LOW-COMPLEXITY COMPRESSIVE SENSING DETECTION FOR MULTI-USER SPATIAL MODULATION SYSTEMS

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ABSTRACT

In this work we present a low-complexity detection scheme for spatial modulation (SM) systems in the large-scale multiple access channel (MAC). The proposed strategy is based on compressive sensing (CS) and it exploits the sparsity and structure of the transmitted SM signals in the MAC to enhance the detection performance. The analytical and simulation results presented in this paper show that the proposed technique outperforms conventional CS and linear detectors with a reduced signal processing complexity.

***Index Terms*—** Spatial modulation, large-scale MIMO, multiple access, compressive sensing.

1. INTRODUCTION

The severe growth in the achievable rate requirements of future wireless communication systems has promoted the incorporation of a high number of antennas at the communication ends [1, 2]. For instance, systems with large-scale multiple-input multiple-output (MIMO) base stations (BSs) have been shown to achieve significant performance gains when compared to their small scale counterparts by using linear precoding and detection techniques [2–4]. However, these improvements come at the expense of an increase in the circuit power consumption, which directly impacts on the global energy efficiency [5, 6]. To cope with this, SM has been presented as a strategy that offers a trade-off between spectral efficiency and total power consumption by reducing the number of antennas simultaneously active [1]. In this paper, we focus on combining the benefits of having a massive BS with the reduced power consumption offered by the use of SM-based mobile stations (MSs) in the MAC.

As yet, the development of detection and pre-scaling strategies particularly tailored for SM systems has been mostly concentrated on peer-to-peer (P2P) systems [1, 7–9]. For example, a low-complexity detection based on compressive sensing (CS) for P2P generalized space shift keying (GSSK) systems was introduced in [9]. The proposed strategy is based on normalizing the channel matrix before applying conventional greedy CS algorithms to improve the detection accuracy. However, the application of the scheme developed in [9] is restricted to P2P GSSK systems and the particular structure of multi-user SM transmission is not considered.

The extension of SM to the MAC has been recently considered in [10–12]. In this scenario, each MS has a limited number of radio frequency (RF) chains and only activates a given number of antennas for transmission accordingly [10]. With the purpose of detecting the spatial-constellation symbols, local search detection and message passing detection (MPD) algorithms for large-scale systems are developed in [12]. The MPD algorithm, which has also been shown to be useful in CS [13], allows SM to outperform conventional MIMO systems with identical spectral efficiency [12]. This entails, however, an increase in the signal processing (SP) load due to the significant number of messages that must be constantly transmitted between a large amount of nodes [13].

In this paper we concentrate on reducing the detection complexity of SM signals in the large-scale MAC via CS. Intuitively, the proposed strategy aims at offering an improved performance by incorporating the knowledge of the number of RF chains per user to the conventional CS-based detection. In particular, the proposed technique reduces the complexity of the algorithms developed in [12], while enabling the use of CS-based strategies in SM multi-user systems thanks to the exploitation of the MAC structure [9]. Additionally, in this paper we perform a thorough complexity analysis to accurately characterize the SP improvements offered by the proposed scheme. This allows us to derive novel conclusions when compared to [9, 14], where the more inaccurate complexity order is used as a complexity metric.

2. SYSTEM MODEL

Consider a scenario where K MSs communicate with a BS comprised of $N \gg K$ receive antennas. Each MS incorporates n_t antennas and $M = K \cdot n_t$ represents the total number of antennas at the MSs. This system can be described by [2]

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

where $\mathbf{y} \in \mathbb{C}^{N\times 1}$ is the signal received at the BS and $\mathbf{x} \in \mathbb{C}^{M\times 1}$ denotes the signal transmitted by the MSs. Moreover, $\mathbf{H} \in \mathbb{C}^{N\times M}$ represents a frequency flat Rayleigh fading channel satisfying $h_{n,m} = \mathcal{CN}(0, 1)$, and $\mathbf{w} \in \mathbb{C}^{N\times 1} \sim$

This work was supported by the Royal Academy of Engineering, UK and the EPSRC under grant EP/M014150/1.

$\mathcal{CN}(\mathbf{0}, \sigma_n^2 \mathbf{I}_N)$ is the additive white Gaussian noise with variance σ_n^2. Here, $\mathbf{I}_N$ represents the $N \times N$ identity matrix.

In the following and without loss of generality we consider a single-RF SM transmission system in which each MS activates a single antenna according to the input bit stream [1]. In this setting, a total of $B_{\text{sp}} = \log_2(n_t)$ bits are encoded into the spatial antenna position whereas $B_{\text{mod}} = \log_2(Q)$ bits are transmitted via the amplitude and phase signal variations. In the previous expression, Q denotes the modulation order. The signal transmitted by the k-th user can be then expressed as

$$\mathbf{x}_k = [0 \, \cdots \, s_l^q \, \cdots \, 0]^T, \tag{2}$$

where s^q is the q-th symbol of the transmit constellation $\mathcal{Q}$ and $l \in [1, n_t]$ denotes the index of the active antenna. The joint transmit signal given by $\mathbf{x} = \left[\mathbf{x}_1^T \, \mathbf{x}_2^T \, \cdots \, \mathbf{x}_K^T\right]^T$ is only comprised of $P = K$ non-zero entries, where P represents the total number of active antennas throughout the MSs [1,9].

Motivated by the low complexity and close-to-optimal performance of linear detection in large-scale MIMO [3], we employ a linear detector at the BS in the form

$$\mathbf{g} = \mathbf{D}\mathbf{y} = \left[\left(\mathbf{H}^H\mathbf{H} + \xi\mathbf{I}_M\right)^{-1}\mathbf{H}^H\right](\mathbf{H}\mathbf{x} + \mathbf{w}), \tag{3}$$

where $\mathbf{D} = \left(\mathbf{H}^H\mathbf{H} + \xi\mathbf{I}_M\right)^{-1}\mathbf{H}^H$ corresponds to the zero forcing ($\xi = 0$) or the minimum mean square error ($\xi = M\sigma_n^2/K$) linear detection matrix [3]. Here, $(\cdot)^H$ and $(\cdot)^{-1}$ denote the Hermitian and the inverse matrices respectively. Note that (3) can also be expressed via linear least squares (LS) problem formulations [6]. From this decision vector, the constellation symbol and the index of the antenna activated at the k-th MS can be obtained as

$$\hat{l} = \arg\max_l |g_l^{\{k\}}|, \qquad \hat{q} = \mathcal{D}\left(g_{\hat{l}}^{\{k\}}\right), \tag{4}$$

where $g_{\{l,\hat{l}\}}^{\{k\}}$ is the $\{l, \hat{l}\}$-th entry of the decision vector of the k-th user $\mathbf{g}^{\{k\}}$, and $\mathcal{D}$ is the demodulation function [1]. However, the fact that only P antennas are active (sparsity) and the knowledge that each user can only activate a given number of antennas (structure) are not exploited in (3). Moreover, the use of SM conventionally entails an increase in the number of antennas allocated at each MS to preserve the spectral efficiency of conventional MIMO transmission $B_{\text{MIMO}} = n_t \cdot \log_2(Q)$, which in turn harms the performance of conventional linear detection [1, 12]. For these reasons, in spite of being conventionally considered for systems with $N < M$, in this paper we consider the use of a CS-based detector that translates the benefits of conventional linear detection in massive MIMO to SM transmission in the large-scale MAC.

3. CS AND SM IN THE LARGE-SCALE MAC

3.1. The Straightforward Approach: Conventional CS

CS-based strategies take advantage of the signal sparsity in the signal detection to increase performance [15, 16]. In particular, CS guarantees an accurate reconstruction of a sparse signal $\mathbf{x}$ as long as the channel matrix $\mathbf{H}$ satisfies the restricted isometry property (RIP) of order P given by [15, 16]

$$(1 - \delta_P)\|\mathbf{x}\|_2^2 \leq \|\mathbf{H}\mathbf{x}\|_2^2 \leq (1 + \delta_P)\|\mathbf{x}\|_2^2, \tag{5}$$

where $\delta_P \in (0, 1)$ and $\|\cdot\|_2$ denotes to the ℓ_2 norm. These relationships are satisfied with $\delta_P \leq 0.1$ by matrices formed by $h_{n,m} = \mathcal{CN}(0, 1)$ independent entries as long as $N \geq cP\log(M/P)$ holds, where c is a small constant [15]. Note that this kind of matrices represent highly scattered Rayleigh fading scenarios, hence providing the possibility of performing an accurate signal detection by employing strategies such as the ℓ_1-norm minimization [15, 16]

$$\begin{aligned} &\underset{\mathbf{x}}{\text{minimize}} \ \|\mathbf{x}\|_1 \\ &\text{subject to } \|\mathbf{H}\mathbf{x} - \mathbf{y}\|_2 \leq \eta \end{aligned} \tag{6}$$

Here, $\|\cdot\|_1$, denotes the ℓ_1 norm and η bounds the noise ($\|\mathbf{w}\|_2 \leq \eta$). However, alternatives with a reduced complexity such as greedy algorithms are more relevant to the signal detection problem due to the real-time processing requirements [6]. Among these, in this paper we focus on the Compressive Sampling Matching Pursuit (CoSaMP) algorithm due to its reduced complexity when compared to other greedy algorithms and its error guarantees under noisy conditions, which jointly make their use convenient for detection [14].

At this point we remark that the poor detection accuracy of the CS-based detectors highlighted in [9] is circumvented by the availability of a high number of antennas at the BS. Still, the straightforward use of CS strategies can lead to inaccurate results in the MAC because the knowledge of the structure that arises due to the limited number of active antennas per user is not exploited. For this reason we explore an alternative tailored for the MAC of SM systems that incorporates this knowledge to further improve the performance and convergence speed of conventional CS-based algorithms.

3.2. Proposed Enhanced Technique: Exploiting the Signal Structure of SM in the Large-Scale MAC

In this section we describe a strategy to exploit the SM signal structure in the MAC for the CoSaMP algorithm, although it is clear that the same concept can be incorporated to other CS algorithms such as the ones based on MPD [12, 13, 21]. The structured CS-based detection in the large-scale MAC is referred to as spatial modulation matching pursuit (SMMP) and its operation can be described as follows: Let the first signal approximation be $\tilde{\mathbf{x}}^0 \triangleq \mathbf{0}$. Initially, the algorithm generates a simple decision metric $\mathbf{p} \in \mathbb{C}^{M \times 1}$ given by

$$\mathbf{p} = \mathbf{H}^H \mathbf{r}^{(i-1)}, \tag{7}$$

where $\mathbf{r}^i \triangleq \mathbf{H}\left(\mathbf{x} - \tilde{\mathbf{x}}^i\right) + \mathbf{w}$ is the residual signal at the i-th iteration. Note that for the first iteration ($i = 1$), the output of the matched filter (MF) detector $\mathbf{p}$ is expected to concentrate the signal energy on the components with the active

Table 1: Complexity in number of real floating-point operations (flops) of different large-scale MIMO detectors.

Detector	***Complexity in flops***
Zero Forcing detector • QR factorization [17–19] • Cholesky factorization [18–20] • Conjugate gradient [14, 19]	• $C_{\text{QR}} \simeq 8M^2N - (8/3)\, M^3 + 4N^2 + 8NM$ • $C_{\text{Chol}} \simeq 4M^2N + (4/3)\, M^3 + 11M^2 + 8NM$ • $C_{\text{CG}} \simeq (8MN + 7M) + \left[i_{max}^{ls} \times (16MN + 27M)\right]$
Spatial Modulation Matching Pursuit • Matched filter [17] • Least Squares problem – First SMMP iteration with CG – Rest of SMMP iterations with CG • Compute residual [17]	$C_{\text{SMMP}} \simeq i_{max} \times (8MN + 8PN) + C_{ls}^{1} + \left[(i_{max} - 1) \times C_{ls}^{p>1}\right]$ • $C_{\text{MF}} = 8MN$ • Least Squares problem (C_{ls}) – $C_{ls}^{i=1} = (8PN + 7P) + \left[i_{max}^{ls} \times (16PN + 27P)\right]$ – $C_{ls}^{i>1} \leq (16(2P)N + 18(2P)) + \left[i_{max}^{ls} \times (16(2P)N + 27(2P))\right]$ • $C_{\text{res}} \approx 8PN$

antennas [14]. Instead, for $i > 1$ the residual accumulates the energy on the entries with a more significant error, which helps to amend the mistakes in the active antenna detection of the previous iterations. Based on the above, the set Ω is built by selecting the K components with highest energy from $\mathbf{p}$ as in the original CoSaMP algorithm but also considering that

$$\|\mathbf{x}_k\|_0 = 1, \qquad k \in [1, K], \tag{8}$$

holds. Here, $\|\cdot\|_0$ denotes the ℓ_0-norm, i.e., the number of non-zero entries [15, 16]. Note that in conventional CS algorithms the additional constraint (8) is not accounted for, which translates to a higher number of errors as shown hereafter [14, 15, 21]. The set that includes the possible active antenna candidates for the current iteration $\mathcal{S}$ is then defined as [14]

$$\mathcal{S} \triangleq \Omega \cup \operatorname{supp}\left(\tilde{\mathbf{x}}^{i-1}\right), \tag{9}$$

where $\operatorname{supp}(\cdot)$ returns the K indexes of the non-zero entries. The cardinality of $\mathcal{S}$ determines the dimensions of the zero forcing (ZF) or, equivalently, LS problem

$$\underset{\mathbf{b}|_{\mathcal{S}}}{\text{minimize}} \ \|\mathbf{H}_{\mathcal{S}}\mathbf{b}|_{\mathcal{S}} - \mathbf{y}\|_2^2. \tag{10}$$

Here, $\mathbf{b}|_{\mathcal{S}}$ denotes the entries of the vector $\mathbf{b} \in \mathbb{C}^{M\times 1}$ supported in $\mathcal{S}$, whereas $\mathbf{H}_{\mathcal{S}}$ refers to the submatrix obtained by selecting the columns $\mathcal{S}$ of $\mathbf{H}$. At this point, we remark that $2K < M$ in (10), which allows us to reduce the algorithmic complexity of (3). Moreover, the benefits of using linear detectors in large-scale MIMO systems can be exploited in (10) since $K \ll N$ holds [3]. Finally, the estimated signal $\tilde{\mathbf{x}}^i$ is computed from $\mathbf{b}$ by selecting the entries with highest energy following (8). The pseudocode of the proposed detection algorithm is provided in Algorithm 1 for clarity, where i_{max} refers to the maximum number of iterations.

Algorithm 1 Structured Compressive Sensing SM Detection

Inputs: $\mathbf{H}, \mathbf{y}, K, i_{max}$.
Output: $\tilde{\mathbf{x}}^i \triangleq K$-sparse approximation
$\tilde{\mathbf{x}}^0 \leftarrow \mathbf{0}, \mathbf{r}^0 \leftarrow \mathbf{y}, i \leftarrow 0$ {Initialization}
while convergence criterion *false* **do**
  $i \leftarrow i + 1, \mathbf{b} \leftarrow \mathbf{0}$
  $\mathbf{p} \leftarrow \mathbf{H}^H\mathbf{r}^{(i-1)}$ {MF to estimate active antenna indexes}
  $\Omega \leftarrow$ {Select indexes with highest energy per user from $\mathbf{p}$}
  $\mathcal{S} \leftarrow \Omega \cup \operatorname{supp}(\tilde{\mathbf{x}}^{i-1})$ {Combine supports}
  $\mathbf{b}|_{\mathcal{S}} \leftarrow$ minimize $\|\mathbf{H}_{\mathcal{S}}\mathbf{b}|_{\mathcal{S}} - \mathbf{y}\|_2^2$ {Least-squares}
  $\tilde{\mathbf{x}}^i \leftarrow$ {Select entries with highest energy per user from $\mathbf{b}$}
  $\mathbf{r}^i \leftarrow \mathbf{y} - \mathbf{H}\tilde{\mathbf{x}}^i$ {Update residual}
end while

4. COMPLEXITY ANALYSIS

In this section we perform an accurate characterization of the complexity of the proposed strategy. This study is motivated by the iterative structure of the CoSaMP and SMMP algorithms, for which an analysis of the complexity order is of limited utility. Indeed, the results of this section applied for practical scenarios lead us to conclude that the detection complexity is dominated by the need of solving (10), which contrasts with the results obtained in [9, 14].

As pointed out in [14], the critical operation of Algorithm 1 is the LS operation (10), which can be solved either via direct or iterative methods [19]. On the one hand, direct methods such as the costly Cholesky and QR decompositions concentrate the complex operations at the beginning of each channel coherence period [18]. On the other hand, iterative algorithms such as the conjugate gradient (CG) avoid the storage-intensive decompositions by refining an initial estimate. The convergence speed of iterative algorithms depend on the accuracy of the initial solution and the condition number $\Theta \in [1, \infty]$ of the LS matrix $\mathbf{H}_{\mathcal{S}}$ given by [19]

$$\Theta\left(\mathbf{H}_{\mathcal{S}}\right) = \frac{\lambda_{\max}\left(\mathbf{H}_{\mathcal{S}}\right)}{\lambda_{\min}\left(\mathbf{H}_{\mathcal{S}}\right)}, \tag{11}$$

where $\lambda_{\min}(\cdot)$ and $\lambda_{\max}(\cdot)$ are the minimum and maximum singular values respectively. This makes their use convenient in Algorithm 1 due to the increasingly higher accuracy obtained by using $\tilde{\mathbf{x}}|_{\mathcal{S}}^{i-1}$ as an initial estimate in (10), and because $N \gg K$ ensures a good conditioning of $\mathbf{H}$ [14, 19, 21].

Based on the above, the number of floating point operations required by the ZF and SMMP detectors is shown in Table 1 for an arbitrary number of active antennas P. To obtain these results, the assumption that a real multiplication (division) has the same complexity of a summation (subtraction) has been adopted [17]. In particular, the computational load of ZF detection is only determined by the complexity of solving a LS problem whereas in the case of SMMP and CoSaMP is also influenced by the complexity of the MF in (7) and the residual update. Moreover, the fact that the complexity of the CG algorithm varies depending on the availability of an initial estimate is also considered in Table 1, where i_{max}^{ls} limits the number of CG iterations. We remark that the results also reflect that the LS matrix for the CS-based schemes has P columns for $i = 1$ whereas it has a number of columns less or equal than $2P$ for $i > 1$, which can be derived by inspecting (9) and noting that supp $\left(\tilde{\mathbf{x}}^0\right) = \varnothing$, where $\varnothing$ is the empty set.

Finally, we point out that, in spite of having a higher complexity in the initial detection, most of the computations performed by the ZF-SM or MMSE-SM detectors with direct methods can be reused in subsequent channel uses [6, 18]. Specifically, only $C = 8MN + 8M^2$ flops must be computed after the first symbol detection by the ZF-SM detector with Cholesky decomposition [18]. This does not apply to CS-based algorithms due to the constant variation of $\mathcal{S}$ in (10), which leads us to conclude that the use of CS for SM detection is specially convenient in fast fading scenarios where the channel needs to be constantly updated. Moreover, as opposed to [9, 14], the results of Table 1 allows us to determine that, in spite of having a smaller complexity order, the complexity of solving the LS problem dominates the global complexity for realistic system dimensions as shown in the following.

5. SIMULATION RESULTS

In this section we present the numerical results to evaluate the complexity and performance improvements offered by the proposed technique. In particular, we compare the proposed strategy in the large-scale MAC with conventional MIMO systems with spatial multiplexing and the same spectral efficiency S_e in coherence with [12, 22]. Moreover, to quantify the improvements of SMMP in systems with SM transmission, we also depict the performance of the conventional linear detectors detailed in (3) and the CoSaMP algorithm.

Fig. 1(a) shows the bit error rates (BERs) of the considered techniques in a system with $N = 128$, $K = 32$, and increasing signal-to-noise ratios (SNRs). The number of antennas allocated at the MSs is $n_t = 4$ for SM transmission whereas the modulation order and n_t is varied for conventional MIMO transmission to guarantee a fixed spectral efficiency of $S_e = 128$ bits per channel use (bpcu). The results show that the proposed strategy outperforms the rest of the alternatives for a range of practical SNRs. Specifically, it can be seen that incorporating $n_t = 2$ antennas in each MS allows obtaining the closest performance to the proposed scheme. However, this comes at the cost of incorporating additional RF circuitry, a complication avoided when single-RF SM is used. Similar results are shown in Fig. 1(b), where the BERs are depicted for varying number of users K and SNR $= 6$ dB. It can be seen that the benefits of the proposed strategy are maximized for a small number of users whereas the use of conventional MIMO transmission is beneficial for large K.

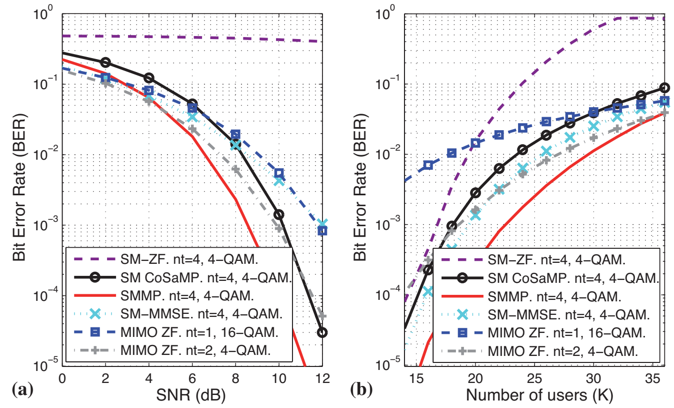

Fig. 1: (a) BER vs. SNR for $N = 128$, $K = 32$. (b) BER vs. K for $N = 128$ and SNR $= 6$ dB. SMMP and CoSaMP with $i_{max} = 3$.

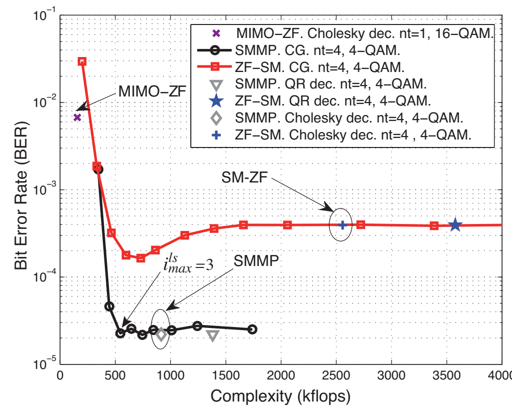

Fig. 2: BER vs. complexity (i_{max}^{ls}) for $N = 128$, $K = 16$, SNR $=$ 6 dB, $S_e = 64$ bpcu. SMMP with $i_{max} = 2$.

The evolution of the performance for increasing levels of complexity obtained from the results of Table 1 is shown in Fig. 2 for a large-scale MAC with $N = 128$, $K = 16$ and SNR $= 6$ dB. The results of this figure show that, in spite of having a higher complexity than conventional single-antenna MIMO transmission, significant performance improvements can be obtained when SM mobile stations are used. Moreover, it can be seen that SMMP allows obtaining a performance improvement of an order of magnitude w.r.t. conventional ZF detection with similar complexity. It should also be noted that in this scenario the CG algorithm requires $i_{max}^{ls} = 3$ iterations to achieve convergence and that it accounts for 70% of the global detection complexity, hence corroborating the importance of performing an accurate complexity characterization.

6. CONCLUSION

In this paper, a low-complexity strategy based on CS to detect SM signals in the large-scale MAC has been introduced. The proposed scheme aims at improving the system performance by exploiting the signal structure of SM signals in the MAC. The complexity analysis and the simulation results characterize the computational and performance enhancements that the proposed technique offers in the large-scale MAC.

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