Low-Complexity Detection Scheme for Generalized Spatial Modulation

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Abstract**—**Generalized spatial modulation was recently proposed, in which only part of the transmit antennas are activated to send the same complex symbol. Compared to Spatial Modulation (SM), it can offer spatial diversity. Moreover, it is no longer limited to the number of the transmit antennas. In this letter, a low complexity detection scheme is presented, which can achieve a near Maximum-Likelihood (ML) performance and reduce the complexity compared to ML. In the proposed algorithm, the antenna index is ordered first based on the Hermitian angle between the received vector $\mathbf{y}$ and the combined channel vector $\mathbf{h}_j$. With the antenna index list, the constellation symbol can be estimated by calculating the difference between the normalized projection of received symbol in the direction of combined channel and the actual transmitted symbols. We can make a tradeoff between the performance and the complexity by changing the number of the candidate transmit antennas. The simulation results show that the proposed algorithm can achieve a near-ML performance with lower complexity.

Index Terms—Generalized spatial modulation, low complexity, maximum likelihood, multiple-input-multiple-output

I. Introduction

Multiple-Input-Multiple-Output (MIMO) system is a key technique to boost the spectral efficiency and reliability of communication system. It has been exploited in different ways to achieve multiplexing, diversity, or antenna gains. Spatial multiplexing gain could be achieved by employing the vertical Bell Laboratories layered space-time architecture [1] while diversity gain could be attained by the space time block code [2] to improve bit error performance. However, the high Inter-Channel Interference (ICI) at the receiver due to simultaneous transmission on the same frequency from multiple antennas is unavoidable. Besides this, the number of receive antennas must be greater or equal to the number of the transmit antennas.

Spatial Modulation (SM) [3]-[5] is an efficient and low-complexity scheme for MIMO system, which was proposed to convey the active transmit antenna indices (spatial constellation) and the transmitted signals (signal constellation). The main characteristic of SM is that only one antenna is activated for data transmission at one time slot. In this way, the ICI can be effectively avoided at the receiver. What is more, SM systems can be applied to the MIMO systems in which the number of receive antennas is less than the number of transmit antennas.

Compared with the conventional MIMO systems, the above key features make SM detection more complicated, which needs to demodulate transmit antenna indices except transmitted symbols. The detection algorithm [6] was originally proposed, which has low complexity but suboptimum performance. ML algorithm [7] was proposed to improve the performance, which searches all the transmit antennas and symbols from the constellation. It has optimal performance but the computational complexity is too high. SM Sphere Decoding (SD) algorithms [8] is a modified algorithm of ML. It provides a near-ML performance and reduces the complexity in the case of large number of receive antennas. Two ways was proposed in [9] to reduce the complexity of SD. Signal vector based detection (SVD) [10] method was proposed, which has a lower complexity compared to ML. However, a comment on SVD algorithm [11] was proposed to prove that the SVD scheme performs very poorly compared to the optimal detection.

Generalized Spatial Modulation (GSM) scheme was further proposed, and the current deployments of GSM consider two distinct approaches: the single-stream transmission [12]-[16], where all active antennas emit the same symbol; and the multi-stream case [17], in which each active antenna transmits independent symbols. The first one will be considered in this work.

The main advantage of GSM scheme is that it not only retains the key advantage of SM, which is the complete avoidance of ICI at the receiver, but also offers spatial diversity gains and increases the reliability of the wireless channel by providing replicas of the transmitted signal to the receiver. Different to the case in SM, the number of transmit antennas in GSM is no longer limited to a power of two, instead an arbitrary number of transmit antennas can be used.

Recently, enhanced Bayesian compressive sensing algorithm [18] was proposed for GSM with multi-stream transmission, and it takes a new approach to exploit the inherent sparsity in the transmitted signals. In this paper, an improved SVD algorithm is proposed, in which a list of best candidate transmit antenna index is sorted, and similar concepts was employed for transmit antenna selection in [19]-[20]. With the antenna index list, the constellation symbol can be estimated by calculating the difference between the normalized projection of the received symbol w_j in the direction of combined channel

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and the actual transmitted symbols. At last, the optimal combination of transmit antenna and constellation symbol is calculated. The simulation results show that the proposed algorithm has a near-ML performance but with a lower complexity.

The rest of this paper is organized as follows. Section II presents the system model and the discussion on the ML optimum detector. In Section III, the SVD algorithm and the proposed algorithm with its performance analysis and computational complexity analysis for GSM system are described. Section IV presents the comparison of BER performance and complexity between the proposed algorithm and other algorithms. Finally, Section V concludes the paper.

II. System Model

The system model for generalized spatial modulation is shown in Fig. 1. The GSM-MIMO communication system with N_{t} transmit antennas and N_{r} receive antennas is considered in this letter. GSM uses more than one transmit antenna to send the same complex symbol. In which N_a ($N_a < N_t$) antennas are activated in each time slot. Therefore, there are total $C_{N_{\mathrm{t}}}^{N_a}$ combinations, where $C_{N_{\mathrm{t}}}^{N_a}$ represents the binomial coefficient. To modulate the information bits, only $N_c = 2^{\lfloor \log_2 (\mathrm{C}_{Nt}^{Na}) \rfloor}$ antenna combinations are permitted and the other combinations are considered illegimate, where $\lfloor x \rfloor$ is the greatest integer smaller than x.

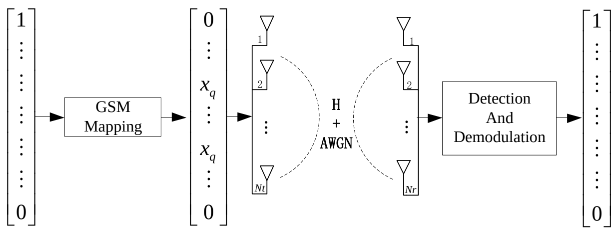

Fig. 1. System model for generalized spatial modulation

The incoming data bits are mapped to the mapping table shown in Table I. The mapping procedure maps the first bits $m_\ell = \lfloor \log_2 (\mathrm{C}_{N_t}^{N_a}) \rfloor$ to the antenna combinations, and the remaining bits $m_s = \log_2 M$ are modulated using M-QAM modulation, where $M = 2^{m_s}$. Therefore, the number of total bits that can be transmitted using GSM is given by

$$m = m_\ell + m_s = \left\lfloor \log_2 \left(C_{N_t}^{N_a} \right) \right\rfloor + \log_2 M \tag{1}$$

Let $j_1, j_2, \cdots, j_{N_c}$ denote the indices of the Transmit Antenna Combinations (TACs). Then the modulated QAM symbols will be transmitted by the antennas in the combination index j_k and the other $N_t - N_a$ antennas remain silent, where $k \in \{1, 2, \cdots, N_c\}$. Finally, we obtain the transmitted signal vector $\mathbf{x} = [\cdots, 0, x_q, 0, \cdots, 0, x_q, 0, \cdots]^T$, in which there are N_a non-zero values and $N_t - N_a$ zeros. It has a dimension of $N_t \times 1$, and x_q denotes the symbol carried by the active antenna from an M-ary constellation with $q \in [1 : M]$ .The mapping table is depicted in Table I, in which $N_t = 5$, $N_a = 2$ and BPSK modulation is employed.

TABLE I: THE MAPPING TABLE OF SPATIAL MODULATION

Bit stream	Space bit	Antenna index	Modulation bit	Symbol	Output
0000	000	(1,2)	0	-1	[-1, -1,0,0,0]
0001	000	(1,2)	1	+1	[+1,+1,0,0,0]
0010	001	(1,3)	0	-1	[-1,0, -1,0,0]
0011	001	(1,3)	1	+1	[+1,0,+1,0,0]
0100	010	(1,4)	0	-1	[-1,0,0, -1,0]
0101	010	(1,4)	1	+1	[+1,0,0,+1,0]
0110	011	(1,5)	0	-1	[-1,0,0,0, -1]
0111	011	(1,5)	1	+1	[+1,0,0,0,+1]
1000	100	(2,3)	0	-1	[0, -1, -1,0,0]
1001	100	(2,3)	1	+1	[0,+1,+1,0,0]
1010	101	(2,4)	0	-1	[0, -1,0, -1,0]
1011	101	(2,4)	1	+1	[0,+1,0,+1,0]
1100	110	(2,5)	0	-1	[0, -1,0,0, -1]
1101	110	(2,5)	1	+1	[0,+1,0,0,+1]
1110	111	(3,4)	0	-1	[0,0, -1, -1,0]
1111	111	(3,4)	1	+1	[0,0,+1,+1,0]

The modulated symbols are transmitted over a MIMO Rayleigh flat fading wireless channel $\mathbf{H}$, whose entries follow a complex Gaussian distribution with a mean of zero and a variance of one. Then, the $N_r \times 1$ received vector at one time slot can be written as follow,

$$\mathbf{y} = \sum_{k=1}^{N_a} \mathbf{h}_{j,k} s + \mathbf{n} \tag{2}$$

where the vector $\mathbf{h}_j = \sum_{k=1}^{N_a} \mathbf{h}_{j,k}$ contains the summation of the active antennas' channel vectors, and $\mathbf{h}_{j,k}$ is the k-th column of the channel matrix $\mathbf{H}$. $\mathbf{n} \in^{N_r \times 1}$ is additive white Gaussian noise with a mean of zero and a variance of σ^2.

In the receiver, the optimal ML-Optimum detector searches all the transmit antennas combinations and the constellations symbols, and then takes the group with minimum Euclidean distance from the received vectors as output. The optimal ML joint detection can be given by

$$\begin{aligned}[j_{ML}, s_{ML}] &= \arg \min_{j \in \{1, \cdots, N_c\}, q \in \{1, \cdots, M\}} \left\| \mathbf{y} - \mathbf{h}_j x_q \right\|^2 \\ &= \arg \min_{j \in \{1, \cdots, N_c\}, q \in \{1, \cdots, M\}} \{ \sum_{r=1}^{N_r} \left| y_r - h_{j,r} x_q \right|^2 \},\end{aligned} \tag{3}$$

where $\|\cdot\|^2$ is the Frobenius norm, y_r and $h_{j,r}$ are the r-th entries of $\mathbf{y}$ and $\mathbf{h}_j$, respectively. ML detection searches all the transmit antennas, receive antennas and constellations symbols, so that it can achieve optimum performance while with a very high complexity, which can be shown in the complexity analysis in later sections.

III. Proposed Low Complexity SVD Algorithm

A. SVD Algorithm

We apply The SVD algorithm depicted in [9] to GSM systems. Without consideration of the noise, the combined received vector $\mathbf{h}_j x_q$ is with the same direction of the combined channel vector $\mathbf{h}_j$. Fig. 2 shows the Hermitian angle between the combined channel vector $\mathbf{h}_j$ and the received vector $\mathbf{y}$.

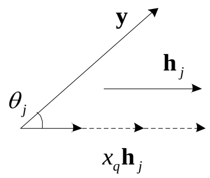

Fig. 2. Hermitian angle between $\mathbf{h}_j$ and $\mathbf{y}$

Let θ_j denote the Hermitian angle between $\mathbf{h}_j$ and $\mathbf{y}$, then θ_j can be expressed as follows,

$$\theta_j = \arccos \rho_j \text{ with } \alpha_j = \frac{<\mathbf{h}_j, \mathbf{y}>}{\|\mathbf{h}_j\|\|\mathbf{y}\|} \text{ and } \rho_j = \|\alpha_j\| \quad (4)$$

where $\langle .,. \rangle$ denotes the inner product in the Hilbert space. Then, the TAC can be estimated by

$$j_{SVD} = \arg \min_{j\in\{1,\ldots,N_c\}} \theta_j \quad (5)$$

For symbol detection, the traditional demodulation is performed to recover the constellation symbol, assuming the antennas in $j_{SVD} - th$ TAC being activated. The symbol can be estimated by

$$q_{SVD} = \arg \min_{q\in\{1,\ldots,M\}} \left\|\mathbf{y} - \mathbf{h}_{jsvd} x_q\right\|^2 \quad (6)$$

B. Proposed Low-Complexity Algorithm Based on SVD

To improve the performance of SVD algorithm, after obtaining $\boldsymbol{\theta}$=$\{\theta_1,\cdots,\theta_{N_c}\}$ calculated by (4), we sort the weighting factor values and obtain the ordered TACs as

$$\Gamma = [j_1, j_2, \cdots, j_p, \cdots, j_{N_c}] = \arg sort(\boldsymbol{\theta}) \quad (7)$$

where Γ denotes the list of candidate antennas combinations, $sort(\cdot)$ defines an ordering function for recording the input vector in ascending order, and j_1, j_{N_c} are the indices of the minimum and maximum values in $\boldsymbol{\theta}$, respectively. In this case, we obtain the ordered TACs with the weighting indices $[j_1, j_2, \cdots, j_p, \cdots, j_{N_c}]$, where p is the number of TACs we will choose for a tradeoff between the performance and complexity of the proposed algorithm.

For constellation symbol detection, the complexity will increase rapidly if it searches all the constellation symbols for each antenna in the list Γ. To reduce the complexity, the proposed algorithm obtains constellation symbol of the first p TACs in the list Γ instead of searching all the TACs. For a given TAC, the normalized projection of $\mathbf{y}$ in the direction of the combined channel $\mathbf{h}_j$ is given by

$$\omega_j = \frac{\|\mathbf{y}\|\cos\theta_j}{\|\mathbf{h}_j\|} = \frac{<\mathbf{h}_j, \mathbf{y}>}{\|\mathbf{h}_j\|^2}, \quad (8)$$

where $j \in [1:p]$, the estimated symbol can be obtained as follows,

$$\hat{x}_{q_j} = \arg \min_{q\in\{1,\cdots,M\}} \left|\omega_j - x_q\right|^2. \quad (9)$$

Then, the final antenna index and constellation symbol can be formally written as

$$[j, q] = \arg \min_{j\in\Gamma} \left\|\mathbf{y} - \mathbf{h}_j \hat{x}_{q_j}\right\|. \quad (10)$$

Therefore, the proposed algorithm can be described as Table II.

Table II: Summary of Proposed Algorithm

Input: Receive vector $\mathbf{y}$, Channel Matrix $\mathbf{H}$, the number of chosen TACs p
Output: the TACs index j ,demodulated symbol q

1. Calculate the angle between the received vector $\mathbf{y}$ and the combined channel vector $\mathbf{h}_j$
   for $j = 1: N_c$
   $$\theta_j = \arccos \rho_j \ with\ \alpha_j = \frac{\langle \mathbf{h}_j, \mathbf{y} \rangle}{\|\mathbf{h}_j\|\|\mathbf{y}\|}\ and\ \rho_j = \|\alpha_j\|$$
   end for
2. List of antenna index
   $\Gamma = [j_1, j_2, \cdots, j_p \cdots, j_{N_c}]$=arg$sort(\theta)$
3. Estimate symbol for a given TAC
   for $j = 1: p$
   $$\omega_j = \frac{\|\mathbf{y}\|\cos\theta_j}{\|\mathbf{h}_j\|} = \frac{<\mathbf{h}_j, \mathbf{y}>}{\|\mathbf{h}_j\|^2}$$
   $$x_{\hat{q}_j} = \arg \min_{q\in\{1,\cdots,M\}} \left|\omega_j - x_q\right|^2$$
   end for
4. Calculate the optimal combination
   $$[j, q] = \arg \min_{j\in\{j_1,\cdots,j_p\}} \left\|\mathbf{y} - \mathbf{h}_j x_{\hat{q}_j}\right\|$$

C. Performance Analysis

As shown in Fig. 3, the vector decomposition of $\mathbf{y}$ in the direction of $\mathbf{h}_j$ can be given as

$$\mathbf{y}_h = \mathbf{y}\cos\theta_j \quad (11)$$

and its Frobenius norm can be denoted as d_1. The Euclidean distance between $\mathbf{y}$ and $\mathbf{y}_h$ can be given by

$$d_2 = \|\mathbf{y}\|\sin\theta_j. \quad (12)$$

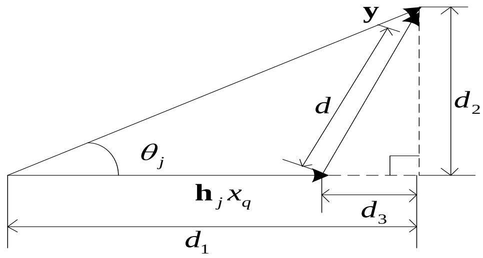

Fig. 3. The vector decomposition of $\mathbf{y}$ in the direction of $\mathbf{h}_j$

As shown in Fig. 3, in fact, the ML detection of (3) can be rewritten as follows,

$$\begin{aligned}[j_{ML}, s_{ML}] &= \arg \min_{j\in\{1,\cdots,N_c\},q\in\{1,\cdots,M\}} \left\|\mathbf{y}-\mathbf{h}_j x_q\right\|^2 \\ &= \arg\min \|d\|^2 \\ &= \arg\min(\|d_2\|^2 + \|d_3\|^2)\end{aligned} \tag{13}$$

and Euclidean distance d_3 between $\mathbf{y}_h$ and $\mathbf{h}_j x_q$ can be rewritten as follows,

$$\begin{aligned} d_3 &= \|\mathbf{y}\|\cos\theta_j - \|\mathbf{h}_j x_q\| \\ &= \|\mathbf{h}_j\| \left|\alpha_j \cdot \|\mathbf{y}\| / \|\mathbf{h}_j\| - x_q\right| \\ &= \|\mathbf{h}_j\| \left|w_j - x_q\right| \end{aligned} \tag{14}$$

where $w_j = \alpha_j * \|\mathbf{y}\| / \|\mathbf{h}_j\|$. From (13)-(14) we can roughly see that, if θ_j gets smaller, both the d_2 and d will get shorter, and that is why SVD algorithm can achieve the real transmitted symbols in most cases. As in (14), d_3 is affected by $\mathbf{h}_j$ and $\mathbf{y}$, but the SVD algorithm did not give full consideration of d_3. So it has a performance loss compared to ML algorithm. In the proposed algorithm, a list of best candidate transmit antenna index is sorted. We choose the top p possible TACs with the list instead of choosing the one with minimum θ_j in SVD, so the proposed algorithm can have a better performance than SVD. From (14), it is obvious that we can use (9) to estimate the symbol after obtaining $\mathbf{h}_j$, which can reduce the complexity compared to searching all the transmitted symbol in SVD.

D. Complexity Analysis

We use the total number of real-valued multiplications (division is also considered as multiplication) of the detectors to describe the complexity of the algorithms.

1) The computational complexity of ML algorithm

$$[j_{ML}, s_{ML}] = \arg \min_{j\in\{1,\cdots,N_c\},q\in\{1,\cdots,M\}} \left\|\mathbf{y}-\mathbf{h}_j x_q\right\|^2 .$$

(a) calculating $\mathbf{h}_j x_q$ needs $4N_r$ real-valued multiplications .

(b) calculating

$$\left\|\mathbf{y}-\mathbf{h}_j x_q\right\|^2 = (\Re(\mathbf{y}-\mathbf{h}_j x_q))^2 + (\Im(\mathbf{y}-\mathbf{h}_j x_q))^2$$

needs $2N_r$ real-valued multiplications .

Obviously, the search space size is $N_c M$, hence, the total computational complexity of ML detector is $6N_r N_c M$.

2) The computational complexity of SVD algorithm

$$j = \arg \min_{j\in\{1\dots N_c\}} \theta(j),\ \ \theta(j) = \arccos\left\|\frac{<\mathbf{h}_j, \mathbf{y}>}{\|\mathbf{h}_j\|\|\mathbf{y}\|}\right\|$$

$$x_q = \arg \min_{q\in\{1,\ \cdots,\ M\}} \left\|\mathbf{y}-\mathbf{h}_j x_q\right\|$$

(a) calculating $<\mathbf{h}_j, \mathbf{y}>$ needs $4N_r$ real-valued multiplications .

(b) calculating

$$\left\|<\mathbf{h}_j, \mathbf{y}>\right\| = \sqrt{[\Re(<\mathbf{h}_j, \mathbf{y}>)]^2 + [\Im(<\mathbf{h}_j, \mathbf{y}>)]^2}$$

needs 2 real-valued multiplications.

(c) calculating $\|\mathbf{h}_j\| = \sqrt{\sum_{i=1}^{N_r}\{[\Re(h_i)]^2 + [\Im(h_i)]^2\}}$

needs $2N_r$ real-valued multiplications.

(d) calculating $\|\mathbf{y}\| = \sqrt{\sum_{i=1}^{N_r}\{[\Re(y_i)]^2 + \Im[(y_i)]^2\}}$

needs $2N_r$ real-valued multiplications .

(e) calculating $\|\mathbf{h}_j\|\|\mathbf{y}\|$ needs 1 real-valued multiplication, and calculating $\dfrac{<\mathbf{h}_j, \mathbf{y}>}{\|\mathbf{h}_j\|\|\mathbf{y}\|}$ needs 1 real-valued multiplications.

Obtaining $\theta(j)$ needs $4N_r + 2N_r + 2N_r + 1 + 1 + 2$ real-valued multiplications. In the process to obtain $\theta_{\min}(j)$, $\|\mathbf{y}\|$ only needs to be calculated once, so we need total $(4N_r + 2N_r + 1 + 1 + 2)N_c + 2N_r$ real-valued multiplications. After obtaining $\theta_{\min}(j)$, calculating $\mathbf{h}_j x_q$ needs $4N_r$ real-valued multiplications and calculating $\left\|\mathbf{y}-\mathbf{h}_j x_q\right\|^2 = (\Re(\mathbf{y}-\mathbf{h}_j x_q))^2 + (\Im(\mathbf{y}-\mathbf{h}_j x_q))^2$ needs $2N_r$ real-valued multiplications. Thus, the total computational complexity is $(6N_r + 4)N_c + 2N_r + 6N_r M$.

3) The computational complexity of proposed detector.

(a) as shown above, calculating the Hermitian angle detection needs $(6N_r + 4)N_t + 2N_r$ real-valued multiplications.

(b) calculating $<\mathbf{h}_j, \mathbf{y}>$ and $\|\mathbf{h}_j\|^2$ does not need extra calculations, and the j in $\mathbf{h}_j$ varies from 1 to p, so calculating $\omega_j = \dfrac{\|\mathbf{y}\|\cos\theta_j}{\|\mathbf{h}_j\|} = \dfrac{<\mathbf{h}_j, \mathbf{y}>}{\|\mathbf{h}_j\|^2}$ needs p real-valued multiplications.

(c) for $\left|\omega_j - x_q\right|^2 = (\Re(\omega_j - x_q))^2 + (\Im(\omega_j - x_q))^2$, the q in x_q varies from 1 to M, and the chosen antennas combinations vary from 1 to p, so calculating $\left|\omega_j - x_q\right|^2$ needs $2pM$ real-valued multiplications.

(d) the total computational complexity for constellation symbol estimation is $6pN_r$.

So, the total computational complexity of the proposed algorithm is $(6N_r+4)N_c+p+2N_r+2pM+6pN_r$, that is $\left(6N_r+4\right)N_c+2N_r+\left(6N_r+2M+1\right)p$. Hence, the total complexity of all algorithms mentioned above can be concluded as

$$C_{ML}=6MN_cN_r$$
$$C_{SVD}=(6N_r+4)N_c+2N_r+6N_rM$$
$$C_{proposed}=\left(6N_r+4\right)N_c+2N_r+\left(6N_r+2M+1\right)p$$

where $C_{.}$ denotes the complexity of the algorithm.

IV. Simulation Result

MATLAB is used as the simulation platform. The parameters in the simulation experiment are shown in Table III.

TABLE III: SIMULATION PARAMETERS

Parameters	Value
Channel	Rayleigh fading channel
Receive antennas	4

A. BER Performace

As stated in [12], the BER performance of SM and GSM are almost identical, so we only give the BER performance of the proposed algorithm in GSM systems rather than SM systems in this paper. Simulations are performed for uncoded GSM systems with 2 antennas being activated. The spectral efficiency is 6 bits per time slot and 8 bits per time slot under Rayleigh fading channel, respectively. For the case of 6 bits per time slot, two configurations of SM system are considered. One is 4 transmit antennas with 16-QAM modulation, and the other is 5 transmit antennas with 8-QAM modulation. For the case of 8 bits per time slot, two configurations are also considered, one of which is 7 transmit antennas with 16-QAM modulation, and the other is 9 transmit antennas with 8-QAM modulation.

One of the abovementioned configurations is higher order modulation with less transmit antennas, and the other is lower order modulation with more transmit antennas. For convenience, we call them high order system and low order system, respectively. The BER performance comparing between ML, SVD and the proposed algorithm with p = 2 and p = 3 are simulated for high order system and low order system, respectively.

The simulation results with the spectral efficiency of 6 bits per time slot can be found in Fig. 3 and Fig. 4. While the simulation results of 8 bits per time slot can be found in Fig. 5 and Fig. 6.

As 8-QAM and 5 transmit antennas are employed in Fig. 3, the spectra efficiency is 6 bits per time slot. When BER = 1.0×10^{-4}, the proposed algorithm with p = 2 has about 3.5 dB performance gain compared to the SVD, while about 0.6 dB performance loss compared to the ML detection. When p = 3, the performance of the proposed algorithm is much closer to that of the ML, and we can predict that if p = 4, the proposed algorithm almost has the same performance as ML.

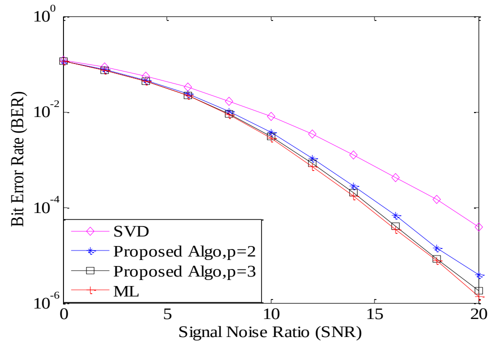

Fig. 3. BER performance versus SNR, for $N_t=5$ and $M=8$

Similar result can be found in Fig. 4, where the normalized 16-QAM is employed. To keep the same spectral efficiency (6 bits per time slot), the number of the transmit antennas is 4. The proposed algorithm also performs much better than SVD in the high order system. When BER = 2.0×10^{-3} the proposed algorithm with p = 2 has about 2 dB performance gain compared to SVD, while about 0.2 dB performance loss compared to the ML detection. And when p = 3, the proposed algorithm almost has the same performance as ML.

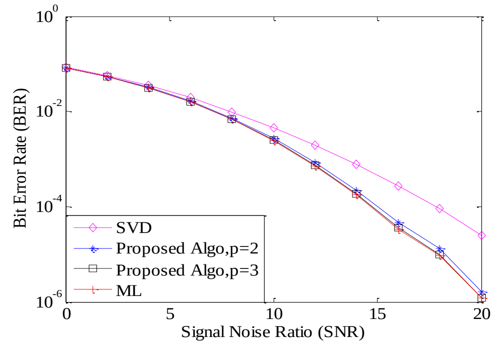

Fig. 4. BER performance versus SNR, for $N_t=4$ and $M=16$

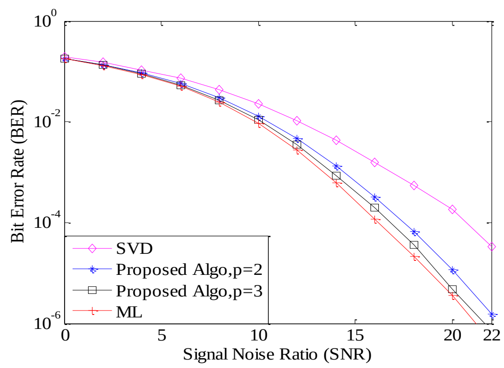

Fig. 5. BER performance versus SNR, for $N_t=9$ and $M=8$

The simulation results with the spectral efficiency of 8 bits per time slot can be found in Fig. 5 and Fig. 6. The low order modulation and larger number of antenna bits are simulated in Fig. 5. As 8-QAM is employed, the number of transmit antennas is set to 9. Fig. 6 shows the BER performance comparisons in high order system, where the 16-QAM and 7 transmit antennas are employed.

As shown in Fig. 5, the advantage of the proposed algorithm is obvious. When BER = 2×10^{-3}, the proposed algorithm with p = 2 has about 3.5 dB performance gain compared to the SVD, while about 1.0 dB performance loss compared to ML detection. And when p = 3, the proposed algorithm has about 0.5 dB performance loss compared to the ML detection.

Similar result is shown in Fig. 6. The proposed detector also keeps advantage compared to the SVD detector. When BER = 2×10^{-3}, the proposed algorithm with p = 2 has about 2.3 dB performance gain compared to the SVD, while smaller than 0.5 dB performance loss compared to the ML detection. The proposed algorithm with p = 3 also has about 0.25 dB performance loss compared to the ML detection. Therefore, if p=4, the performance of the proposed algorithm almost has the same performance as ML.

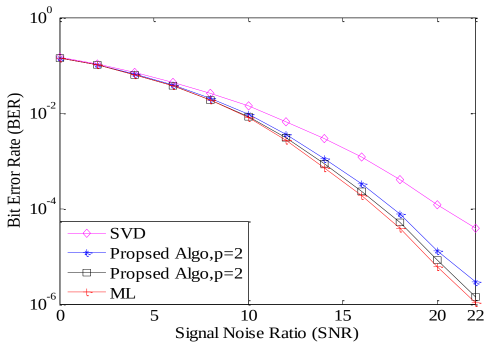

Fig. 6. BER performance versus SNR, for $N_t = 7$ and $M = 16$

From Fig. 3 to Fig. 6, it is obvious that the proposed algorithm has a better performance than SVD and can achieve a near-ML performance in both high order system and low order system. Moreover, the proposed algorithm can make an effective tradeoff between the performance and the complexity by changing the value of p.

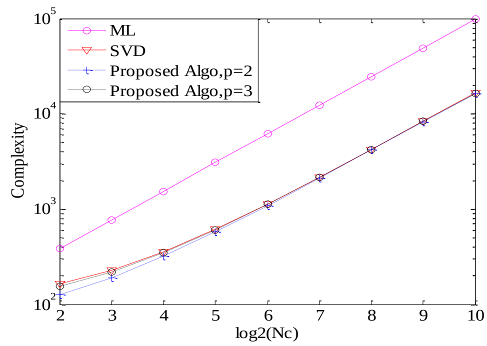

Fig. 7. Complexity comparison, for $M = 8$

B. *Computational Complexity*

The number of transmit antennas and the size of the modulation order are two main factors which we have to consider for the complexity of the algorithms. By exploiting some ways to reduce the complexity of the proposed algorithm, it has a lower complexity compared to SVD in most cases, which can be roughly seen in Fig. 7 and Fig. 8.

As shown in Fig. 7, with the number of TACs getting increased, the complexity of the three algorithms above is getting higher and ML is the highest. When $\log_2 N_c \le 5$, the complexity of the proposed algorithm ($p = 2, p = 3$) is little lower than SVD, and when $\log_2 N_c > 5$,their complexity is almost identical.

Similar result can be seen in Fig. 8. With the increase of the modulation order, the complexity of the three algorithms above is getting higher and ML is again the highest, but the complexity of the proposed algorithm ($p = 2, p = 3$) is lower than SVD in most cases whether the system is in high order or in low order.

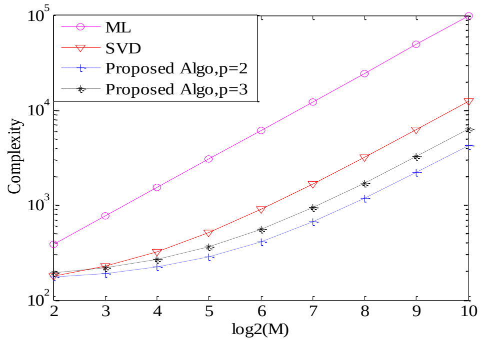

Fig. 8. Complexity comparison, for $N_c = 4$

V. Conclusions

In this paper, a low-complexity signal vector based detection algorithm has been proposed for GSM systems. It has been proved that the proposed algorithm can achieve a near-ML performance with much lower complexity especially in the case of high order modulation and large number of transmit antennas. We can make a trade-off between the performance and the complexity by changing the number of the candidate transmits antennas.

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