Near-Optimal Signal Detector Based on Structured Compressive Sensing for Massive SM-MIMO

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Abstract—Massive spatial modulation (SM)-MIMO, which employs massive low-cost antennas but few power-hungry transmit radio frequency (RF) chains at the transmitter, is recently proposed to provide both high spectrum efficiency and energy efficiency for future green communications. However, in massive SM-MIMO, the optimal maximum likelihood (ML) detector has the prohibitively high complexity, while state-of-the-art low-complexity detectors for conventional small-scale SM-MIMO suffer from an obvious performance loss. In this paper, by exploiting the structured sparsity of multiple SM signals, we propose a low-complexity signal detector based on structured compressive sensing (SCS) to improve the signal detection performance. Specifically, we first propose the grouped transmission scheme at the transmitter, where multiple SM signals in several continuous time slots are grouped to carry the common spatial constellation symbol to introduce the desired structured sparsity. Accordingly, a structured subspace pursuit (SSP) algorithm is proposed at the receiver to jointly detect multiple SM signals by leveraging the structured sparsity. In addition, we also propose the SM signal interleaving to permute SM signals in the same transmission group, whereby the channel diversity can be exploited to further improve the signal detection performance. Theoretical analysis quantifies the performance gain from SM signal interleaving, and simulation results demonstrate the near-optimal performance of the proposed scheme.

Index Terms—Spatial modulation (SM), massive MIMO, signal detection, structured compressive sensing (SCS), signal interleaving.

I. INTRODUCTION

Spatial modulation (SM)-MIMO exploits the pattern of one or several simultaneously active antennas out of all available transmit antennas to transmit extra information [1], [2]. Compared with small-scale SM-MIMO which only introduces the limited gain in spectrum efficiency, massive SM-MIMO is recently proposed by integrating SM-MIMO with massive MIMO working at 3~6 GHz to achieve higher spectrum efficiency [1]. In massive SM-MIMO systems, the base station (BS) uses a large number of low-cost antennas for higher spectrum efficiency but only one or several power-hungry transmit radio frequency (RF) chains for power saving, while the user can compactly employ the multiple receive diversity antennas with low correlation [2]. Since the power consumption and hardware cost are largely dependent on the number of simultaneously active transmit RF chains (especially the power amplifier), massive SM-MIMO outperforms the traditional MIMO schemes in higher spectrum efficiency, reduced power consumption, lower hardware cost, etc. In practice, SM can be adopted in conventional massive MIMO systems as an energy-efficient transmission mode. Meanwhile, massive SM-MIMO can be also considered as an independent scheme to reduce both the power consumption and hardware cost. To date, in addition to the combination of massive MIMO and SM, the concept of SM has also been integrated into various applications [2] including cognitive radio [3], [4], physical-layer security [5].

SM-MIMO maps a block of information bits into two information carrying units: the spatial constellation symbol and the signal constellation symbol. For massive SM-MIMO, due to the small number of receive antennas at the user and massive antennas at the BS, the signal detection is a challenging large-scale underdetermined problem. When the number of transmit antennas becomes large, the optimal maximum likelihood (ML) signal detector suffers from the prohibitively high complexity [6]. Low-complexity signal vector (SV)-based detector has been proposed for SM-MIMO [6], but it is confined to SM-MIMO with single transmit RF chain. In [7]–[9], the SM is generalized, where more than one active antennas are used to transmit independent signal constellation symbols for spatial multiplexing. Linear minimum mean square error (LMMSE)-based signal detector [1] and sphere decoding (SD)-based detector [10] can be used for SM-MIMO systems with multiple transmit RF chains. But they are only suitable for well or overdetermined SM-MIMO with \( N_r \geq N_t \), and suffer from a significant performance loss in underdetermined SM-MIMO systems with \( N_r < N_t \), where \( N_r \) and \( N_t \) are the numbers of transmit and receive antennas, respectively. Due to the fact that the number of active antennas is smaller than the total number of transmit antennas, SM signals have the inherent sparsity, which can be considered by exploiting the compressive sensing (CS) theory [11], [12] for improved signal detection performance. By far, CS has been widely used in wireless communications [13]–[16], and the CS-based signal detectors have been proposed for underdetermined small-scale SM-MIMO [13], [16]. However, their bit-error-rate (BER) performance still has a significant
gap compared with that of the optimal ML detector, especially in massive SM-MIMO with large $N_t$, $N_r$, and $N_r \ll N_t$.

To this end, this paper proposes a near-optimal structured compressive sensing (SCS)-based signal detector with low complexity for massive SM-MIMO. Specifically, we first propose the grouped transmission scheme at the BS, where multiple SM signals in several successive time slots are grouped to carry the common spatial constellation symbol to introduce the desired structured sparsity. Accordingly, we propose a structured subspace pursuit (SSP) algorithm at the user to detect multiple SM signals in the same transmission group, whereby their structured sparsity is leveraged for improved signal detection performance. Moreover, the SM signal interleaving is proposed to permute SM signals in the same transmission group, so that the channel diversity can be exploited. Theoretical analysis and simulation results verify that the proposed SCS-based signal detector outperforms existing CS-based signal detector.

**Notation:** Boldface lower and upper-case symbols represent column vectors and matrices, respectively. $\mathbb{J}$ denotes the integer floor operator. The transpose, conjugate transpose, and Moore-Penrose matrix inversion operations are denoted by $\cdot^T$, $(\cdot)^*$ and $(\cdot)^+$, respectively. The $l_p$ norm operation is given by $\| \cdot \|_p$, and $| \cdot |$ denotes the cardinality of a set. $E \{ \cdot \}$, var $\{ \cdot \}$, Re $\{ \cdot \}$, and Im $\{ \cdot \}$ are operators to take the expectation, variance, the real part, and the imaginary part of a random variable. $\text{Tr} \{ \cdot \}$ is the trace operation for a matrix. If a set has $n$ elements, the number of $k$-combinations is denoted by the binomial coefficient $\binom{n}{k}$. The index set of non-zero entries of the vector $x$ is called the support set of $x$, which is denoted by $\text{supp} \{ x \}$. $x_i$ denotes the $i$th entry of the vector $x$, and $H_i$ denotes the $i$th column vector of the matrix $H$. $x^T$ denotes the entries of $x$ defined in the set $\Gamma$, while $H^T$ denotes a sub-matrix of $H$ with indices of columns defined by the set $\Gamma$.

## II. System Model

The SM-MIMO systems can be illustrated in Fig. 1. The transmitter has $N_t$ transmit antennas but $N_a < N_t$ transmit RF chains, and the receiver has $N_r$ receive antennas. Each SM signal consists of two symbols: the spatial constellation symbol obtained by mapping $\log_2 \left( \frac{N_a}{N_t} \right)$ bits to a pattern of $N_a$ active antennas out of $N_t$ transmit antennas, and $N_a$ independent signal constellation symbols coming from the $M$-ary signal constellation set (e.g., QAM). Hence, each SM signal carries the information of $N_a \log_2 M + \log_2 \left( \frac{N_t}{N_a} \right)$ bits.

At the receiver, the received signal $y \in \mathbb{C}^{N_r \times 1}$ can be expressed as $y = Hx + w$, where $x \in \mathbb{C}^{N_t \times 1}$ is the SM signal transmitted by the transmitter, $w \in \mathbb{C}^{N_r \times 1}$ is the additive white Gaussian noise (AWGN) vector with independent and identically distributed (i.i.d.) entries following the circular symmetric complex Gaussian distribution $CN(0, \sigma^2_w)$, $H = R^{1/2}HR^{1/2} \in \mathbb{C}^{N_r \times N_t}$ is the correlated flat Rayleigh-fading MIMO channel, entries of $H$ are subjected to the i.i.d. distribution $CN(0, 1)$, $R$, and $R^*$ are the receiver and transmitter correlation matrices, respectively [17]. The correlation matrix $R$ is given by $r_{ij} = r^{\lfloor i-j \rfloor}$, where $r_{ij}$ is the $i$th row and $j$th column element of $R$, and $r$ is the correlation coefficient of neighboring antennas.

It should be pointed out that since $H$ is used for conveying information, it should be known by the receiver and can be acquired by channel estimation [17]. To achieve both high spectrum efficiency and energy efficiency for future green communications, massive SM-MIMO, which employs massive low-cost antennas but few power-hungry transmit RF chains at the BS to serve the user with comparatively small number of receive antennas, is recently proposed [1]. However, its signal detection is a challenging large-scale underdetermined problem, since $N_t$, $N_r$ can be large and $N_r \ll N_t$, e.g., $N_t = 64$ and $N_r = 16$ are considered [1].

For the SM signal $x$, the spatial constellation symbol of $\left[ \log_2 \left( \frac{N_t}{N_a} \right) \right]$ bits is mapped into the spatial constellation set $\mathbb{A}$, where the pattern of $N_a$ active antennas selected from $N_t$ transmit antennas is regarded as the spatial constellation symbol. Hence there are $|\mathbb{A}| = 2^{\left[ \log_2 \left( \frac{N_t}{N_a} \right) \right]}$ kinds of patterns of active antennas, i.e., $\text{supp} \{ x \} \in \mathbb{A}$. Meanwhile, the signal constellation symbol of the $i$th active antenna, denoted as $x^{(i)}$ for $1 \leq i \leq N_a$, is mapped into the $M$-ary signal constellation set $\mathbb{B}$. Therefore, the signal detection in SM-MIMO can be formulated as the $M^{N_r}2^{\left[ \log_2 \left( \frac{N_t}{N_a} \right) \right]}$-hypothesis detection problem. Clearly, the optimal signal detector to this problem is ML signal detector, which can be expressed as

$$\hat{x}_{\text{ML}} = \arg \min_{\text{supp}(x) \in \mathbb{A}, x^{(i)} \in \mathbb{B} \ 1 \leq i \leq N_a} \| y - Hx \|_2. \quad (1)$$

However, the computational complexity of the optimal ML signal detector is $O(M^{N_r}2^{\left[ \log_2 \left( \frac{N_t}{N_a} \right) \right]})$, which can be unrealistic when $N_t$, $N_a$, and/or $M$ become large.

To reduce the complexity, SV-based signal detector has been proposed [9], but it only considers the case of $N_a = 1$. LMMSE-based signal detector with the complexity of $O\left(2N_rN_t^3 + N_t^3\right)$ [1] and SD-based signal detector with the complexity of $O\left(\max\{N_t^3, N_tN_r^2, N_r^2N_t\}\right)$ [10] have been proposed for well or overdetermined SM-MIMO with $N_r \geq N_t$. 

![Fig. 1. Spatial constellation symbol and signal constellation symbol in SM-MIMO systems, where $N_t = 4$, $N_a = 1$, and QPSK are considered as an example.](image)


III. PROPOSED SCS-BASED SIGNAL DETECTOR

In this section, an SCS-based signal detector is proposed for downlink single-user massive SM-MIMO, which can be illustrated in Fig. 2. We first propose a grouped transmission scheme and an SM signal interleaving at the transmitter. Then, the corresponding deinterleaving and SSP algorithm for signal detection at the receiver are provided, whereby multiple SM signals with the structured sparsity are jointly processed for the improved signal detection performance with low complexity.

A. Grouped Transmission and Interleaving at the Transmitter

Similar to conventional SM-MIMO systems, we assume that signal constellation symbols in the proposed scheme are mutually independent. However, unlike conventional SM signals, where spatial constellation symbols are independent in different time slots, we propose the grouped transmission scheme at the transmitter, where every SM signal in $G$ consecutive time slots are considered as a group, and SM signals in the same transmission group share the same spatial constellation symbol, i.e.,

$$\text{supp}(x^{(1)}) = \text{supp}(x^{(2)}) = \cdots = \text{supp}(x^{(G)}),$$

where $x^{(1)}, x^{(2)}, \ldots, x^{(G)}$ are SM signals in $G$ consecutive time slots. Due to the conveyed common spatial constellation symbol, $x^{(1)}, x^{(2)}, \ldots, x^{(G)}$ in the same transmission group share the same support set and thus have the structured sparsity. It is clear that to introduce such structured sparsity, the effective information bits carried by spatial constellation symbols will be reduced. However, as will be discussed in Section IV-C and demonstrated in our simulations, such structured sparsity allows more reliable signal detection performance and eventually could even improve the BER performance of the whole system without the reduction of the total bit per channel use (bpcu).

On the other hand, due to the temporal channel correlation, channels in several consecutive time slots can be considered to be quasi-static, i.e., $H^{(1)} = H^{(2)} = \cdots = H^{(G)}$, where $H^{(t)}$ for $1 \leq t \leq G$ is the channel associated with the $t$th SM signal in the group. This implies that if channels used for SM fall into the deep fading, such deep fading usually remains unchanged during $G$ time slots, and the corresponding signal detection performance will be poor. To solve this issue, we further propose the SM signal interleaving at the transmitter. Specifically, after the original SM signals $x^{(t)}$s are generated, the actually transmitted signals are given by $\Pi^{(t)} x^{(t)}$s, where each column and row of $\Pi^{(t)} \in \mathbb{C}^{N_t \times N_t}$ only has one nonzero element with the value of one, and $\Pi^{(t)}$ can permute the entries in $x^{(t)}$. We consider that $\Pi^{(t)}$’s for $1 \leq t \leq G$ are different in different time slots, and they are predefined and known by both the transmitter and receiver. In this way, the active antennas vary in different time slots from the same transmission group even though $x^{(t)}$’s share the common spatial constellation symbol. Hence, the channel diversity can be appropriately exploited to improve the signal detection at the receiver. Note that the object of the SM signal interleaving is the spatial constellation symbol after constellation mapping, which is different from the widely used bit-interleaving whose object is the bit stream before constellation mapping [18]. In Section IV-B, such diversity gain will be further discussed.

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Fig. 2. Illustration of the proposed SCS-based signal detector, where $N_t = 4$, $N_r = 2$, $N_a = 1$, $G = 2$, and QPSK are considered. The used spatial and signal constellation symbols can be illustrated in Fig. 1. Note that the white dot block in MIMO channels denotes the deep channel fading.
Algorithm 1 Proposed SSP Algorithm.

Input: Received signal \( y^{(t)} \), the channel matrix \( H^{(t)} \), and the number of active antennas \( N_a \), where \( 1 \leq t \leq G \).

Output: Estimated SM signal \( \hat{x}^{(t)} \) for \( 1 \leq t \leq G \).

1. \( \Omega^0 = \emptyset \); % Empty \( \Omega^0 \) as \( \emptyset \), and \( \Omega^k \) is the estimated support set in the \( k \)th iteration.
2. \( x^{(t)} = y^{(t)} \), \( \forall t \); % Initial residual, \( x^{(t)} \) is the residual associated with the \( t \)th SM signal.
3. \( k = 1 \); % is the iteration index.
4. while \( k \leq N_a \) do
5. \( a^{(t)} = (H^{(t)})^* r^{(t)}, \forall t \); % Correlation
6. \( \Gamma = \arg \max_{\Gamma} \sum_{t=1}^{G} \| a^{(t)} \|_2^2 \in A \), \( \| \Gamma \| = \min \{ 2N_a, N_r \} \) if \( k = 1 \)
7. % Estimate potential supports.
8. \( \Xi = \Omega^{k-1} \cup \Gamma \); % Merge estimated supports in the previous and current iteration.
9. \( \Omega^k = \arg \max_{\Omega} \sum_{t=1}^{G} \| b^{(t)} \|_2^2 \in \Omega \) \( \forall \Omega \in A \) and \( \| \Omega \| = N_a \); % Prune the estimated support set.
10. \( c^{(t)} = (H^{(t)})^* y^{(t)}, \forall t \); % Least squares
11. \( r^{(t)} = y^{(t)} - H^{(t)} c^{(t)}, \forall t \); % Compute residual
12. \( k = k + 1 \);
13. end while
14. \( \hat{x}^{(t)} = c^{(t)}, \forall t \);

B. SCS-Based Signal Detector at the Receiver

At the receiver, the received signal in the \( t \)th time slot can be expressed as

\[
y^{(t)} = H^{(t)} \Pi^{(t)} x^{(t)} + w^{(t)}
= H^{(t)} x^{(t)} + w^{(t)}, 1 \leq t \leq G,
\]

where \( H^{(t)} = H^{(t)} \Pi^{(t)} \) can be considered as the deinterleaving processing.

From (3), we observe that \( x^{(t)} \)'s share the structured sparsity due to the grouped transmission scheme at the transmitter, but they have different non-zero values due to the mutually independent signal constellation symbols. According to the theory of SCS, the structured sparsity of \( x^{(t)} \)'s can be exploited to improve the signal detection performance compared with the conventional CS-based signal detectors [11]. Under the framework of SCS theory, the solution to (3) can be achieved by solving the following optimization problem:

\[
\min_{\text{supp}(x^{(t)}) \in A} \left( \sum_{t=1}^{G} \| x^{(t)} \|_p^q \right)^{1/q},
\text{s.t. } y^{(t)} = H^{(t)} x^{(t)}, \text{ supp}(x^{(t)}) = \text{ supp}(x^{(i)}), 1 \leq t \leq G.
\]

In this paper, based on the classical subspace pursuit (SP) algorithm [12], we propose an SSP algorithm by utilizing the structured sparsity to solve the optimization problem in a greedy way, where \( p = 0 \) and \( q = 2 \) are advocated [11].

The proposed SSP algorithm is described in Algorithm 1. Specifically, Lines 1~3 perform the initialization. In the \( k \)th iteration, Line 5 performs the correlation between the MIMO channels and the residual in the previous iteration; Line 6 obtains the potential true indices according to Line 5; Line 7 merges the estimated indices obtained in Lines 8~9 in the previous iteration and the estimated indices in Line 6 in the current iteration; after the least squares in Line 8, Line 9 removes wrong indices and selects \( N_a \) most likely indices; Line 10 estimates SM signal according to \( t \); Line 11 acquires the residue. The iteration stops when \( k > N_a \). Compared with the classical SP algorithm which only reconstructs one sparse signal from one received signal, the proposed SSP algorithm can jointly recover multiple sparse signals with the structured sparsity but having different measurement matrices, where the structured sparsity of multiple sparse signals can be leveraged for improved signal detection performance. Therefore, the classical SP algorithm can be regarded as a special case of the proposed SSP algorithm when \( G = 1 \), and more details will be further discussed in Section IV-A. Another difference should be pointed out that in the steps of Line 6 and 9 in Algorithm 1, the selected support set should belong to the predefined spatial constellation set \( A \) for enhanced signal detection performance. However, the classical SP algorithm and existing CS-based signal detectors do not exploit this priori information of the expected support set [15], [16]. By using the proposed SSP algorithm, we can acquire the estimation of the spatial constellation symbol according to \( \xi^{(t)} \)'s and the rough estimation of signal constellation symbols. By searching for the minimum Euclidean distance between the rough estimation of signal constellation symbols and legitimate constellation symbols, we can finally estimate signal constellation symbols.

IV. PERFORMANCE ANALYSIS

In this section, we will provide the performance analysis from four aspects as follows.

A. Comparison Between SCS-Based Signal Detector and CS-Based Signal Detectors

Typically, existing CS-based signal detectors utilize one received signal vector to recover one sparse SM signal vector, which is equivalent to solving the single measurement vector (SMV) problem in CS, i.e., \( y = Hx + w \). If multiple sparse signals share the common support set and identical measurement matrix, i.e., \( \left[ y^{(1)}, y^{(2)}, \cdots, y^{(G)} \right] = H \left[ x^{(1)}, x^{(2)}, \cdots, x^{(G)} \right] + w \), the reconstruction of \( x^{(t)} \)'s from \( y^{(t)} \)'s for \( 1 \leq t \leq G \) can be considered as the multiple measurement vectors (MMV) problem in SCS theory [11]. The SCS theory has proven that with the same size of the measurement vector, the recovery performance of SCS algorithms is superior to that of conventional CS algorithms [11]. This implies that with the same number of receive antennas

1For the classical SP algorithm, when the residual of current iteration is not less than that of the last iteration, the iteration stops and the estimation in the last iteration is used as the final output, which is different from the proposed stopping criterion with the fixed number of iteration. Simulation results confirm both stopping criteria are equivalent in most cases and they share the very similar performance for the proposed SSP algorithm. Besides, for real-time or delay sensitive applications, it is usually desirable to have the number of iteration be fixed or bounded, so that the speed of decoding and power consumption is manageable.
Moreover, we can have the proposed SSP algorithm relies on the correlation operation in the antenna in the problem, and furthermore if \( G = 1 \), it reduces to the SMV problem. Therefore, our formulated problem can be regarded as a generalized MMV (GMMV) problem.

### B. Performance Gain from SM Signal Interleaving

We discuss the performance gain from the SM signal interleaving by comparing the detection probability of the proposed SSP algorithm with and without SM signal interleaving. Since CS algorithms are nonlinear, it is difficult to exactly provide the closed-form expression of the signal detection probability. Hence, we consider a simplified scenario with \( N_a = 1 \) and uncorrelated Rayleigh-fading MIMO channels. Let \( m \) be the index of the active antenna, and for any given \( l \), \( \mathbf{H}^{(l)} \) for \( 1 \leq t \leq G \) are mutually independent \(^4\) where \( 1 \leq m, l \leq N_t \). Based on these assumptions, the received signal is given by

\[
y^{(t)} = \mathbf{a}^{(t)} \mathbf{H}^{(m)} + w^{(t)}
\]

where \( \mathbf{H}^{(m)} = \mathbf{H}^{(m)} + w^{(m)} \). For \( 1 \leq l \leq N_t \), due to large \( N_r \) in practice, we have

\[
\mathbf{F}(m,l) = \mathbf{H}(m) \mathbf{H}(m) + w(m)
\]

with \( \mu_1 = 0, \sigma_4^2 = \frac{(N^2 + N_2)\sigma}{2(M = 2)} + \frac{N_2\sigma}{2}, \) and \( \mathbf{F}(m,l) \) according to central limit theorem \(^{[19]}\). Similarly, both

\[
\text{Re} \{ \mathbf{F}(m,l) \} \text{ and } \text{Im} \{ \mathbf{F}(m,l) \} \text{ follow the distribution } \mathcal{N}(\mu_2, \sigma_4^2)
\]

where \( \mu_2 = 0, \sigma_4^2 = \frac{N_2\sigma}{2}, \) the associated proof will be provided in Appendix. Note that \( \sigma_4^2 \) is the central chi-squared distribution with the degrees of freedom \( n \).\(^{[19]}\) Algorithm 1 only has one iteration and \( |\Gamma| = |\Xi| = 2 \) in the iteration for \( N_a = 1 \), we consider

\[
P_{\text{GMMV}}(C_m - C_l[2] > 0|l \neq m) = \frac{1}{f_0} f_{\sigma} f_{\sigma}[x-z] dz dx.
\]

For the conventional MMV problem with identical channel matrices, similar to the previous analysis, we have

\[
P_{\text{MMV}}(C_m - C_l[2] > 0|l \neq m) = \frac{1}{f_0} f_{\sigma} f_{\sigma}[x-z] dz dx.
\]

To intuitively compare the signal detection probability, we compare

\[
P_{\text{GMMV}}(C_m - C_l[2] > 0|l \neq m) \text{ and } P_{\text{MMV}}(C_m - C_l[2] > 0|l \neq m) = \frac{1}{f_0} f_{\sigma} f_{\sigma}[x-z] dz dx.
\]

In this way, we have

\[
P_{\text{GMMV}}(C_m - C_l[2] > 0|l \neq m) = f_{\sigma} f_{\sigma}[x-z] dz dx.
\]

\[
f_1(x) \text{ and } f_2(x), \text{ respectively. The PDF of } C_{l}[2] \text{ with } l \neq m \text{ is } f_{2}(x) = \frac{(N_1 - N_2)}{(N_1 - N_2) - 2}(1 - f_{2}(x))f_{2}(x), \text{ where } f_{2}(x) \text{ is the cumulative density function of } f_{2}(x). \]

In this way, we have

\[
P_{\text{GMMV}}(C_m - C_l[2] > 0|l \neq m) = f_{\sigma} f_{\sigma}[x-z] dz dx.
\]

To achieve the goal that \( \mathbf{H}^{(l)} \) s, \( l = 1, \ldots, L \), are mutually independent as much as possible, we consider the pseudo-random permutation matrix \( \Pi^{(l)} \), which can be predefined and known by both the BS and user. In Section V, simulation results confirm the good performance gain of the channel diversity from SM signal interleaving, whose performance gain approaches that of the case of mutually independent channel matrices in the same group.

### C. Spectral Efficiency

The proposed scheme has the spectrum efficiency \( N_a \log_2 M + \log_2 |\Lambda| / G \) bpcu due to the grouped transmission scheme, which is slightly smaller than conventional SM-MIMO systems with \( N_a \log_2 M + \log_2 |\Lambda| \) bpcu. In SM-MIMO, the detection of spatial constellation symbols is essential since it is the prerequisite of the following detection of signal constellation symbols. Conventional low-complexity signal detectors such as the proposed signal detectors perform poorly in massive SM-MIMO systems, and thus the signal constellation symbol is usually limited to low-order modulation to guarantee the reliable signal detection. However, the detection of spatial constellation symbol can be improved by the proposed scheme, so higher-order modulation of signal constellation symbol can be used to achieve the same or even higher bpcu. Besides, the spectrum efficiency can be further increased by using a large number of low-cost transmit antennas to expand the degree of spatial freedom in massive SM-MIMO. Finally, simulation results in the following section will show that even with small \( G = 2 \), the proposed SCS-based signal detector can achieve much better BER improvement even with higher total bpcu than the conventional signal detectors.
the good tightness with the simulation results. In addition, the analytical SCSER derived in Section IV-B have
proposed SCS-based signal detector outperforms the conventional LMMSE-based signal detector, since the structured sparsity
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D. Computational Complexity

The optimal ML signal detector has the computational complexity of \(O(M N^2 (\log_2(N_t^2)))\), which is prohibitively high when \(N_a, N_t\), and/or \(M\) become large. The conventional signal detectors [1, 10, 16] have the complexity of \(O(N_t^3)\) as mentioned in Section II which implies that their complexity is still high in massive SM-MIMO systems with large \(N_t\). By contrast, for the proposed SCS-based signal detector, the main computational burden comes from the step of least squares with the computational complexity of \(O(G(2N_r N_a^2 + N_a^3))\) [20], or equivalently \(O(2N_r N_a^2 + N_a^3)\) per SM signal in each time slot. This indicates that the proposed SCS-based signal detector enjoys the same order of complexity with the CS-based signal detector [15].

V. SIMULATION RESULTS

A simulation study was carried out to compare the performance of the proposed SCS-based signal detector with that of the conventional LMMSE-based signal detector [1] and the CS-based signal detector [16]. The performance of the optimal ML detector [9] is also provided as the benchmark for comparison.

Fig. 3 compares the simulated and analytical spatial constellation symbol error rate (SCSER) of the SCS-based signal detector in different cases over uncorrelated Rayleigh-fading MIMO channels, where \(N_t = 64, N_r = 16, N_a = 1\), and 8-PSK are considered. For the GMMV case, “i.i.d.” denotes the case that \(H^{(t)} = H^{(i)}\) for \(1 \leq t \leq G\) and \(H^{(i)}\)’s are independently generated, while “interleaving” denotes the case that \(H^{(1)} = H^{(2)} = \cdots = H^{(G)}\) and \(H^{(i)} = H^{(i)} \Pi^{(i)}\) with different permutation matrices \(\Pi^{(i)}\)’s. From Fig. 3, we can find that the analytical SCSER derived in Section IV-B have the good tightness with the simulation results. In addition, the proposed SCS-based signal detector outperforms the conventional CS-based signal detector, since the structured sparsity of multiple sparse SM signals is exploited for the improved

SCSER. Moreover, since the channel diversity can be exploited to further improve the SCSER, the SCS-based signal detector with mutually independent channel matrices (GMMV) is superior to that with identical channel matrices (MMV) by more than 4 dB if the SCSER of \(10^{-3}\) is considered. Finally, the performance of the SCS-based signal detector with SM signal interleaving approaches that with mutually independent channel matrices, which indicates that the proposed SM signal interleaving can fully exploit the channel diversity.

Fig. 4 provides SCSER comparison of different signal detectors over correlated Rayleigh-fading MIMO channels, where \(r_t = r_r = 0.4\) and \(N_t = 16\).

Fig. 5 shows the BER comparison between the traditional CS-based signal detector and the proposed SCS-based signal detector over correlated Rayleigh-fading MIMO channels, where \(r_t = r_r = 0.4\) and \(N_t = 16\).
out interleaving. Moreover, it has the similar performance with that with mutually independent channel matrices (i.e., $H^{(t)} = H^{(t)}$ for $1 \leq t \leq G$ and $H^{(t)}$'s are independently generated), which indicates the good performance gain of the channel diversity from interleaving even in correlated MIMO channels.

Fig. 5 provides the BER performance comparison of the existing CS-based signal detector and the proposed SCS-based signal detector with interleaving over correlated Rayleigh-fading MIMO channels with $r_t = r_r = 0.4$ and $N_r = 16$. The existing scheme adopts two transmission modes: 1) $N_t = 64$, $N_a = 1$, BPSK with 7 bpcu and 2) $N_t = 65$, $N_a = 2$, no signal constellation symbol with 11 bpcu. In contrast, the SCS-based signal detector with $N_t = 65$, $N_a = 2$ and $G = 2$ adopts QPSK and 8-PSK, respectively, and the corresponding data rates are 9.5 bpcu and 11.5 bpcu. From Fig. 5 it can be observed that the proposed SCS-based signal detector with even higher bpcu achieves better BER performance than the conventional CS-based signal detector. For example, when BER of $10^{-3}$ is considered, the proposed SCS-based signal detector with 9.5 bpcu outperforms the conventional CS-based signal detector with 7 bpcu by about 2 dB.

In Fig. 6 we compare the BER performance between the conventional CS-based signal detector and the proposed SCS-based signal detector with interleaving over correlated Rayleigh-fading MIMO channels with $r_t = r_r = 0.4$ and different $G$’s, where an extreme case that $N_t = 65$, $N_r = 3$, $N_a = 2$, and 8-PSK is considered. The conventional CS-based signal detector works poorly, since the limitation $N_r > 2N_a + 1$ is required by conventional CS theory [11]. By contrast, the BER performance of the proposed SCS-based signal detector improves when $G$ becomes large, since the SCS theory can relax the limitation as $N_r > N_a + 1$ [11].

Fig. 7 compares the performance of the proposed SCS-based signal detector with interleaving and the optimal ML signal detector, where $r_t = r_r = 0.4$, $N_t = 65$, $N_r = 16$, $N_a = 2$, and 8-PSK are considered. From Fig. 7 we can find that with the increasing $G$, the BER performance gap between the SCS-based signal detector and the optimal ML signal detector becomes smaller. When $G = 2$, the SCS-based signal detector approaches the optimal ML signal detector with a small performance loss. For example, if the BER of $10^{-4}$ is considered, the performance gap between the SCS-based signal detector with $G = 3$ and the optimal ML detector is less than 0.2 dB. Thus, the near-optimal performance of the proposed SCS-based signal detector can be verified.

VI. CONCLUSIONS

This paper has proposed a near-optimal SCS-based signal detector with low complexity for the emerging massive SM-MIMO. First, the grouped transmission scheme can introduce the desired structured sparsity of multiple SM signals in the same transmission group for improved signal detection.

The proposed scheme may require a relatively large number of receive antennas to achieve its competitive advantage, and it can be applied for the mobile stations such as laptop or tablet, where the relatively large number of antennas may be possible at the mobile stations, especially when the higher working frequency of 3~6 GHz is considered.

APPENDIX

We will investigate the distribution of $F_{m,t} = (\alpha H'_{m,t} + \omega)H_{t}'$, where the superscript $(t)$ is omitted for simplicity. Specifically, let $h_{m,n}$, $h_{r,n}$, and $w_{n}$ denote the $n$th element of the vector $H'_{m,t}$, $H'_{r}$, and $\omega$, respectively. In
this way, we have $F_{m,l} = \alpha \sum_{n=1}^{N_r} h_{m,n}^* h_{l,n} + \sum_{n=1}^{N_r} w_{m,n}^* h_{l,n}$. Since $F_{m,l}$ can be expressed as the summation of multiple mutually independent random variables, $F_{m,l}$ approximately follows the Gaussian distribution, when $N_r$ is sufficiently large according to central limit theorem. Obviously, we have $E\{F_{m,l}\} = 0$, since $\text{Re}\{h_{l,n}\} = h_{l,n}^*$ and $\text{Im}\{h_{l,n}\} = h_{l,n}^\prime$. 

$\text{Re}\{h_{m,n}\} = h_{m,n}^\prime$ and $\text{Im}\{h_{m,n}\} = h_{m,n}^\prime$. Follow $\mathcal{N}(0,0.5)$, both $\text{Re}\{w_{m,n}\} = w_{m,n}^\prime$ and $\text{Im}\{w_{m,n}\} = w_{m,n}^\prime$ follow $\mathcal{N}(0, \sigma_w^2/2)$, and $E\{\alpha\} = 0$. For the case of $m = l$, we have

$$F_{m,m} = \alpha \sum_{n=1}^{N_r} h_{m,n}^2 + \sum_{n=1}^{N_r} w_{m,n}^2 h_{m,n} = \sum_{n=1}^{N_r} \text{Re}\{\alpha\} \left( (h_{m,n}^\prime)^2 + (h_{m,n}^\prime)^2 \right) + h_{m,n}^r w_{m,n}^r + h_{m,n}^i w_{m,n}^i + \text{Im}\{\alpha\} \left( (h_{m,n}^\prime)^2 + (h_{m,n}^\prime)^2 \right) - h_{m,n}^r w_{m,n}^r + h_{m,n}^i w_{m,n}^i.$$  

Furthermore, we can have

$$E\left\{\text{Re}\{F_{m,m}\}^2\right\} = \sum_{n=1}^{N_r} \text{Re}\{\alpha\}^2 \left( (h_{m,n}^\prime)^2 + (h_{m,n}^\prime)^2 \right) + h_{m,n}^r w_{m,n}^r + h_{m,n}^i w_{m,n}^i + \text{Im}\{\alpha\}^2 \left( (h_{m,n}^\prime)^2 + (h_{m,n}^\prime)^2 \right) - h_{m,n}^r w_{m,n}^r + h_{m,n}^i w_{m,n}^i.$$  

Similarly, we have

$$E\left\{\text{Im}\{F_{m,m}\}^2\right\} = E\left\{\text{Im}\{\alpha\}^2\right\} \left( N_r^2 + N_r \right) + N_r \sigma_w^2/2.$$

For BPSK with $M = 2$, we have $E\left\{\text{Re}\{\alpha\}^2\right\} = \sigma_s^2$ and $E\left\{\text{Im}\{\alpha\}^2\right\} = 0$, while for the higher constellation modulation with $M > 2$ (e.g., $M$-QAM or $M$-PSK), we have $E\left\{\text{Re}\{\alpha\}^2\right\} = \sigma_s^2/2$ and $E\left\{\text{Im}\{\alpha\}^2\right\} = \sigma_s^2/2$.

For the case of $m \neq l$, the associated result can be derived similarly to (7) and (8).

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