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CONTENTS

Part I: Signal and Image Processing

Low Complexity Detection for Spatial Modulation Aided Single Carrier Systems

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Abstract—**Spatial modulation (SM), which is a novel transmission scheme, is developed by using active transmit antenna indexes and modulated signals to convey the information. In this paper, a low complexity detection is proposed for SM aided single-carrier (SM-SC) systems with dispersive channels. In the proposed detection, we estimate the K frame transmitted signal vectors in sequence by separating the channel matrix into K rows which can avoid the exhaustive search of all possible transmitted signal vectors. Compared to the conventional detection schemes, which are partial interference cancellation receiver with successive interference cancellation (PIC-R-SIC) detection and the optimal maximum likelihood (ML) detection, our proposed scheme achieves a lower computational complexity. Simulation results show that the proposed detection degrades the bit error rate (BER) performance compared to the PIC-R-SIC detection and the ML detection, while the complexity is greatly reduced.**

Index Terms—**spatial modulation (SM), low complexity, maximum likelihood (ML)**

I. Introduction

Spatial modulation (SM) [1]–[3] is an attractive and special transmission scheme in multi-input multi-output (MIMO) systems which employs the active transmit antenna and transmitted signals to convey the information. In SM, the information bits are divided into blocks and each block has $\log_2(N_tM)$ bits, , where N_t and M are the transmit antenna number and the constellation order, respectively. In each block, $\log_2(N_t)$ bits are used to select an antenna from N_t transmit antennas for data transmission and $\log_2(M)$ bits are used to select a symbol from the M-ary constellation set. Since only one transmit antenna is active during each time slot in SM, the inter-channel interference (ICI) can be perfectly avoided at the receiver.

The detection algorithm was original introduced in [4] which has a suboptimal performance. In order to enhance the performance, the optimal maximum likelihood (ML) detection in SM systems was proposed in [5], while the complexity is increased with N_t and M. Recently, lots of low complexity detection methods were proposed in SM systems. In [6], signal vector based (SVD) method was proposed to achieve a low complexity while the performance extremely degrades compared with ML detection. In order to solve this problem, adaptive SVD (ASVD) method was proposed to achieve ML detection with a slight performance loss [7]. Recently, a SM aided single carrier (SM-SC) system with zero-padded (ZP) cyclic prefix (CP) was proposed in [8], [9]. In [9], partial interference cancellation receiver with successive interference cancellation (PIC-R-SIC) was proposed to reduce the complexity of ML detection. Note that computing the projection matrices in PIC-R-SIC still leads a high complexity, especially with a large P, N_t and K, where P and K are the number of multi-path links and the number of data frame in the transmitted vector, respectively.

In this paper, we propose a low complexity detection for SM-SC systems. In the proposed detection, the transmitted signal vectors were detected separately without calculating the projection matrices. Note that we only need a submatrix, which is composed of K rows of the channel matrix, to estimate the transmitted signal vectors. Since the transmitted vectors in one data frame are estimated one by one and the projection matrices are not considered, the computational complexity is significantly reduced. In simulation results, it can be seen that the performance of our proposed detection provides an acceptable loss compared with that of PIC-R-SIC detection.

The rest of the letter is organized as follows. In section II, we introduce the system model for the SM-SC system. The proposed detection algorithm is presented in section III. Section IV presents simulation results and complexity analysis. Finally, the paper is concluded in Section V.

II. System Model

A. SM-SC System Model

We consider a MIMO system with N_t transmit and N_r receive antennas over a disperse channel having P multi-path links between each transmit and receive antenna pairs. The received signal vector during the i-th channel use is given by

$$\mathbf{y}_i = \sum_{j=0}^{P-1} \mathbf{H}_j \mathbf{x}_{i-j} + \mathbf{n}_i, \tag{1}$$

where $\mathbf{x}_k \in \mathbb{C}^{N_t\times 1}$ and $\mathbf{y}_k \in \mathbb{C}^{N_r\times 1}$ denote the transmitted symbol and received signal vectors in the k-th channel use, $\mathbf{H} \in \mathbb{C}^{N_r\times N_t}$ denotes the channel matrix at the j-th path with entries which are assumed to be independent identically distributed (i.i.d.) complex Gaussian random variables with zero mean and unit variance and $\mathbf{n}_k \in \mathbb{C}^{N_r\times 1}$ is an additive

$$\underbrace{\begin{bmatrix} \mathbf{y}_1 \\ \mathbf{y}_2 \\ \vdots \\ \mathbf{y}_{K+P-1} \end{bmatrix}}_{\tilde{\mathbf{y}} \text{ of size } (K+P-1)N_r \times 1} = \underbrace{\begin{bmatrix} \mathbf{H}_0 & \mathbf{0} & \cdots & \mathbf{0} & \mathbf{0} \\ \mathbf{H}_1 & \mathbf{H}_0 & \cdots & \mathbf{0} & \mathbf{0} \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ \mathbf{H}_{P-1} & \mathbf{H}_{P-2} & \cdots & \mathbf{H}_0 & \mathbf{0} \\ \mathbf{0} & \mathbf{H}_{P-1} & \cdots & \mathbf{H}_1 & \mathbf{H}_0 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ \mathbf{0} & \mathbf{0} & \cdots & \mathbf{H}_{P-1} & \mathbf{H}_{P-2} \\ \mathbf{0} & \mathbf{0} & \cdots & \mathbf{0} & \mathbf{H}_{P-1} \end{bmatrix}}_{\tilde{\mathbf{H}} \text{ of size } (K+P-1)N_r \times KN_t} \underbrace{\begin{bmatrix} \mathbf{x}_1 \\ \mathbf{x}_2 \\ \vdots \\ \mathbf{x}_K \end{bmatrix}}_{\tilde{\mathbf{x}} \text{ of size } KN_t \times 1} + \underbrace{\begin{bmatrix} \mathbf{n}_1 \\ \mathbf{n}_2 \\ \vdots \\ \mathbf{n}_{K+P-1} \end{bmatrix}}_{\tilde{\mathbf{n}} \text{ of size } (K+P-1)N_r \times 1}, \quad (2)$$

white Gaussian noise vector with zero mean and covariance matrix $\sigma^2 \mathbf{I}_{N_r}$.

Assuming that the data frame is K and the received data frame is given by (2), where $\mathbf{0} \in \mathbb{C}^{N_r \times N_t}$ denotes the zero matrix. In the SM system, the transmitted symbol vector can be written as

$$\mathbf{x}_k = [0, \ldots, s_k, 0, \ldots]^T, \quad (3)$$

where s_k is a symbol from the M-ary constellation set $\mathcal{S}$ with $1 \leq k \leq K$.

For a given perfect channel state information (CSI) at the receiver, the ML detection in the SM-SC system is expressed as

$$\hat{\tilde{\mathbf{x}}}_{ML} = \arg \min_{\tilde{\mathbf{x}} \in \mathcal{X}} \|\tilde{\mathbf{y}} - \tilde{\mathbf{H}}\tilde{\mathbf{x}}\|_F^2, \quad (4)$$

where $\mathcal{X}$ is the set of all possible transmitted symbol vectors with size of $(N_t M)^K$. Due to the exhaustive search of all vectors, the complexity of the ML detection is exponentially increased with N_t, M and K.

B. PIC-R-SIC Detection

The PIC-R-SIC detection was introduced in [9] which is to reduce the complexity of the ML dection. The equation (2) can be rewritten as

$$\tilde{\mathbf{y}} = \sum_{i=1}^{K} \mathbf{G}_{\mathcal{I}_i} \mathbf{x}_i + \tilde{\mathbf{n}}, \quad (5)$$

where $\mathcal{I}_i = \{N_t(i-1)+1, N_t(i-1)+2, \ldots, N_t i\}$ and $\mathbf{G}_{\mathcal{I}_i}$ is the submatrix of $\tilde{\mathbf{H}}$ with the column indices $\mathcal{I}_i$.

In the PIC-R-SIC detection, the data frame $\mathbf{x}_K, \mathbf{x}_{K-1}, \ldots, \mathbf{x}_1$ are detected in sequence. Firstly, let us define

$$\mathbf{G}_{\mathcal{I}_k}^c = [\mathbf{G}_{\mathcal{I}_1}, \mathbf{G}_{\mathcal{I}_2}, \ldots, \mathbf{G}_{\mathcal{I}_{k-1}}]. \quad (6)$$

The projection matrix of the space of $\mathbf{G}_{\mathcal{I}_k}^c$ can be expressed as

$$\mathbf{Q}_{\mathcal{I}_k} = \mathbf{G}_{\mathcal{I}_k}^c ((\mathbf{G}_{\mathcal{I}_k}^c)^H \mathbf{G}_{\mathcal{I}_k}^c)^{-1} (\mathbf{G}_{\mathcal{I}_k}^c)^H. \quad (7)$$

Hence, the projection matrix that projects a vector onto the orthogonal complementary space of $\mathbf{G}_{\mathcal{I}_k}^c$ is given by []

$$\mathbf{P}_{\mathcal{I}_k} = \mathbf{I}_{(K+P-1)N_r} - \mathbf{Q}_{\mathcal{I}_k}. \quad (8)$$

Thus, we have $\mathbf{P}_{\mathcal{I}_k} \mathbf{G}_{\mathcal{I}_i} = \mathbf{0}$, $1 \leq i \leq K$ and $i \neq k$. We define $\tilde{\mathbf{y}}^{(t)} = \sum_{i=1}^{t} \mathbf{G}_{\mathcal{I}_i} \mathbf{x}_i + \tilde{\mathbf{n}}$ for $1 \leq t \leq K$. Then, Let $t = K$ and calculate

$$\begin{aligned} \mathbf{Z}_{\mathcal{I}_t} = \mathbf{P}_{\mathcal{I}_t} \tilde{\mathbf{y}}^{(t)} &= \mathbf{P}_{\mathcal{I}_t} \sum_{i=1}^{t} \mathbf{G}_{\mathcal{I}_i} \mathbf{x}_i + \mathbf{P}_{\mathcal{I}_t} \tilde{\mathbf{n}} \\ &= \mathbf{P}_{\mathcal{I}_t} \mathbf{G}_{\mathcal{I}_t} \mathbf{x}_t + \mathbf{P}_{\mathcal{I}_t} \tilde{\mathbf{n}}. \end{aligned} \quad (9)$$

The data $\mathbf{x}_t$ is estimated as

$$(\hat{\mathbf{x}}_t)_{PIC-R-SIC} = \arg \min_{\mathbf{x}_t \in \mathcal{X}_{SM}} \|\mathbf{Z}_{\mathcal{I}_t} - \mathbf{P}_{\mathcal{I}_t} \mathbf{G}_{\mathcal{I}_t} \mathbf{x}_t\|_F^2, \quad (10)$$

where $\mathcal{X}_{SM}$ is the set of all possible transmitted symbol vectors with size of $N_t M$ in the SM system. We update $t = t - 1 (t > 1)$ while continue the next estimation by equations (9) and (10). When $t = 1$, PIC-R-SIC detection is not suitable to be used because of the nonexistence of the $\mathbf{P}_{\mathcal{I}_1}$. In this case, $\mathbf{x}_1$ is estimated by ML detection

$$(\hat{\mathbf{x}}_1)_{ML} = \arg \min_{\mathbf{x}_1 \in \mathcal{X}_{SM}} \|\tilde{\mathbf{y}}^{(1)} - \mathbf{G}_{\mathcal{I}_1} \mathbf{x}_1\|_F^2. \quad (11)$$

III. The Proposed Low Detection Algorithm

In this section, we propose a low detection algorithm for the SM-SC system, which can approach the performance of the optimal ML detector.

In the proposed detection algorithm, the data frame $\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_K$ are detected in sequence. Since only one transmit antenna is active during each time slot, $\hat{\mathbf{H}}$ can be expressed as

$$\hat{\mathbf{H}} = \begin{bmatrix} \mathbf{h}_0(l_1) & \mathbf{0} & \cdots & \mathbf{0} & \mathbf{0} \\ \mathbf{h}_1(l_1) & \mathbf{h}_0(l_2) & \cdots & \mathbf{0} & \mathbf{0} \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ \mathbf{h}_{P-1}(l_1) & \mathbf{h}_{P-2}(l_2) & \cdots & \mathbf{h}_0(l_{(K-1)}) & \mathbf{0} \\ \mathbf{0} & \mathbf{h}_{P-1}(l_2) & \cdots & \mathbf{h}_1(l_{(K-1)}) & \mathbf{h}_0(l_K) \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ \mathbf{0} & \mathbf{0} & \cdots & \mathbf{h}_{P-1}(l_{(K-1)}) & \mathbf{h}_{P-2}(l_K) \\ \mathbf{0} & \mathbf{0} & \cdots & \mathbf{0} & \mathbf{h}_{P-1}(l_K) \end{bmatrix}, \quad (12)$$

where l_i is the active antenna index in the i-th time slot for $1 \leq i \leq K$ and $\mathbf{h}_j(l_i)$ denotes the l_i-th column of $\mathbf{H}_j$ for $0 \leq j \leq P-1$. According to equation (2), the first K terms of $\hat{\mathbf{y}}$ is given as

$$\tilde{\mathbf{y}}_K = \tilde{\mathbf{H}}_K \mathbf{s} + \tilde{\mathbf{n}}_K, \quad (13)$$

where $\tilde{\mathbf{y}}_K = [\mathbf{y}_1^T, \mathbf{y}_2^T, \ldots, \mathbf{y}_K^T]^T$, $\mathbf{s} = [s_1, s_2, \ldots, s_K]$, $\tilde{\mathbf{H}}_K$ denotes the KN_r rows of $\mathbf{H}$ and $\tilde{\mathbf{n}}_K = [\mathbf{n}_1^T, \mathbf{n}_2^T, \ldots, \mathbf{n}_K^T]^T$.

In the first step, we consider $\mathbf{y}_1$ to estimate the first data $\mathbf{x}_1$. Based on equation (13), $\mathbf{y}_1$ can be written as

$$\mathbf{y}_1 = \mathbf{H}_0 \mathbf{x}_1 + \mathbf{n}_1 = \mathbf{h}_0(l_1) s_1 + \mathbf{n}_1. \quad (14)$$

The candidate vector $\mathcal{L}$ of the index l_1 can be estimated from the angles between $\mathbf{y}_1$ and $\mathbf{h}_0(l_1)$ by list signal vector based detection (LSVD) []

$$\mathcal{L}_{l_1} = \arg \underset{l_1 \in \{1, \ldots, N_t\}}{\text{asd}} \{\theta(l_1)\}, \quad (15)$$

where $\theta(l_1) = \arccos \frac{\|\langle \mathbf{h}_0(l_1), \mathbf{y}_1 \rangle\|}{\|\mathbf{h}_0(l_1)\| \|\mathbf{y}_1\|}$ and asd$\{\cdot\}$ denotes the ascending function of an vector. Let $\tilde{\mathcal{L}}_{l_1} = [g_{l_1}^1, g_{l_1}^2, \cdots, g_{l_1}^L]$ denote a vector which has the smallest L values of $\mathcal{L}_{l_1}$ for $1 \leq L \leq N_t$. Then, the estimation of l_1 and s_1 are obtained as

$$[\hat{l}_1, \hat{s}_1] = \arg \min_{l_1 \in \tilde{\mathcal{L}}_{l_1}, s_1 \in \mathcal{S}} \|\mathbf{y}_1 - \mathbf{h}_0(l_1) s_1\|_F^2. \quad (16)$$

In the second step, we consider $\mathbf{y}_2$ to estimate the second data $\mathbf{x}_2$. $\mathbf{y}_2$ can be written as

$$\mathbf{y}_2 = \mathbf{h}_1(l_1) s_1 + \mathbf{h}_0(l_2) s_2 + \mathbf{n}_2. \quad (17)$$

Since l_1 and s_1 were already detected in the previous step, the received vector without the interference can be obtained as

$$\bar{\mathbf{y}}_2 = \mathbf{y}_2 - \mathbf{h}_1(\hat{l}_1)\hat{s}_1 = \mathbf{h}_0(l_2) s_2 + \mathbf{n}_2. \quad (18)$$

We use LSVD again to obtain $\tilde{\mathcal{L}}_{l_2} = [g_{l_2}^1, g_{l_2}^2, \cdots, g_{l_2}^L]$ and the estimation of l_2 and s_2 are obtained as

$$[\hat{l}_2, \hat{s}_2] = \arg \min_{l_2 \in \tilde{\mathcal{L}}_{l_2}, s_2 \in \mathcal{S}} \|\bar{\mathbf{y}}_2 - \mathbf{h}_0(l_2) s_2\|_F^2. \quad (19)$$

The above-mentioned detection process will be terminated after K steps and yield the estimated data frame $[\hat{\mathbf{x}}_1, \hat{\mathbf{x}}_2, \ldots, \hat{\mathbf{x}}_K]$.

The proposed detection algorithm for SM-SC systems is summarized in Algorithm 1.

IV. Simulation Results and Complexity Analysis

In this section, we first show simulation results to illustrate the performance of the proposed detection and compare them with the performances of the PIC-R-SIC detection and ML detection in SM-SC systems. In our simulations, we consider the flat Rayleigh fading channels in SM-SC systems. Then, the complexity of the proposed detection is analyzed and compared with the complexity of the PIC-R-SIC detection and the ML detection in SM-SC systems.

A. Simulation Results

In this subsection, the Monte Carlo simulations are performed such that at least 10^6 symbols have been transmitted for each signal-to-noise ratio (SNR), where the SNR is denoted as E_s/N_0. Firstly, we set $K = P = 3$ for 2×2 SM-SC system. Fig.1 shows the BER performances of the proposed detection, the PIC-R-SIC detection and the ML detection with QPSK modulation under the spectral efficiency $m = \log_2(MN_t) = 3$ bits/s/Hz. It can be seen that the proposed detection has a performance loss compared with other two detections in the SM-SC system. At the BER $= 10^{-5}$, the proposed detection has about 0.5dB performance loss compared with the ML detection and about 2dB performance loss compared with the ML detection in the SM system.

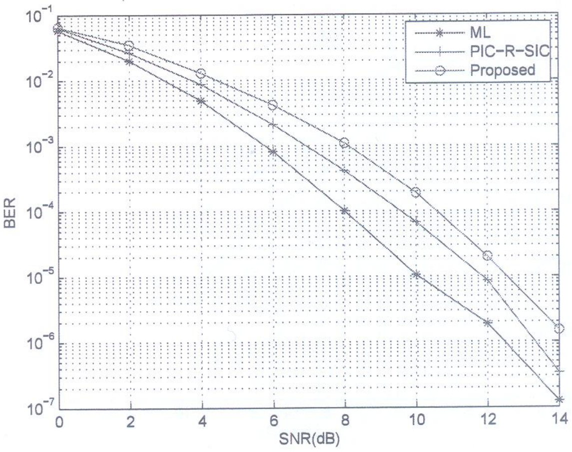

Fig. 1. BER performance comparison with $N_t = N_r = 2$ and $K = P = 3$, using QPSK for SMSC systems.

Note that in the proposed detection algorithm, the estimation of each current transmitted signal is based on the previous estimation in one data frame, which means the error detection happens if any signal is wrongly detected. Hence, the performance of our proposed detection is the worse than that of two detections which was already proved in Fig.1. Similar results

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Algorithm 1: The Proposed Detection Algorithm

Input: N_t, N_r, K, P, $\hat{\mathbf{y}}_K$, $\hat{\mathbf{H}}_K$

Calculate $\hat{l}_1$ and $\hat{s}_1$ by (16).

For $t = 2 : K$

1: The received signal without interference is

$$\bar{\mathbf{y}}_t = \mathbf{y}_t - \sum_{i=1}^{t-1} \mathbf{h}_{t-i}(\hat{l}_i)\hat{s}_i$$

and $\mathbf{h}_{t-i}(\hat{l}_i)$ is set as a zero vector if $t - i > P - 1$.

2: Calculate $\mathcal{L}_{l_t}$ by (15) and get

$$\tilde{\mathcal{L}}_{l_t} = [g_{l_t}^1, g_{l_t}^2, \cdots, g_{l_t}^L].$$

3: $\hat{l}_t$ and $\hat{s}_t$ are obtained as

$$[\hat{l}_t, \hat{s}_t] = \arg \min_{l_t \in \tilde{\mathcal{L}}_{l_t}, s_t \in \mathcal{S}} \|\bar{\mathbf{y}}_t - \mathbf{h}_0(l_t) s_t\|_F^2.$$

End for

9. Output $[\hat{l}_1, \hat{l}_2, \ldots, \hat{l}_K]$ and $[\hat{s}_1, \hat{s}_2, \ldots, \hat{s}_K]$.

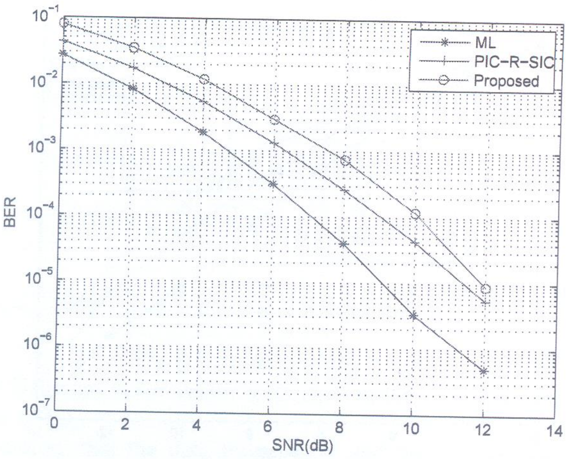

Fig. 2. BER performance comparison with $N_t = N_r = 2, K = 4$ and $P = 3$, using BPSK for SMSC systems.

can be seen as well in Fig.2. We consider the different values of K and P as 4 and 3 in 2×2 SM-SC system with BPSK modulation and the spectral efficiency $m = 2$ bits/s/H$_z$. The proposed detection still degrades the performance compared to the PIC-R-SIC detection and ML detection. There is an acceptable performance loss of 0.5dB at the BER $= 10^{-5}$.

B. Complexity Analysis

In this subsection, we compare the complexity of our proposed detection with that of PIC-R-SIC detection and the ML detection in SM systems by using the computational complexity, where the computational complexity is defined as the number of real-valued multiplications [10] in all schemes.

Firstly, we calculate the complexity of PIC-R-SIC detection (ignore the complexity of matrix inversion and $\tilde{\mathbf{y}}^{(t)}$ is already given before). For the given t $(1 < t \leq K)$, we define $C = (K+P-1)$ and $D_t = (t-1)N_t$. Calculating $\mathbf{P}_{\mathcal{I}_t}$ or $\mathbf{Q}_{\mathcal{I}_t}$ (using $\mathbf{G}^c_{\mathcal{I}_t}$) needs $8C(D_t)^2 + 4C^2 D_t$ real-valued multiplications. Calculating $\mathbf{Z}_{\mathcal{I}_t}$ needs $4C^2$ real-valued multiplications. For computing the complexity of $\|\mathbf{Z}_{\mathcal{I}_t} - \mathbf{P}_{\mathcal{I}_t}\mathbf{G}_{\mathcal{I}_t}\mathbf{x}_t\|_F^2$, $\mathbf{P}_{\mathcal{I}_t}\mathbf{G}_{\mathcal{I}_t}$ is firstly considered. Calculating $\mathbf{P}_{\mathcal{I}_t}\mathbf{G}_{\mathcal{I}_t}$ needs $4C^2 N_t$ real-valued multiplications. Calculating $\mathbf{P}_{\mathcal{I}_t}\mathbf{G}_{\mathcal{I}_t}\mathbf{x}_t$ and $\|\cdot\|_F^2$ need $4CN_t$ and $2C$ real-valued multiplications, respectively. Since $|\mathcal{X}_{SM}| = N_t M$, the computational complexity of ML detection for this step is $4C^2 + 4C^2 N_t + (4CN_t + 2C)N_T M$. When $t = 1$, the computational complexity is $(4CN_t + 2C)N_T M$. The overall computational complexity of PIC-R-SIC detection is

$$C_{\text{PIC-R-SIC}} = \sum_{t=2}^{K} 8C(D_t)^2 + 4C^2 D_t + (4CN_t + 2C)N_t MK + (4C^2 + 4C^2 N_t)(K-1).$$

Then, the computational complexity of ML detection is given by

$$C_{ML} = (4CKN_t + 2CN_r)(N_t M)^K.$$

The order of ML detection is $(N_t M)^K$. $\tilde{\mathbf{H}}\tilde{\mathbf{x}}$ needs $4CKN_t$ real-valued multiplications. $\|\cdot\|_F^2$ needs $2CN_r$ real-valued multiplications.

Finally, the complexity of the proposed detection is calculated as follows. At each step, LSVD needs $(6N_t+4)N_t+2N_r$ real-valued multiplications. ML detection needs $6N_r ML$ real-valued multiplications. If $K \geq P$, all $\bar{\mathbf{y}}_t$ $(2 \leq t \leq K)$ needs $2P(P-1)N_r + 4(K-P)(P-1)N_r$ real-valued multiplications. If $K < P$, all $\bar{\mathbf{y}}_t$ $(2 \leq t \leq K)$ needs $2K(K-1)N_r$ real-valued multiplications. Then the overall computational complexity of the proposed detection is

$$\begin{aligned} C_P =& ((6N_t + 4)N_t + 2N_r + 6N_r ML)K \\ &+ (4K - 2P)(P-1)N_r, (K \geq P), \\ C_P =& ((6N_t + 4)N_t + 2N_r + 6N_r ML)K \\ &+ 2K(K-1)N_r, (K < P). \end{aligned}$$

The complexity of the proposed detection, the PIC-R-SIC detection and the ML detection is presented in Table I. It is shown that the complexity of our proposed detection is significantly reduced compared to PIC-R-SIC and ML detection. In 2×2 SM-SC system, the proposed detection almost reach the 62% complexity reduction compared to the PIC-R-SIC detection and 98% complexity reduction compared to the ML detection with $K = P = 3$ and $M = 4$. The similar case of complexity reduction is presented in 2×2 SM-SC system with $K = 4$, $P = 3$ and $M = 4$.

TABLE I
COMPLEXITY COMPARISONS OF DIFFERENT DETECTIONS

$N_t = 2,\ N_r = 2,\ P = 3,\ M = 4$			
	ML	PIC-R-SIC	proposed
$K = 3$	71680	3200	1260
$K = 4$	884736	7632	1704

V. CONCLUSION

In this paper, we presented a low complexity detection for SM-SC systems. In the proposed detection, we separately detect each transmitted signal vector in every data frame. The estimation of every signal vector is affected by the previous estimation of signal vectors. In the simulation results, the proposed detection provides an acceptable performance loss compared to the PIC-R-SIC detection and the ML detection. Complexity analysis shows that our proposed detection achieve the significant computational complexity reduction compared to that of the PIC-R-SIC detection and the ML detection.

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REFERENCES

[1] R. Mesleh, H. Haas, C. W. Ahn, and S. Yun, "Spatial modulation - a new low complexity spectral efficiency enhancing technique," in *Proc. Conf. Comm. and Netw. China*, Oct. 2006, pp. 1-5.

[2] M. Di Renzo, H. Haas, and P. M. Grant, "Spatial modulation for multiple-antenna wireless systems: A survey," *IEEE Commun. Mag.*, vol. 49, no. 12, pp. 182-191, Dec. 2011.

[3] M. Di Renzo, H. Haas, A. Ghrayeb, S. Sugiura, and L. Hanzo, "Spatial modulation for generalized MIMO: challenges, opportunities and implementation," *Proceedings of the IEEE*, vol. 102, no. 1, pp. 56-103, Jan. 2014.

[4] R. Mesleh, H. Haas, S. Sinanovic, C. W. Ahn, and S. Yun, "Spatial modulation," *IEEE Trans. Veh. Technol.*, vol. 57, no. 4, pp. 2228-2241, Jul. 2008.

[5] J. Jeganathan, A. Ghrayeb, and L. Szczecinski, "Spatial modulation: optimal detection and performance analysis," *IEEE Commun. Lett.*, vol. 12, no. 8, pp. 545-547, 2008.

[6] J. Wang, S. Jia, and J. Song, "Signal vector based detection scheme for spatial modulation," *IEEE Commun. Lett.*, vol. 16, no. 1, pp. 19-21, Jan. 2012.

[7] W. Zhang, and Q. Yin, "Adaptive signal vector based detection for spatial modulation," *IEEE Commun. Lett.*, vol. 18, no. 11, pp. 2059-2062, 2014.

[8] P. Som and A. Chockalingam, "Spatial modulation and space shift keying in single carrier communication," *in Proc. IEEE PIMRC*, pp. 1991-1996, Sept. 2012.

[9] R. Rajasherkar, K. V. S. Hari, and L. Hanzo, "Spatial modulation aided zero-padded single carrier transmission for dispersive channels," *IEEE Trans. Commun.*, vol. 61, no. 6, pp. 2318-2329, June 2013.

[10] R. Rajashekar, K. V. S. Hari, and L. Hanzo, "Reduced-complexity ML detection and capacity-optimized training for spatial modulation systems," *IEEE Trans. Commun.*, vol. 62, no. 1, pp. 112-125, Jan. 2014.