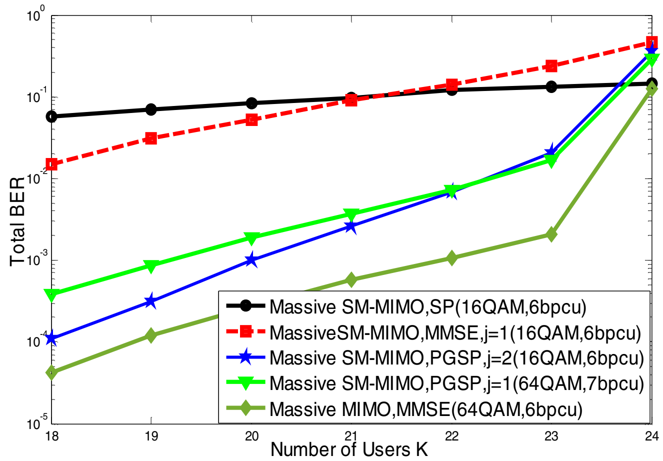

Fig. 9 Total BER performance of massive SM-MIMO and massive MIMO.

V. CONCLUSIONS

In this paper, massive SM-MIMO had been suggested instead of massive MIMO for UL transmission. Where BS utilizes hundreds of antennas with small number of RF chains and every user utilizes multiple of antennas with one RF chain. This leads to reduce power consumption and hardware cost. Owing to large numbers of TAs at the users and small number of RF chains at BS, signal detection becomes challenging problem. Therefore, joint grouped transmission scheme at the users had been proposed to introduce group sparsity of multiple SM signals in addition to GSP based signal detection at BS to leverage distributed sparsity of SM signal. By utilizing these sparse features, the proposed GSP based signal detection can detect SM signals more reliability than other detection techniques. Simulation results proved that BER performance of proposed GSP based signal detection outperforms classical SP based signal detection by 3dB at BER=10^{-4}. This means that the proposed GSP based signal detection achieves a better signal detection performance than classical SP based signal detection.

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