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Research Article

Low-Complexity Detection Algorithms for Spatial Modulation MIMO Systems

Xinhe Zhang,[1] **Yuehua Zhang**,[1] **Chang Liu**,[2] **and Hanzhong Jia**[3]

[1]*School of Electronic and Information Engineering, University of Science and Technology Liaoning, Anshan 114051, China*
[2]*National Key Laboratory of Science and Technology on Communications, University of Electronic Science and Technology of China, Chengdu 611731, China*
[3]*State Grid Liaoning Information and Communication Company, Shenyang 110006, China*

Correspondence should be addressed to Xinhe Zhang; cdaszxh@sina.com

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In this paper, the authors propose three low-complexity detection schemes for spatial modulation (SM) systems based on the modified beam search (MBS) detection. The MBS detector, which splits the search tree into some subtrees, can reduce the computational complexity by decreasing the nodes retained in each layer. However, the MBS detector does not take into account the effect of subtree search order on computational complexity, and it does not consider the effect of layers search order on the bit-error-rate (BER) performance. The ost-MBS detector starts the search from the subtree where the optimal solution is most likely to be located, which can reduce total searches of nodes in the subsequent subtrees. Thus, it can decrease the computational complexity. When the number of the retained nodes is fixed, which nodes are retained is very important. That is, the different search orders of layers have a direct influence on BER. Based on this, we propose the oy-MBS detector. The ost-oy-MBS detector combines the detection order of ost-MBS and oy-MBS together. The algorithm analysis and experimental results show that the proposed detectors outstrip MBS with respect to the BER performance and the computational complexity.

1. Introduction

To meet the demand of wireless communication systems for higher data transmission rate, multiple-input multiple-output (MIMO) technology has been adopted in mobile terminals. MIMO technology improves data throughput without increasing additional bandwidth and transmit power. Spatial modulation (SM) [1–3] is an emerging transmission scheme for MIMO systems. The main characteristic of SM is that only one transmit antenna is activated at one time slot, but simultaneously, the SM systems can use the original signal domain (signal constellation) and the transmit antenna (TA) indices (spatial constellation) to convey information. Compared to MIMO systems, SM systems can only equip one radio frequency (RF) chain, avoid interchannel interference (ICI) and interantenna synchronization (IAS), and also reduce the complexity of demodulation.

For the detection of SM signals, maximum ratio combining (MRC) algorithm was proposed in [4], in which the active-antenna index and the transmit symbol are separately estimated. The MRC detector has a low computational complexity and only performs well on the constrained channels. This detector was improved in [5], and it further can be applied in conventional channel conditions. The optimum maximum likelihood (ML) detector which involves joint detection of the TA index and of the transmit symbol was proposed in [6]. However, the computational complexity linearly grows as the number of TA (N_T), the number of receive antennas (N_R), and the size of the modulation scheme (N_M). In order to obtain the near-optimal solution with a lower computational complexity, several low-complexity detectors have been put forward [7–17]. In [7, 8], two low-complexity hard-limiter-based ML (HL-ML) detectors which have the same BER performance as the ML detector were proposed for M-PSK and square- or rectangular-QAM modulation. The computational complexity has nothing to do with the constellation size. In [9–11], sphere-decoding (SD) algorithms were put forward for SM systems, which are capable of achieving near-optimal performance with a lower computational complexity on average. At worst, the computational complexity is equivalent to that of the ML detector. However, its detection performance depends mainly on the initial search radius and the transmit parameters. Compared with SD detectors, SD aided by the ordering strategy proposed in [12] can greatly reduce the computational complexity. Two matched filter-(MF-) based detectors were proposed in [13]. In [14], Wang et al. proposed a novel signal vector-based detection (SVD) scheme. Tang et al. [15] presented a distanced-based ordered detection (DBD) algorithm to reduce the receiver complexity and achieve a near-maximum likelihood performance. To reduce the detection complexity of ML detection, Xu [16] presented simplified ML-based optimal detection (OD) and simplified multistage detection (MD). In the simplified ML-based detection and multistage detection schemes, the signal set is firstly partitioned into four "level-one subsets". Each level-one subset is further partitioned into four "level-two subsets" if each subset contains more than four signals. The simple low-complexity detection (SLCD) and adaptive simple low-complexity detection (ASLCD) were proposed in [17].

In [18, 19], the M-algorithm to maximum likelihood (MML) detector with prioritized tree-search structure was presented. The detection is considered as a breadth-first search tree with $N_\mathrm{T}N_\mathrm{M}$ branches and N_R layers, in which the ith layer corresponds to the ith receive antenna (RA). The MML detector only examines partial nodes in the tree, whereas the ML detector traverses all nodes. Compared with the ML detector, the MML detector can achieve a lower computational complexity. In [20], a low-complexity symbol detection based on modified beam search (MBS) was proposed. The detection process of the MBS algorithm can be represented by constructing a tree with N_T subtrees and $2N_\mathrm{R}$ layers, where each subtree has N_M complete paths from the root node to the leaf nodes, and each of the paths stands for a candidate solution. The solution is found by performing modified beam search. Compared with the MML algorithm, the MBS algorithm reduces the computational complexity by discarding unpromising candidate solutions.

In the MBS detector, the detection sequence of different subtrees is confined to the ascending order of the subtree indices, whereas it ignores the influence of different search orders on the computational complexity. Moreover, the detection of all layers is confined to the ascending order of the layer indices, whereas it ignores the influence of different search orders on its bit-error-rate (BER) performance. That is to say, the influence of different search orders on the BER performance and the computational complexity is not considered in the MBS detector. In recent years, the sorting strategy has attracted more and more attention. To some degree, the sorting strategy can improve the algorithm detection performance. In [12, 21], different ordering strategies were proposed to improve the detection performance. In this paper, we proposed three MBS-based detectors with novel ordering strategies: (1) the ost-MBS detector rearranges the search order of subtrees; (2) the oy-MBS detector performs SM signal detection in a descending order of the received signal amplitude; (3) the detection orders of the abovementioned two detectors were jointly considered in the ost-oy-MBS detector.

The rest of this paper is organized as follows. In Section 2, the system model of SM systems is introduced. Section 3 gives a brief overview of the MBS detector. The ordering strategy is introduced to the MBS detector. Section 4 demonstrates ost-MBS, oy-MBS, and ost-oy-MBS detectors. Section 5 illustrates the simulation results. Finally, we conclude the paper with a summary in Section 5.

Notations. Boldface upper/lower case symbols denote matrices and column vectors; $\|\cdot\|_\mathrm{F}$ is the Frobenius norm of a vector or a matrix; $|\cdot|$ is the amplitude of a complex quantity or the cardinality of a set; $\Re(\cdot)$ and $\Im(\cdot)$ are the real and imaginary parts of a complex-valued quantity; $(\cdot)^\mathrm{H}$ is the conjugate transpose of a vector or a matrix; $\mathscr{CN}(\mu,\sigma^2)$ denotes a complex Gaussian random variable with mean μ and variance σ^2.

2. System Model

Consider an $N_\mathrm{T}\times N_\mathrm{R}$ SM system with constellation $S=\{s_1,s_2,\ldots,s_{N_\mathrm{M}}\}$. In each time slot, the incoming data bits are rearranged into blocks of $\log_2 N_\mathrm{T}N_\mathrm{M}$ bits, in which $\log_2 N_\mathrm{T}$ bits are used to select the activated TA and $\log_2 N_\mathrm{M}$ bits are used to select the transmit symbol $s_\mathrm{m}\in \mathrm{S}$, $m\in\{1,2,\ldots,N_\mathrm{M}\}$. Hence, the system model for SM systems can be represented by

$$\mathbf{r}=\mathbf{G}\cdot\mathbf{s}+\mathbf{w}, \tag{1}$$

where $\mathbf{r}\in\mathbb{C}^{\mathbb{N}_\mathrm{R}}$ is the received signal vector; $\mathbf{s}\in\mathbb{C}^{\mathbb{N}_\mathrm{T}}$ is the transmit symbol vector, whose element is s_m at the lth position and zero at the other positions; $\mathbf{G}\in\mathbb{C}^{\mathbb{N}_\mathrm{R}\times\mathbb{N}_\mathrm{T}}$ and $\mathbf{w}\in\mathbb{C}^{\mathbb{N}_\mathrm{R}}$ are the channel matrix and the noise vector, whose elements follow the circularly symmetric complex Gaussian distributions with $\mathscr{CN}(0,1)$ and $\mathscr{CN}(0,\sigma^2)$, respectively. The system model expressed in (1) can be reshaped as

$$\mathbf{y}=\begin{bmatrix}\Re(\mathbf{G}) & -\Im(\mathbf{G})\\ \Im(\mathbf{G}) & \Re(\mathbf{G})\end{bmatrix}\cdot\begin{bmatrix}\Re(\mathbf{s})\\ \Im(\mathbf{s})\end{bmatrix}+\begin{bmatrix}\Re(\mathbf{w})\\ \Im(\mathbf{w})\end{bmatrix}=\mathbf{H}\cdot\mathbf{x}+\mathbf{n}, \tag{2}$$

where $\mathbf{H}\in\mathbb{R}^{2N_\mathrm{R}\times 2N_\mathrm{T}}$, $\mathbf{x}\in\mathbb{R}^{2N_\mathrm{T}}$, and $\mathbf{n}\in\mathbb{R}^{2N_\mathrm{R}}$. Since only one TA is activated in each time slot, the system model expressed in (2) can be simplified as

$$\mathbf{y}=\begin{bmatrix}\mathbf{h}_\mathrm{l} & \mathbf{h}_{\mathrm{l}+\mathrm{N_T}}\end{bmatrix}\cdot\begin{bmatrix}\Re(\mathrm{s}_\mathbf{m})\\ \Im(\mathrm{s}_\mathbf{m})\end{bmatrix}+\mathbf{n}, \tag{3}$$

where $\mathbf{h}_\mathrm{l}$ is the lth column of $\mathbf{H}$.

It follows from (3) that the optimal ML-based demodulator can be formulated as

$$\left(\hat{l},\hat{s}_{\mathrm{m}}\right)=\arg\min_{(l,s_{\mathrm{m}})\in\Lambda}\left\|\mathbf{y}-\left[\,\mathbf{h}_{l}\ \ \mathbf{h}_{l+N_{\mathrm{T}}}\right]\cdot\begin{bmatrix}\Re\left(s_{\mathrm{m}}\right)\\ \Im\left(s_{\mathrm{m}}\right)\end{bmatrix}\right\|_{F}^{2}=\arg\min_{l,s_{\mathrm{m}}\in\Lambda}A^{(l,s_{\mathrm{m}})},\quad(4)$$

where Λ denotes the set containing all possible transmit antenna indices and complex constellation points, $\Lambda=\left\{(l,s_{\mathrm{m}})\mid l\in\{1,2,\ldots,N_{\mathrm{T}}\},s_{\mathrm{m}}\in\left\{s_{1},s_{2},\ldots,s_{N_{\mathrm{M}}}\right\}\right\}$, $A^{(l,s_{\mathrm{m}})}=\sum_{k=1}^{2N_{R}}|y_{k}-h_{k,l}\cdot\Re(s_{\mathrm{m}})-h_{k,l+N_{\mathrm{T}}}\cdot\Im(s_{\mathrm{m}})|^{2}$, and $h_{k,l}$ is the $(k,l)^{th}$ entry of matrix $\mathbf{H}$.

3. MBS Detector

According to Kim and Yi [20], the detection of the SM signal can be regarded as a tree with N_{T} subtrees and $2N_{\mathrm{R}}$ layers, where each subtree has N_{M} complete paths from the root node to the leaf nodes. For ease of understanding, we give an illustration (Figure 1) for the idea of the MBS detector. Suppose we have a 2×2 SM system with 4QAM modulation; thus the search tree has 4 layers and 8 branches. 4 branches of each subtree (TA) correspond to 4 symbols from the 4QAM constellation. We define the branch metric of node (l,s_{m}) at the kth layer as the squared Euclidean distance between the received and the transmit signals, which can be denoted as $B_{k}^{(l,s_{\mathrm{m}})}=|y_{k}-h_{k,l}\cdot\Re(s_{\mathrm{m}})-h_{k,l+N_{\mathrm{T}}}\cdot\Im(s_{\mathrm{m}})|^{2}$. The accumulated metric of node (l,s_{m}) at the kth layer is the summation of the branch metric at the kth layer and the accumulated metric at $(k-1)$th layer, which can be expressed as $A_{k}^{(l,s_{\mathrm{m}})}=B_{k}^{(l,s_{\mathrm{m}})}+A_{k-1}^{(l,s_{\mathrm{m}})}$.

In the first subtree, the M_k nodes in the kth layer with the smallest accumulated metrics are kept as the candidate nodes for the next layer. At the last layer, the node with the smallest accumulated metric is considered as the solution in the first subtree. The smallest accumulated metric and its corresponding TA index and the transmit symbol are represented by ρ_{Ω} and $\Omega=\left\{\hat{l},\hat{s}_{\mathrm{m}}\right\}$, respectively. In the subsequent subtrees, ρ_{Ω} and Ω are gradually updated. In the kth layer, at most M_k nodes with the accumulated metrics smaller than the threshold value, ρ_{Ω} are selected as the survival branches for the next layer. If the accumulated metric is not less than ρ_{Ω}, the search of the current branch is terminated. Otherwise, we should continue to search the next branch. If the accumulated metric is smaller than ρ_{Ω} at the last layer, ρ_{Ω} and Ω are updated. Repeat the search process until all subtrees are checked. The cross symbol in Figure 1 shows that the branch with the accumulated metric not less than the threshold value ρ_{Ω} is pruned.

4. Proposed Ordering MBS-Based Detectors

In MBS detector, the detection of the SM signal is in the ascending order of the subtree indices and the RA indices. Essentially, the MBS detector is used to calculate (4) and select partial reserved nodes. When the number of the reserved nodes is a constant, it is of great importance to choose which nodes. In other words, the computation order of (4) can directly affect the BER performance and the computational complexity. In this section, in order to investigate the influence of different detection orders on the BER performance and computational complexity, we propose three ordering MBS-based detectors by adjusting the search orders.

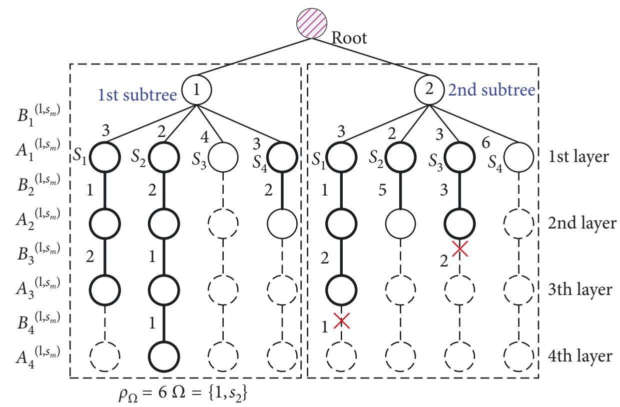

Figure 1: The tree structure of 2×2 SM with 4QAM and $M=[3,2,2,1]$.

4.1. Ost-MBS Detector. The computational complexity of the MBS detector is reduced by pruning the branches, whose accumulated metric is larger than or equal to ρ_{Ω}. However, the MBS algorithm does not take into account the influence of subtree search order on the computational complexity. If the optimal solution stands in the first subtree, only fewer nodes are searched in the subsequent subtrees. But, if the optimal solution exists in the last subtree, we need to search more nodes in the top $N_{\mathrm{T}}-1$ subtrees. In other words, searching firstly from the subtree where the optimal solution most probably belongs to can reduce total searches of nodes in the subsequent subtrees. Thus, it can decrease the computational complexity. That is, the searching order of subtrees directly affects the computational complexity. We propose the ost-MBS detector, which estimates the optimal solution by rearranging the order of subtrees. In the first stage, we order the TA indices based on the suboptimal antenna detection algorithm. In the second stage, we first search from the most probable TA index, the estimated solution is obtained by searching all N_{T} subtrees. The proposed ost-MBS detector works as follows.

Stage 1. Reorder the TA indices in descending order using the suboptimal modified maximum ratio combining (MMRC) algorithm proposed in [5]. The MMRC filter outputs are obtained by

$$t_{j}=\frac{\left|\mathbf{h}_{j}^{H}\mathbf{y}\right|}{\left\|\mathbf{h}_{j}\right\|_{F}},\quad j=1,\ldots,N_{\mathrm{T}}.\quad(5)$$

The higher the value of t_j, the more likely it is that the jth TA was the one activated. The TA indices are sorted in descending order by t_j. The set of ordered TA indices is denoted by $\mathbf{u}$. Suppose $\mathbf{T}=[t_{1},t_{2},\ldots,t_{N_{\mathrm{T}}}]^{\mathrm{T}}$, the ordered TA indices can be obtained as

$$\mathbf{u} = \left(u_1, u_2, \ldots, u_{N_\mathrm{T}}\right) = \operatorname{argsort}(\mathbf{T}), \tag{6}$$

where sort$(\cdot)$ denotes a descending order function and u_1 and u_{N_T} are the indices of the maximum and minimum elements of $\mathbf{T}$, respectively. In other words, u_1 and u_{N_T} are the most likely and the least likely estimates of the TA index, respectively.

Stage 2. Determine the TA index and the transmit symbol using the MBS detector.

4.2. Oy-MBS Detector. Since only one TA is activated at one time slot, assuming that the lth antenna sends symbol s_m, the received signal can be expressed as

$$r_i = g_{l,i} \cdot s_\mathrm{m} + w_i, \quad i = 1, \ldots, N_\mathrm{R}. \tag{7}$$

Each signal at the receiver is related to the channel gain, the transmit symbol, and the white Gaussian noise. Due to the difference of the channel gain and noise in each channel, the channel gain and noise together determine the amplitude of the received signal. Generally speaking, a strong received signal contributes to the demodulation. In the MBS detector, the TA index and the transmit symbol are estimated in ascending order of the RA index from the root node to the leaf nodes. However, the effect of search order on the BER is not taken into account. For this reason, we propose the oy-MBS detector, which detects in descending order of the amplitude of the received signal. The oy-MBS detector is described in detail as follows.

Stage 1. Sort the RA indices in descending order by $|r_i|$. Let $\mathbf{Z} = [z_1, z_2, \ldots, z_{N_\mathrm{R}}]^\mathrm{T}$, where $z_i = |r_i|$, and the set of the ordered RA indices can be obtained as

$$\tilde{v} = \left(\tilde{v}_1, \tilde{v}_2, \ldots, \tilde{v}_{N_\mathrm{R}}\right) = \operatorname{argsort}(\mathbf{Z}), \tag{8}$$

where $\tilde{v}_1$ and $\tilde{v}_{N_\mathrm{R}}$ are the indices of the maximum and minimum values in $\mathbf{Z}$. The layer search order set $\mathbf{v}$ can be obtained as

$$\begin{aligned} v_{2i-1} &= \tilde{v}_i, \\ v_{2i} &= N_\mathrm{R} + \tilde{v}_i, \quad i = 1, \ldots, N_\mathrm{R}. \end{aligned} \tag{9}$$

The new search tree, whose $(2i-1)^{th}$ and $(2i)^{th}$ layers correspond to the $\tilde{v}_i^{th}$ RA, can be built by exchanging the layers of Figure 1.

Stage 2. Determine the TA index and the transmit symbol using the MBS detector.

4.3. Ost-Oy-MBS Detector. In ost-MBS detector, all N_T subtrees are searched in descending order of $|\mathbf{h}_j^H \mathbf{y}|/||\mathbf{h}_j||_\mathrm{F}$. That is to say, we first detect the most probable subtree and then detect the most impossible subtree at last. To some extent, the computational complexity can be reduced. The oy-MBS detector performs the MBS detection in descending order of the received signals amplitude, which can improve the BER performance. In this subsection, we combine the detection orders of ost-MBS and oy-MBS detectors together. We propose the ost-oy-MBS detector whose detection order is based on the subtrees and the received signals. We detect all subtrees in descending order of $|\mathbf{h}_j^H \mathbf{y}|/\|\mathbf{h}_j\|_\mathrm{F}$ and detect each layer of subtrees in descending order of $|r_i|$.

The detection process of the proposed ordering MBS-based detectors is summarized in Algorithm 1. In Algorithm 1, lines 2–6 and 7–11 correspond to subtree-ordering and receiver-ordering strategies, respectively, whereas lines 12–28 describe the detection process of the MBS detector.

5. Simulation Results

In this section, the computational complexity and the BER performance of the proposed detectors and the MML, MBS, ML, simplfied OD, simplified MD, SLCD, and ASLCD detectors are compared. The label, (N_1, N_2) OD, denotes the simplified OD detector with N_1 level-one subsets and N_2 level-two subsets. The label, $(N, N_1$, and $N_2)$ MD, stands for the simplified MD detector with N estimated transmit antennas, N_1 level-one subsets, and N_2 level-two subsets. The label, (N) SLCD, denotes the simplified low-complexity detection with N most probable estimates. The label, (N, α) ASLCD, stands for the adaptive low-complexity detection with N most probable estimates and threshold coefficient α. The ideal channel state information (CSI) is assumed available at the receiver. In the simulation, the signal-to-noise ratio (SNR) is the ratio of the signal power to the noise power, i.e., $\rho = (\sum_{m=1}^{N_\mathrm{M}} s_m^2/N_\mathrm{M})/\sigma^2$.

To validate the BER performance of the abovementioned detectors, the theoretical bound [17] is drawn in BER simulation figures. Figures 2–3 compare the BER performance and the computational complexity of the proposed detectors and existing detectors for 4×4 64QAM SM systems with $M = [64, 26, 26, 8, 8, 2, 2, 1]$ in MBS and the proposed detectors and $M = [256, 104, 104, 32, 32, 8, 8, 1]$ in the MML detector. The BER performance and computational complexity of the proposed detectors are shown in Figures 4–5 with $M = [16, 10, 8, 4, 4, 2, 1, 1]$ in MBS and the proposed detectors and $M = [128, 80, 64, 32, 32, 16, 8, 1]$ in the MML detector for 8×4 16QAM SM systems. Since each level-two subset must contain more than four signals (i.e., the modulation order $N_\mathrm{M} > 16$) in OD and MD detectors, the simulation curves of OD and MD detectors are not listed in Figures 4–5.

To estimate the computational complexity of an algorithm, we define the computational complexity as the total number of the real-valued multiplications/divisions required in the detection process.

In the MML algorithm, we need to compute the accumulated metrics of all $N_\mathrm{T} N_\mathrm{M}$ nodes in the first layer and compute the accumulated metrics of M_{k-1} nodes in the kth $(2 \le k \le 2N_\mathrm{R})$ layer. Since computing the accumulated metrics of one node needs 3 real multiplications, the computational complexity of the MML detector is $3N_\mathrm{T} N_\mathrm{M} + \sum_{i=1}^{2N_\mathrm{R}-1} 3M_i$.

Since the ML detector computes the accumulated metrics of all nodes in the tree, the computational complexity of the ML detector is $6N_\mathrm{T} N_\mathrm{R} N_\mathrm{M}$.

According to Section 3.2 and 3.3 in [16], we can obtain the computational complexity of OD and MD. The

Initialization: $\Lambda_l = \{(l, s_m) | s_m \in \{s_1, \cdots, s_{N_M}\}\}$, for each $l \in \{1, \cdots, N_T\}$.
if subtree-ordering is used **then**
  $\mathbf{u} = (u_1, \ldots, u_{N_T}) = \text{argsort}(|\mathbf{h}_j^H \mathbf{y}| / \|\mathbf{h}_j\|_F)$
else
  $\mathbf{u} = (1, \cdots, N_T)$
end if
if receiver-ordering is used **then**
  $\tilde{v} = (\tilde{v}_1, \ldots, \tilde{v}_{N_R}) = \text{argsort}(|r_i|)$, obtain layer search order $\mathbf{v}$ by Equation (9).
else
$\tilde{v} = (1, \cdots, N_R)$, obtain layer search order $\mathbf{v}$ by Equation (9).
end if
$\rho_\Omega = 0, \Omega = \phi$.
for $i = 1N_T$
  $\Psi = \Lambda_{u_i}$, $[(p,q), \text{value}] = \text{search subtree}(\Psi \mathbf{v})$
  $\Omega = (p,q)$ and $\rho_\Omega = \text{value}$, if (p,q) is not null and value $< \rho_\Omega$.
end for
End the algorithm by returning Ω corresponding to ρ_Ω.
function search subtree($\Psi, \mathbf{v}$)
  For each $(p,q) \in \Psi$, $A^{(p,q)} = 0$.
  for $i = 12N_R$
    $k = v_i$, for each $(p, q \in \Psi)$, $A^{(p,q)} = A^{(p,q)} + B_k^{(p,q)}$.
    while $i < 2N_R$ and $|\Psi| > M_i$
      $\Psi = \Psi - \{(p,q)\}$, where $(p,q) = \underset{(p,q)\in\Psi}{\text{argmax}} A^{(p,q)}$.
    end while
    For each $(p,q) \in \Psi$, $\Psi = \Psi - \{(p,q)\}$, if $A^{(p,q)} \geq \rho_\Omega$.
  end for
  return $[(p,q), \text{value}] = \underset{(p,q)\in\Psi}{\text{argmin}} A^{(p,q)}$, if Ψ not empty; otherwise return null.
end function

Algorithm 1: Ordering-aided MBS-based detectors.

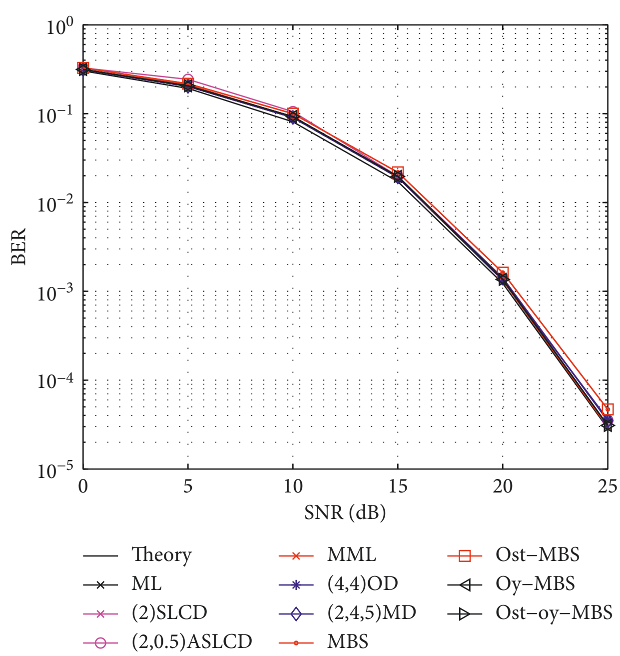

Figure 2: The BER performance of the proposed detectors with $N_T = 4, N_R = 4$, and 64QAM modulation.

computational complexity of the (N_1, N_2) OD detector and (N, N_1, N_2) MD detector is $10N_R(4N_T + 4N_1 + N_M N_2/16)$ and $10N_R(N_T + 4N + 4N_1 + N_M N_2/16)$, respectively.

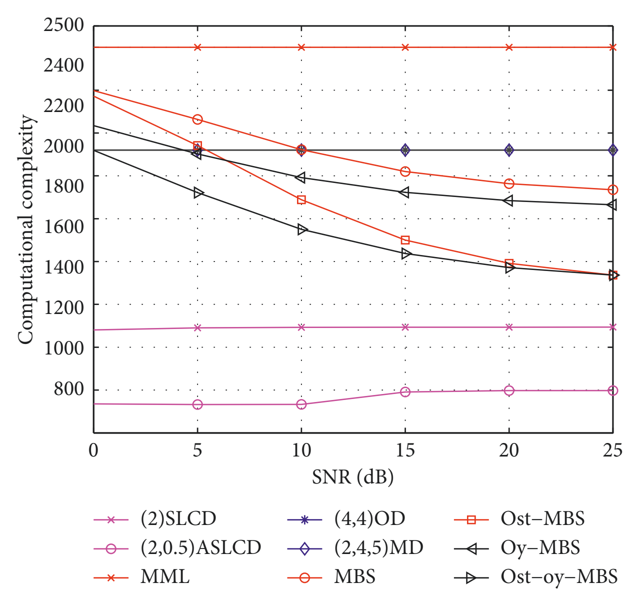

Figure 3: The computational complexity of the proposed detectors with $N_T = 4, N_R = 4$, and 64QAM modulation.

According to Section 3.5 and 3.6 in [17], the computational complexity of SLCD and ASLCD depends on the parameter N and the size of estimated transmit symbol set. Since the size of estimated transmit symbol set is not constant, the computational complexity can only be obtained by simulation.

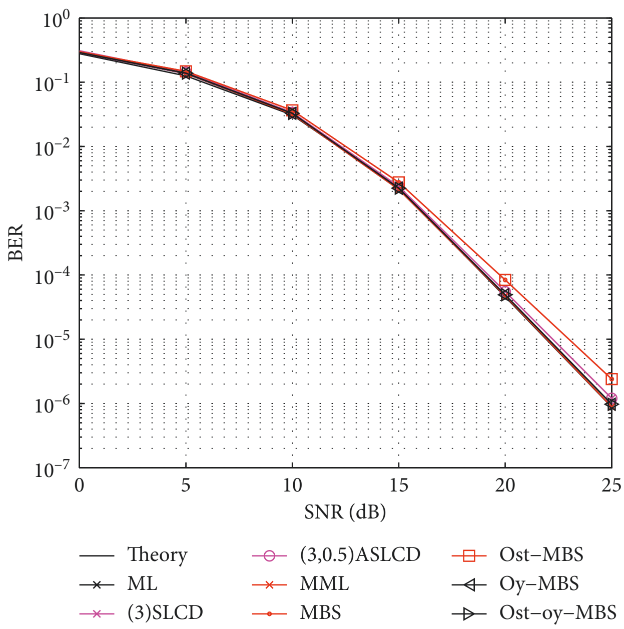

FIGURE 4: The BER performance of the proposed detectors with $N_T = 8, N_R = 4$, and 16QAM modulation.

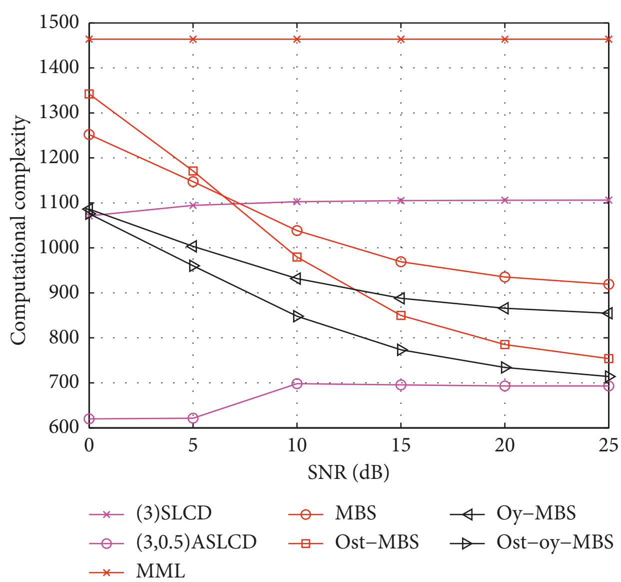

FIGURE 5: The computational complexity of the proposed detectors with $N_T = 8, N_R = 4$, and 16QAM modulation.

From the above analysis, we can conclude that the computational complexity of MML, OD, and MD detectors is lower than that of the ML detector but with a BER performance loss. Meanwhile, the complexity of MML, OD, MD, SLCD, and ASLCD depends on the preset parameters.

The computational complexity of the proposed MBS-based detectors includes the number of real-valued multiplications of computing $|\mathbf{h}_j^H \mathbf{y}|/||\mathbf{h}_j||_F$ and $|r_i|$ in stage 1, and the number of real-valued multiplications of MBS detector in stage 2. The computational complexity of stage 1 can be easily obtained by calculation. The computational complexity of stage 2 depends on the number of retained nodes. In MBS and the proposed MBS-based detectors, the parameter M_k is at most the number of retained nodes in each layer. That is, the number of retained nodes is not fixed. Therefore, the computational complexity of proposed MBS-based detectors can only be obtained by simulation.

From the above simulation curves, we can draw the following conclusions:

(1) The computational complexity of MBS, OD, MD, SLCD, ASLCD, MML, and the proposed detectors is lower than that of the ML detector. Since the number of retained nodes of MML, OD, and MD detectors is fixed under different SNRs, the computational complexity does not change with the SNR. The computational complexity of SLCD, ASLCD, MBS, ost-MBS, oy-MBS, and ost-oy-MBS detectors changes with the SNR.

(2) The BER performance of ost-MBS detector is the same as that of the MBS detector, and the complexity is lower than that of the MBS detector. The ost-MBS detector only changes the search order of subtrees and does not affect the detection performance. Therefore, the ost-MBS and MBS detectors have the same BER performance. The ost-MBS detector searches the subtrees in the descending order of $|\mathbf{h}_j^H \mathbf{y}|/\|\mathbf{h}_j\|_F$, which increases the probability of the optimal solution in the first subtree. Since the accumulated metric of the optimal solution is minimal, the number of retained nodes can be reduced in the subsequent subtrees, thus reducing the total computational complexity.

(3) The BER performance of the oy-MBS detector is superior to that of the MBS detector. The oy-MBS detector estimates the solution in the descending order of the received signals amplitude. To some degree, the strong received signal contributes to the demodulation. Therefore, compared with the MBS detector, the oy-MBS detector has better BER performance. Meanwhile, we also notice that the sorting strategy of oy-MBS also reduces the computational complexity.

(4) The ost-oy-MBS detector and oy-MBS detector have the same BER performance, which is superior to the MBS detector. The ost-oy-MBS detector has the advantages of both ost-MBS and oy-MBS detectors. That is, the ost-oy-MBS detector has the best BER performance and the lowest computational complexity among the proposed MBS-based detectors.

(5) Under the current simulation conditions, the BER performance of OD, MD, SLCD, ASLCD, MML, and ost-oy-MBS detectors is almost the same as the ML detector. Compared to OD and MD detectors, MBS-based detectors have a lower computational complexity in moderate-to-high SNRs.

6. Conclusion

In this paper, novel ordering MBS-based detectors for SM systems are proposed to improve the BER performance and reduce the computational complexity. The ost-MBS detector first searches each subtree from the most probable TA. Compared to the MBS detector, it has the lower computational complexity. The oy-MBS algorithm detects each subtree in the descending order of the received signal amplitude. The BER performance of the oy-MBS detector is superior to that of the MBS detector. The ost-oy-MBS detector combined the orders of ost-MBS and oy-MBS detectors. Among all proposed MBS-based methods, the ost-oy-MBS detector has the best BER performance and the lowest computational complexity. Meanwhile, we notice that the computational complexity and the BER performance of OD, MD, SCLD, ASLCD, MML, and MBS-based detectors depend on the preset parameters. Regrettably, how to select the parameters in the proposed MBS-based detectors can only be obtained by simulation. Next, we will study how to select parameters and try to give a theoretical derivation.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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