Performance Evaluation of Structured Compressed Sensing Based Signal Detection in Spatial Modulation 3D MIMO Systems

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Abstract. Signal detection is one of the fundamental problems in three dimensional multiple-input multiple-output (3D MIMO) wireless communication systems. This paper addresses a signal detection problem in 3D MIMO system, in which spatial modulation (SM) transmission scheme is considered results of advantages of low complexity and high-energy efficiency. SM based signal transmission, typically results in the block-sparse structure in received signal. Hence, structured compressed sensing (SCS) based signal detection is proposed to exploit the inherent block sparsity information in the received signal for the uplink (UL). To extend the potential applications in different modulation based systems, this paper analyzes bit error rate (BER) of SCS-based method, in comparison with conventional methods such as minimum mean square error (MMSE) and zero padding (ZF). Simulation results are also provided to show the stable and reliable performance of the proposed SCS-based algorithm under most modulations.

Keywords: Structured compressed sensing · Signal detection
Structured subspace pursuit algorithm · Spatial modulation

1 Introduction

Spatial Modulation (SM) is an attractive technique with low-complexity and high energy-efficient transmission in three dimension (3D) multiple-input multiple-output (MIMO) systems. It is capable of exploiting the indices of transmit antennas as an additional dimension which can invoke for transmitting information, apart from the traditional amplitude and phase modulation (APM) [1]. Unlike the traditional MIMO systems, the SM transmitter in 3D-MIMO systems uses massive transmit antennas with a few number of radio frequency (RF) chains, which significantly improve energy efficiency of the whole system. Because the power consumption and hardware cost highly depend on the number of RF chains [2]. Moreover, with only one or several

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non-zero components in transmit signal at each slot, the inherent sparsity of 3D-SM-MIMO signals can be utilized in signal detection to reduce computation complexity.

For the novel transmit systems, suitable signal detection algorithms are required to obtain signals. The maximum-likelihood (ML) detector suffers from high complexity which linearly increases with the number of transmit antennas, the number of receive antennas, and the size of the symbol constellation [3]. Linear minimum mean square error (LMMSE)-based signal detector and sphere decoding (SD)-based detector [4] suffer from significant performance loss in SM-MIMO systems [5–7]. To exploit the inherent sparsity of SM signals, compressed sensing (CS) theory can be used to improve the signal detection performance [8, 9]. In [10], CS theory is used for signal detection in large-scale multiple access channels. Paper [11] proposed a structured compressed sensing based signal detector for massive spatial modulation MIMO systems.

To fully extend the applications, this paper analyzes the performance of several compressed sensing signal detectors with different modulation levels in 3D MIMO system. Firstly, we compare the detection performance of several available signal detection algorithms and provide corresponding simulation results. Our simulation study implied that that SSP algorithm based on structured compressed sensing can achieve better performance than others. Additionally, SSP algorithm under different modulation conditions is further analyzed via average bit error rate (BER) standard against with signal to noise ratio (SNR).

The rest of this paper is organized as follows. Section 2 introduces the 3D MIMO system model and Sect. 3 presents structured compressed sensing based signal detection methods. The simulation results and performance analysis of different signal detectors are provided in Sect. 4. Finally, conclusions are drawn in Sect. 5.

2 System Model

In spatial modulation MIMO systems, the transmitter has N_t transmit antennas with $N_a < N_t$ active antennas, and the receiver has N_r receive antennas. The information bit stream is divided into two parts: the first part with $\left\lfloor \log_2 \binom{N_t}{N_a} \right\rfloor$ bits is mapped onto the spatial constellation symbol which indicates different selection schemes of active transmit antennas, and the second part with $\log_2 M$ bits is mapped onto the signal constellation symbols coming from the M -ary signal constellation set (e.g., QAM). Hence, each SM signal carriers the information of $N_a \log_2 M + \left\lfloor \log_2 \binom{N_t}{N_a} \right\rfloor$ bits.

At the receiver, the received signal $\mathbf{y} \in \mathbb{C}^{N_r \times 1}$ can be expressed as $\mathbf{y} = \mathbf{Hx} + \mathbf{w}$, where $\mathbf{x} \in \mathbb{C}^{N_t \times 1}$ is the SM signal transmitted by the transmitter, $\mathbf{w} \in \mathbb{C}^{N_r \times 1}$ is the additive white Gaussian noise (AWGN) vector with independent and identically distributed (i.i.d.) entries following the circular symmetric complex Gaussian distribution $\mathcal{CN}(0, \sigma_w^2)$. $\mathbf{H} = \mathbf{R}_r^{\frac{1}{2}} \tilde{\mathbf{H}} \mathbf{R}_t^{\frac{1}{2}} \in \mathbb{C}^{N_r \times N_t}$ is the correlated flat Rayleigh-fading MIMO channel, entries of $\tilde{\mathbf{H}}$ are subjected to the i.i.d. distribution $\mathcal{CN}(0, 1)$. $\mathbf{R}_r$ and $\mathbf{R}_t$ are the receiver and transmitter correlation matrices respectively [12]. The correlation matrix **R** is given by $r_{ij} = r^{|i-j|}$, where r_{ij} is the i-th row and j-th column element of **R**, and r is the correlation coefficient of neighboring antennas.

Figure 1 shows an example of spatial constellation symbol and signal constellation symbol in spatial modulation 3D-MIMO system. The information bit stream is under both spatial modulation and digital modulation, where spatial modulation increases the energy efficiency and reduces complexity of signal demodulation, and digital modulation improves system throughput.

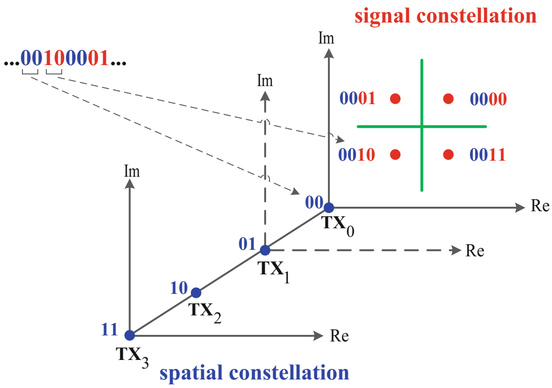

Fig. 1. Spatial constellation symbol and signal constellation symbol in SM 3D-MIMO system, where $N_t = 4$, $N_a = 1$, and 4QAM are considered as for an example.

3 Structured Compressed Sensing Based Signal Detection

3.1 Grouped Transmission Scheme

The SM signal $\mathbf{x}_k = \mathbf{e}_k \mathbf{s}_k$ transmitted by the k th user in a time slot consists of two parts: the spatial constellation symbol $\mathbf{e}_k \in \mathbb{C}^{n_t}$ and the signal constellation symbol $\mathbf{s}_k \in \mathbb{C}$. Due to only a single RF chain employed at each user, only one entry of $\mathbf{e}_k$ associated with the active AE is equal to one, and the rest of the entries of $\mathbf{e}_k$ are zeros, i.e., we have

$$\mathrm{supp}(\mathbf{e}_k) \in \mathbb{A}, \| \mathbf{e}_k \|_0 = 1, \| \mathbf{e}_k \|_2 = 1 \tag{1}$$

where $\mathbb{A} = \{1, 2, \ldots, n_t\}$ is the spatial constellation symbol set. The signal constellation symbol comes from L-ary modulation, i.e., $\mathbf{s}_k \in \mathbb{L}$, where $\mathbb{L}$ is the signal constellation symbol set of size L. Hence, each user's SM signal carries the information of $\log_2(L) + \log_2(n_t)$ bits per channel use (bpcu), and the overall throughput at the transmitter is $K(\log_2(L) + \log_2(n_t))$ bpcu.

At the transmitter, every G consecutive SM signals are divided into a group. The signals in a group have the same active antenna selection scheme and share the same spatial constellation symbol, i.e.,

$$\mathrm{supp}\left(\mathbf{x}_k^1\right) = \mathrm{supp}\left(\mathbf{x}_k^2\right) = \ldots = \mathrm{supp}\left(\mathbf{x}_k^G\right) \tag{2}$$

where $\mathbf{x}_k^1$, $\mathbf{x}_k^2$,…, $\mathbf{x}_k^G$ are SM signal of the k th user in G consecutive symbol slots. Thus they show the feature of structured sparsity, which can be exploited as priori information to improve the performance of the signal detection.

At the receiver, due to the reduced number of RF chains at the BS, only M_{RF} receive antennas can be exploited to receive signals. Since the BS can serve K users simultaneously, the received signal $\mathbf{y}_q \in \mathbb{C}^{M_{RF}}$ for $1 \leq q \leq Q$ of the q th time slot can be expressed as

$$\mathbf{y}_q = \sum\nolimits_{k=1}^{K} \mathbf{y}_{k,q} + \mathbf{w}_q = \sum\nolimits_{k=1}^{K} \mathbf{H}_k \mathbf{x}_k + \mathbf{w}_q \tag{3}$$

where $\mathbf{H}_k \in \mathbb{C}^{M \times n_t}$ is the k th user's MIMO channel matrix. Figure 2 is the illustration of the grouped transmission scheme at the transmitter.

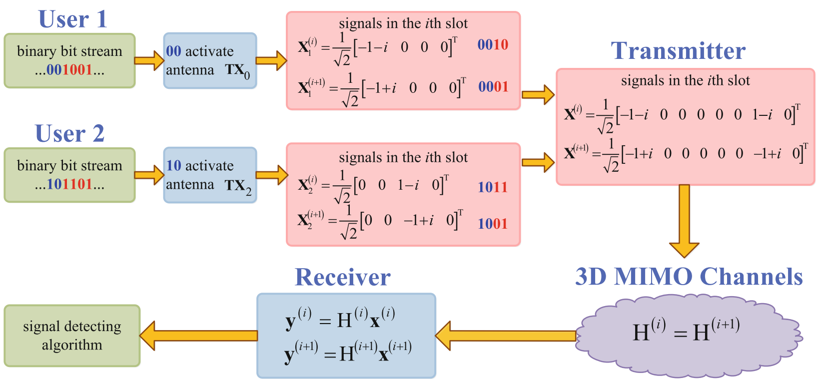

Fig. 2. Illustration of the grouped transmission scheme at the transmitter, where K = 2, N_u = 4, N_a = 1, G = 2, N_t = 8, N_r = 4, and 4QAM are considered.

3.2 Subspace Pursuit Algorithm

The SP algorithm starts by selecting the set of K most reliable information symbols [13, 14]. After each iteration, the estimated support set of size K will be updated according to the correlation between the measurement vector $\mathbf{y}$ and the channel submatrix. Then, the wrong indices will be removed from the estimated support set. The iteration stops when the transient residual is larger than the previous one. The flowchart of SP algorithm is shown in Fig. 3, where input is measurement vector $\mathbf{y}$, channel matrix $\mathbf{H}$, number of active antennas N_a and output is the estimated signal.

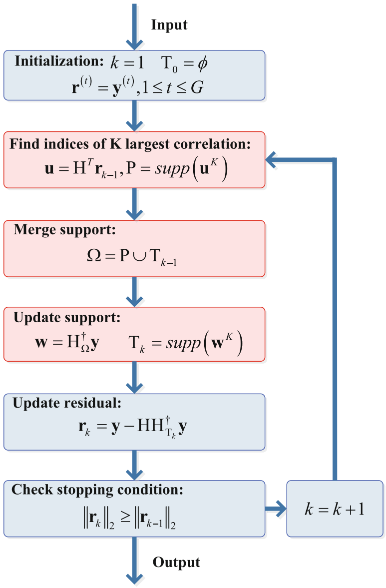

Fig. 3. Flowchart of SP algorithm.

3.3 Structured Subspace Pursuit Algorithm

Different from the SP algorithm, the spatial constellation set will be exploited as priori information in the SSP algorithm. It means that the estimated support set during each iteration should belong to the predefined spatial constellation set. During each iteration, the potential true indices will be obtained according to the correlation between the MIMO channels and the residual in the previous iteration, and then the estimated support set will be updated after the least squares. The flowchart of SSP algorithm is shown in Fig. 4.

It is proved that with the same size of the measurement vector the recovery performance of SCS-based signal detectors is superior to that of conventional CS-based signal detectors [15]. The SSP algorithm can solve multiple sparse signals with the common support set but having different measurement matrices [11].

The description of the SSP algorithm is given as follows:

1. The parameters of input are: the measurement vector $\boldsymbol{y}$, the channel matrix $\boldsymbol{H}$, the number of active antennas N_a.

2. In the support merging section, according to the correlation $\boldsymbol{u}^{(t)}$ between the MIMO channels and the residual in the previous iteration, a potential support set $\boldsymbol{P}$ which makes the correlation $\boldsymbol{u}^{(t)}$ largest will be selected from the predefined spatial constellation set.

3. After updating the current support set $\boldsymbol{T}_k$, wrong indices will be removed and most likely indices will be selected according to the least squares.

4. The parameter of output is the estimated signal $\hat{\boldsymbol{x}}^{(t)} = \left(\boldsymbol{H}_{\boldsymbol{T}_k}^{(t)}\right)^{\dagger}$.

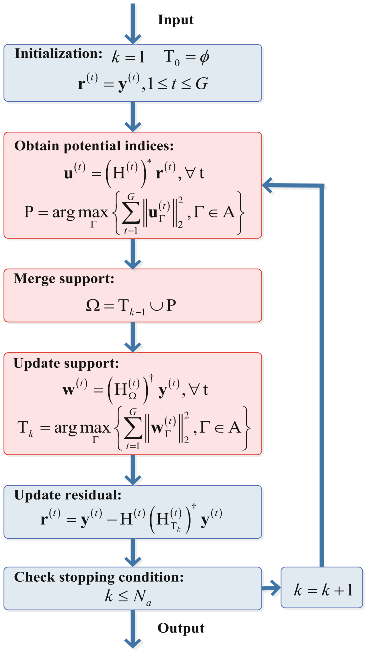

Fig. 4. Flowchart of SSP algorithm.

4 Performance Analysis

The analysis of different signal detecting algorithms including SP, SSP, MMSE and ZF is performed and analyzed using Bit Error Rate (BER) verses Signal to Noise Ratio (SNR) plots in Fig. 5, where $K = 24$, $N_a = 1$, $N_u = 4$, $N_r = 64$, $G = 1$, and 16QAM are considered. One can observe that CS-based signal detectors give better performance than conventional signal detectors, especially when the SNR is comparatively high.

Figure 6 shows BER of SP algorithm and SSP algorithm over different levels of QAM modulation, where $K = 24$, $N_a = 1$, $N_u = 4$, $N_r = 64$, $G = 1$ are considered. From the figure, it is possible to conclude that the performance of SSP algorithm is stable and reliable. Moreover, the lower the level of QAM modulation is, the better the SSP algorithm performs. On the other hand, the SP algorithm suffers from comparatively high performance loss even under modulation of 16 QAM when the SNR is no more than 20 dB.

Figure 7 shows BER of the SSP algorithm over different levels of PSK modulation, where $K = 24$, $N_a = 1$, $N_u = 4$, $N_r = 64$, $G = 1$ are considered. From the figure, it can be observed that the SSP algorithm performs. It is worth noting that BER curves of the proposed algorithm are very close under the modulations of BPSK, QPSK and 8PSK. Also we can deduct that the proposed algorithm can work very well under the low levels of PSK modulation while the BER performance may deteriorate under the high levels such as 32PSK.

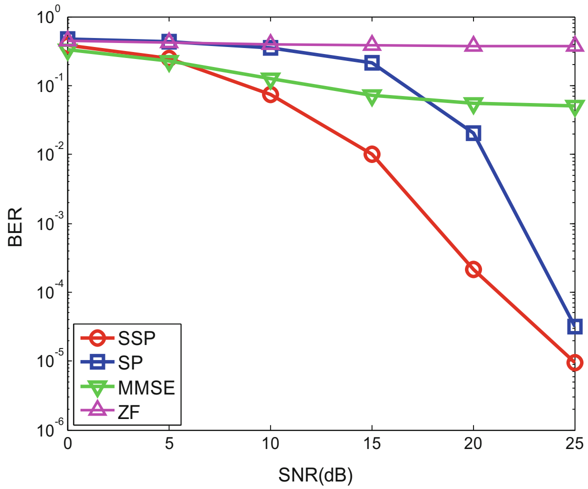

Fig. 5. BER verses SNR plots for different signal detecting algorithm, where $K = 24$, $N_a = 1$, $N_u = 4$, $N_r = 64$, $G = 1$, and 16QAM are considered

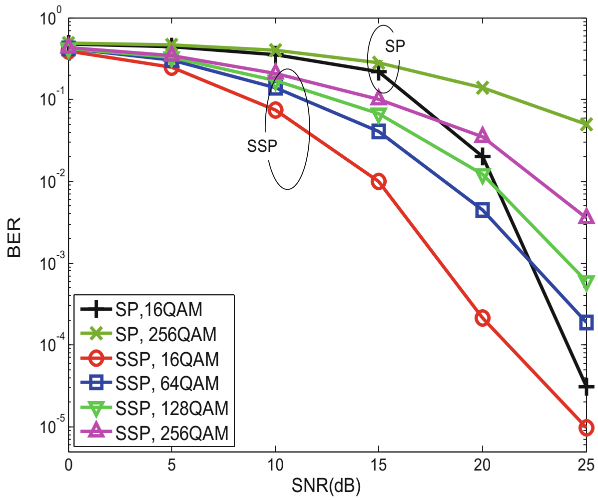

Fig. 6. BER verses SNR plots for SP algorithm and SSP algorithm over different levels of QAM modulation, where $K = 24$, $N_a = 1$, $N_u = 4$, $N_r = 64$, $G = 1$ are considered.

Figure 8 shows BER of SSP algorithm with different sparsity level and a number of received antennas. The figure shows that with larger sparsity level and more received antennas the SSP algorithm performs better.

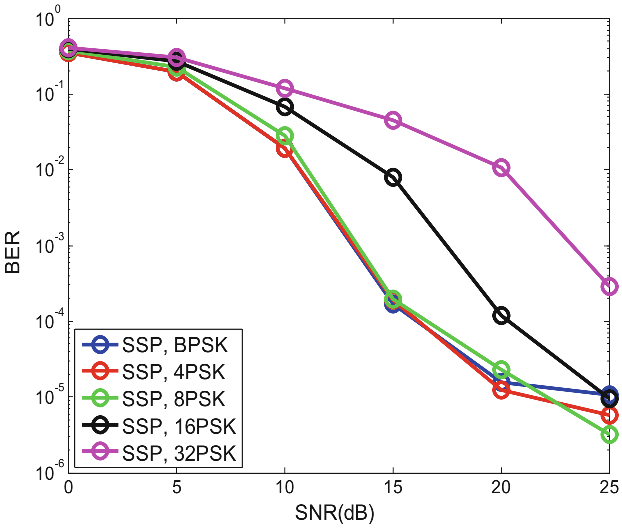

Fig. 7. BER verses SNR plots for SSP algorithm over different levels of PSK modulation, where $K = 24$, $N_a = 1$, $N_u = 4$, $N_r = 64$, $G = 1$ are considered.

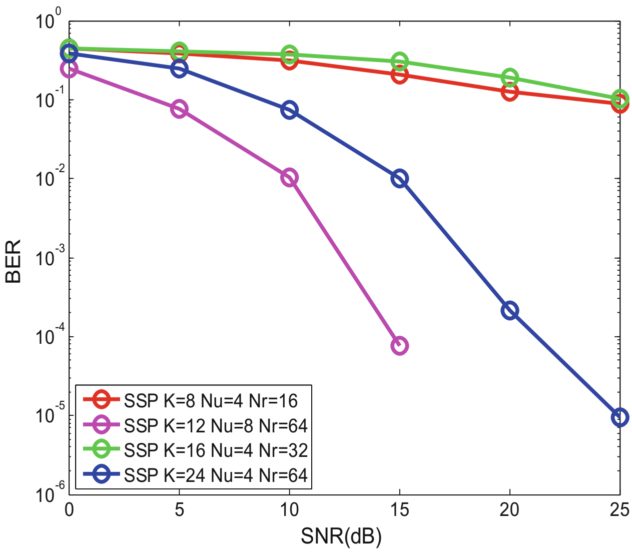

Fig. 8. BER verses SNR plots for SSP algorithm over different sparsity level and number of received antennas.

5 Conclusion

In this paper, we have evaluated the state-of-the-art structured compressed sensing based SSP algorithm in the scenarios of various modulation levels. First of all, we reviewed the structured signal detection method and pointed out its advantage. Secondly, simulation results have been provided to confirm the merits of the proposed methods in detection. Our study was also found that the computational complexity of the proposed method is comparable with conventional methods, e.g. MMSE and ZF. Finally, we gave the additional simulation results to evaluate the SSP algorithm which can perform better in the scenarios of more sparsity level as well as larger number of received antennas.

References

1. Yang, P., Di Renzo, M., Xiao, Y., Li, S.: Design guidelines for spatial modulation. IEEE Commun. Surv. Tutorials **17**, 6–26 (2015)
2. Marco, B., Renzo, D., Haas, H., Ghrayeb, A., Sugiura, S., Hanzo, L.: Spatial modulation for generalized MIMO: challenges, opportunities, and implementation, vol. 102, pp. 56–103 (2014)
3. Zheng, J.: Signal vector based list detection for spatial modulation. IEEE Wirel. Commun. Lett. **1**, 265–267 (2012)
4. Sampaio-Neto, R.: Low-complexity sphere decoding detector for generalized spatial modulation systems. 18, 949–952 (2014)
5. Gao, F., Cui, T., Nallanathan, A.: On channel estimation and optimal training design for amplify and forward relay networks. IEEE Trans. Commun. **7**, 1907–1916 (2008)
6. Gao, F., Zhang, R., Liang, Y.: Optimal channel estimation and training design for two-way relay networks. IEEE Trans. Commun. **57**, 3024–3033 (2009)
7. Cui, T., Gao, F., Ho, T., Nallanathan, A.: Distributed space-time coding for two-way wireless relay networks. In: Proceedings of IEEE ICC, Beijing, China, 19–23 May, 2008, pp. 3888–3892 (2008)
8. Donoho, D.L.: Compressed sensing. IEEE Trans. Inf. Theory **52**, 1289–1306 (2006)
9. Tropp, J.A., Gilbert, A.C.: Signal recovery from random measurements via orthogonal matching pursuit. IEEE Trans. Inf. Theory **53**, 4655–4666 (2007)
10. Garcia-Rodriguez, A., Masouros, C.: Low-complexity compressive sensing detection for spatial modulation in large-scale multiple access channels. IEEE Trans. Commun. **63**, 2565–2579 (2015)
11. Gao, Z., Dai, L., Qi, C., Yuen, C., Wang, Z.: Near-optimal signal detector based on structured compressive sensing for massive SM-MIMO. IEEE Trans. Veh. Technol. **9545**, 1–5 (2016)
12. Wu, X., Claussen, H., Di Renzo, M., Haas, H.: Channel estimation for spatial modulation. IEEE Trans. Commun. **62**, 4362–4372 (2014)
13. Dai, W., Milenkovic, O.: Subspace pursuit for compressive sensing signal reconstruction. IEEE Trans. Inf. Theory **55**, 2230–2249 (2009)
14. Guo, Q., Gui, G., Li, F.: Block-partition sparse channel estimation for spatially correlated massive MIMO systems. In: International Conference on Wireless Communications and Signal Processing (WCSP), Yangzhou, China, 13–15 October, 2016, pp. 1–4 (2016)
15. Duarte, M.F., Eldar, Y.C.: Structured compressed sensing: from theory to applications. IEEE Trans. Sig. Process. **59**, 4053–4085 (2011)